ESSAYS ON THE EMPIRICAL ANALYSIS OF SHIP CHARTERING STRATEGIES

by

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To my family

Alexandros, Rosalia and Amelia

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Declaration

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Abstract

The freight market is one of the most important and vital one in the shipping industry, since its behaviour and state affect the majority of the decisions made in the industry. Considering the important aspects of the freight rates and different types/ sizes of ships in the dry bulk shipping market, this thesis attempts to increase the understanding of the dynamics of physical hedging instruments and provide robust chartering strategies that can be used to increase the profitability of these operations. The chartering strategies are defined as the best mix of contracts that need to be signed in order to optimise the revenues generated by operating in the freight market. The first empirical part (Chapter 2) assesses a widely used approach (i.e. technical trading rules) and examines whether it can allow identifying optimal chartering strategies. Precisely, the study examines the types and aspects of strategies that can formulated while also analysing their profitability. The results show that the evolution of the freight rates is the key factor when attempting to make an optimal decision. The fluctuations in freight rates values are usually due to changes in the demand and supply levels therefore, a new macroeconomic dataset is constructed in Chapter 3 based on a high number of various demand and supply variables that can affect the level of freight rates. The empirical findings highlight important dynamic interactions between the macroeconomic variables and the freight rate curve while it is also observed that a significant percentage of the freight rate variation is attributed to fluctuations in the supply macroeconomic variables. Finally, in Chapter 4 the thesis analyses the relationship between risk and return in shipping investments from a financial and managerial perspective in order to understand the firms' competitive behaviour. The empirical results indicate that the nature of the risk and return relationship is affected by the risk measures, return measures, subsamples, market conditions and macroeconomic variables associated with the freight rate cycle. Overall, the empirical findings of this thesis have important implications on the freight market trading and risk management as well as chartering operations such as the type of contract that should be signed depending on different market conditions.

Chapter 1

Introduction and Summary of the Thesis

The aim of this chapter is to present the motivation, aim, objectives and contributions of the thesis while also provide a brief description of the shipping industry and the main problem that is being investigated. Additionally, an overview of the main empirical results and a description of the content of each section is also provided.

1.1 Motivation and Aim of the Thesis

The shipping industry plays an important role in the world economy and more specifically in the world trade since approximately 90% of the world trade is carried at sea (UNCTAD, 2015). Each commodity being transported has bespoke characteristics and requires a specific type vessel to be transported around the world. This implies that there is a large market for overseas transportation and subsequently many shipping companies (operators). The shipping companies can be distinguished into three groups based on their mode of operation: *liner, tramp* and *industrial* (Lawrence, 1972).

The *industrial operators* own the cargo and try to minimise the cost of transporting it from port A to port B whilst *liner shipping* operates in accordance to pre-published schedules. Finally, the *tramp* or *bulk*[1] *shipping operators*, usually referred to as *taxicab* since ships follow the available cargoes (Stopford, 2009). Bulk operators usually operate under long-term contracts and take on additional cargoes as these become available in order to maximise their profits. Additionally, the *bulk shipping market* consists of two major submarkets: *(i)* the *liquid bulk cargo market* (i.e. crude oil and oil products) and *(ii)* the *dry bulk cargo market* (i.e. iron ore, grain, coking coal and thermal coal) with the latter being the main focus of this study.

[1] According to Harlaftis and Theotokas (2002), the *tramp shipping* was renamed to *bulk shipping* after the landmark decade of 1970's when the market was mainly characterised by the cargoes that were transported instead of the types of ships. Therefore, the term *bulk shipping* will be used throughout this thesis.

The purpose of this thesis is to investigate the economic performance and identify important characteristics of the *ship chartering strategies* that affect the optimisation and efficiency of dry bulk shipping companies. Tsolakis (2004) and Stopford (2009) state that due to the integration existing between the shipping markets, companies can take advantage of the revenues generated from chartering operations by covering their financial costs (i.e. costs of operating, maintenance, financing fleet, etc.), while an effective scheduling of chartering operations could also lead to more efficient investment or divestment decision (Christiansen et al, 2007).

The supply and demand levels are the two most important factors that determine the freight rates. As a simplified example, when there is an excess number of vessels in the market (excess supply), this means that the demand level is low and thus the freight rates are also low as there too many vessels to cover the current demand. Additionally, this results in both low ship prices and number of orders for newbuild vessels. On the other hand, when the supply level is low, the freight rates are high since there are not enough vessels to cover the demand. This also results in an increase in ship prices and number of orders placed for newbuild vessels. The focus of this study is on the freight market since it is the one that links all markets together which highlights the importance of understanding and analysing it in depth.

The problem that ship-owners face is that they own a specific number of ships of set type, size, free of cargo and therefore need to decide which type of contract each ship will be assigned to. This problem is also known as *ship chartering problem*. There are different types of contractual agreements and each of them distributes costs and responsibilities in a slightly different way (Stopford, 2009). More specifically, the freight market is divided into the *derivatives*, *voyage* and *time-charter market* (Stopford, 2009). Therefore, one of the questions that arises and needs to be investigated is what ship chartering decisions are available for each of the three contract. The contractual agreements options are:

1. *Voyage Charter:* the ship-owner agrees to carry a specific cargo on a specific ship for a negotiated price per tonne covering all costs (i.e. operating and voyage)
2. *Time Charter:* an agreement between the owner and charterer to hire the ship and crew for a daily, monthly or yearly fee. In this case, the ship-owner is responsible for the capital costs and operating expenses whilst the

chartering company covers the voyage costs. More specifically, time charter can be distinguished into:

a. *Trip Time Charter* (*TTC*) or *spot* contract whose duration is equal to the one of a single voyage (i.e. 2 months). A *spot* contract allows a ship-owner to take advantage of the positive movements of the spot market but exposes him to the risk related to a sudden decrease of the freight rates.

b. *Period Time Charter* (*PTC*) contract agreed between the ship-owner and the charter that can last for period of months or years (i.e. 6 months – *PTC6m* or 12 months – *PTC12m* or 36 months – *PTC36m*) and cover multiple voyages. Although a *PTC* contract guarantees a fixed freight rate for a predetermined period it does not allow a ship-owner to benefit from a potential increase in freight rates.

3. *Contract of Affreightment (CoA)* where a ship-owner agrees to carry a series of cargo parcels for fixed price per tonne, while the ship-owner covers all the costs.
4. *Bare Boat Charter* that allows a shipping company to have full operational control over the ship without owning it (Stopford, 2009).

The main focus of this thesis is on the voyage and time charter freight contract, which are the most commonly used ones in the industry. The ability to choose between freight contracts with different maturities offers flexibility to both ship-owners and charterers in terms of chartering activities (strategies) but simultaneously introduces significant risks. For instance, the spot (short-term) market is flexible but poses significant price risks while the time charter market is less liquid but at the same time guarantees a fixed freight rate for a set period of time (i.e. 6-, 12- or 36-months).

Designing chartering strategies in the dry bulk shipping market is a challenging task due to factors such as the volatility and uncertainty of the freight market, market conditions, risk preferences, number of contract options and available vessels that can be contracted as well as their location and condition etc. In other words, the high number of factors that affect the chartering strategies and the fact that it can be expanded indefinitely makes it difficult to identify the best option to be signed at the right time.

The focus of the literature on maritime economics has mainly been on the relationship between period time charter rates, trip time charter freight rates and the efficiency of the freight derivatives market. There are only a few studies that attempt to assess how to maximise the revenues generated when operating in the physical market by constructing and analysing a portfolio containing trip time charter contracts and period time charter contracts with different maturities.

Therefore, the main motivation of this thesis is to use multiple methodological approaches with a view to address several issues of the ship-chartering problem for dry bulk shipping companies. The main reason for assessing multiple models for the ship-chartering problem comes from the shipowners' need to ensure an accurate estimation of risk measures, evaluation of investment policies while also successfully implement hedging strategies. Therefore, this thesis presents three closely related essays on the ship-chartering problem, dealing with several factors and issues related to the problem.

As previously mentioned, tackling the ship-chartering problem is a challenging task due to the high number of factors that need to be considered for an optimal decision to be made. Since it would not be feasible to investigate all potential factors at the same time, the study focuses on the three that present a higher academic interest. The triple aim of this thesis is to first identify the best time and type of decision that needs to be made depending on the freight rate level. The second goal is to analyse how the demand and supply factors affect the term structure of freight rates, while the third and final one attempts to explore the dynamic interrelationships between freight rates returns and freight volatilities.

1.2 Thesis Objectives and Contributions

The main objectives of this thesis is first to propose a framework for analysing and modelling the economic performance of ship chartering strategies in the dry bulk shipping market. The second objective is to examine whether the methodological approaches used are able to improve the economic performance of chartering operations, while also identify important characteristics of the ship-chartering problem. Furthermore, this thesis consists of three essays that discuss both theory and applications of the term structure of freight rates with a special focus on identifying methodological approaches that can optimise the profitability of the ship chartering strategies in the dry bulk freight market.

The second chapter, *Investigating the Profitability of Ship Chartering Strategies in the Dry Bulk Market using Market Timing Rules*, is the first empirical chapter of the thesis that examines the profitability of multiple technical trading rules. This chapter, comprehensively analyses the technical trading rules in the dry bulk freight market in order to assess the profitability and provide further insights on what makes them profitable at different times. In addition, the analysis focuses on the difference in terms of profitability between *active* and *passive chartering strategies* that affect the optimisation and efficiency of dry-bulk shipping companies. A *chartering strategy* is defined as a sequence of different contracts types that shipping companies select in order to maximise their operating revenues. A *passive* (or buy-and-hold or benchmark) *strategy* is based on the Efficient Market Hypothesis (EMH) and implies that ship-owners operate their vessels under a single type of contract throughout the planning horizon. An *active strategy* suggests that ship-owners only sign the best performing contracts and try to avoid the worst performing ones that carry significant freight rate risks.

Technical analysis has been widely used in the stock and exchange markets (Park and Irwin (2007); Hsu et al (2016) etc.) however when it comes to the shipping markets their application has been very limited. Previous attempts to apply technical analysis were generally either restricted to the freight futures market (Goulas and Skiadopoulos, 2012 and Nomikos and Doctor, 2013) or only focused on determining the optimal investment decisions in the sale and purchase of vessels (Norman, 1982; Adland, 2000; Adland and Koekebbaker, 2004 and Alizadeh and Nomikos, 2007), except from Adland and Strandenes (2006) and Alizadeh et al (2007) who focused on the physical freight market.

Chapter 2 contributes to the existing literature by initially proposing a methodology (i.e. technical trading rules) to construct and evaluate robust chartering strategies. Additionally, the economic significance of an extended universe of ship-chartering trading rules is assessed using the spread between spot and period charter rates across various vessel types and contracts with different maturities in the dry-bulk market.

Thirdly, existing research tend to only consider a small number of contracts (i.e. exclusively spot or spot and period time charter without specifying the exact duration of a period charter contract when the latter is identified as the most profitable choice), limited sets of technical trading rules, short sample periods, simple performance metrics and basic testing methods which may be subject to data-snooping bias. Therefore, there is an opportunity to develop a large-scale empirical design to investigate if technical analysis can identify profitable chartering strategies on the physical freight market.

Additionally, this study investigates the inefficiencies in the freight market and whether these can generate economically significant returns. More specifically, the EMH implies that chartering strategies based on available market information do not outperform the buy-and-hold (passive) strategy. Therefore, any comparison of risk-adjusted returns between an active and a passive strategy provides a direct test of the EMH. Finally, from a practical perspective, the outcomes of this study increase the understanding and operating performance of the decision making process of ship chartering operators whilst providing assistance in the sale and purchase, shipbuilding and demolition shipping market decisions.

In the third chapter, *The Effects of Macroeconomic Variables on the Term Structure of Freight Rates*, the purpose is to understand how a large number of macroeconomic and latent variables affect the term structure of freight rates. Chapter 2 showed that the evolution of freight rates is the key factor when attempting to make an optimal decision, which also underlines the importance to identify the macroeconomic variables affect the level of freight rates, since the literature shows that the level of freight rates is determined by the demand for trade, the supply of ships and other macro-economic factors of the freight market (Hawdon, 1978; Beenstock and Vergottis, 1989a,b; Evans and Marlow, 1990; Beenstock and Vergottis, 1993).

Multiple studies focus on modelling the demand and supply for transportation using different methodological approaches (e.g. static supply/ demand models, stochastic models, econometric models amongst others) that only focused on the dynamic interactions between shipping markets (Koopmans, 1939; Zannetos, 1966; Hawdon, 1978; Charemza and Gronicki, 1981; Strandenes, 1984; Beenstock, 1985; Beenstock and Vergottis, 1989a,b, 1993, Tvedt, 2003, Tsolakis, 2005 and Adland and Strandenes, 2007) or between the shipping stock market and a limited number of macroeconomic variables (Grammenos and Arkoulis, 2002, Drobetz et al, 2010, 2012; Kalouptsidi, 2013; Greenwood and Hanson, 2014).

All these studies found dynamic interactions between shipping markets, while also they found that macroeconomic variables can explain the movements in the shipping stock market, however they did not assess how the macroeconomic variables relate to the freight rate curve. Therefore, Chapter 3 attempts to grow the literature by investigating the impact of a large number of macroeconomic variables on the term structure of freight rates and the potential existence of dynamic interactions between them.

Rather than consider term structure models from a more technical and finance perspective, the aim is to focus on the interactions between macroeconomics, monetary policy, and the term structure. Therefore, the freight rates are fitted to existing macro-finance models and their forecasting performance is compared within a *Vector Autoregressive* (VAR) framework that contains two existing VAR term structure models extracted from the existing literature (i.e. the latent factor freight rate model without macroeconomic variables and the *Factor-Augmented Vector Autoregressive* – $FAVAR$ model). The purpose of the VAR framework is to identify the impact of macroeconomic factors across the term structure and recognise which ones are more important in terms of explaining freight rates variations throughout the maturity spectrum.

This study attempts to provide a holistic picture of what affects the freight rates by exclusively incorporating all main demand and supply variables that are directly related to the shipping industry. These variables (listed in Table 3.2 and 3.4) produce a total of 59 variables (34 demand and 25 supply variables) which is significantly higher than the ten variables included in the study by Drobetz et al (2010) meaning that the current results provide a more robust and accurate view of the freight rates' behaviour. The large dataset mentioned above is then reduced to 10 main factors (4 demand and 6 supply factors). The goal is to be able to apply for the first time the FAVAR and dynamic latent factor models to the shipping industry in order to accurately analyse the reasons behind the freight rates movements since these two models (which have been proven to be accurate tools for assessing the dynamic interactions between the macroeconomic variables and the freight rates) have only been used in the financial sector.

The fourth chapter, *Prospect Theory and the Conditional Relationship between Risk and Return in the Dry Bulk Shipping Market*, focuses on the nature of the *relationship* between *risk* and *return* in the dry bulk freight market in order to understand firms' competitive behaviour. Most existing studies (Kavussanos and Marcoulis, 2000a,b; Grammenos and Arkoulis, 2002; Syriopoulos and Roumpis, 2009 and Drobetz et al. 2010, 2012) support that the risk and return relationship is positive as indicative in the context of the Capital Asset Pricing Model (CAPM). However, they do not account for the time to build effect nor access the relationship under various scenarios. Therefore, the purpose is to determine the nature of the risk and return relationship and to prove that this relationship is robust using multiple risk and return measures, subsamples, market conditions and macroeconomic variables associated with the freight rate cycle.

The contribution of this chapter is that it investigates the validity of the risk and return relationship as defined by the CAPM, while also it investigates the nature of the risk and return relationship in shipping investments under multiple dimensions such as time and market conditions (i.e. bull and bear) using multiple valuation models and risk attitudes conceptualised by the prospect theory's utility function. The risk-return relationship is expected to be dependent on the particular time period studied and the risk measure used. Additionally, risk-seeking attitudes should be below return levels and risk-averse attitudes above return levels. This means that the risk-return function is an S-shape and the expectation is that there is a negative risk-return association below target levels and a positive risk-return association above target-levels. Finally, the findings should also provide useful insight for investment decisions in the sale and purchase, shipbuilding and demolition shipping markets.

In the fifth chapter *Concluding Remarks and Further Research*, the main empirical findings of this thesis are summarised and potential areas for future development around the current subject are presented.

None of the above topics have been previously examined in the dry bulk freight market literature using the approach proposed by this thesis which makes its findings a new reference source for academics whilst offering practical solutions for members of the shipping industry and especially ship owners. The findings of this thesis provide valuable information on freight rate differentials, volatility behaviour and codependence as well as their predictability which all have important implications for the dry-bulk market participants that deal with trading and risk management as well as chartering market operations. Overall, market agents may be also able to improve the forecasting accuracy and enhance the performance of their hedges.

1.3 Summary of the Thesis Structure

The main contribution of this work is summarised in this chapter and continues in each of the following chapters. The empirical body of the thesis involves Chapter 2 to 4. Every chapter covers a bespoke topic and can be read independently of any previous and subsequent chapters. Earlier work in progress versions of Chapters 2 and 3 were presented at the International Association of Maritime Economics (IAME) conference.

The remainder of this thesis is organised as follows: Chapter 2 focuses on investigating profitable chartering strategies using multiple technical indicators. Chapter 3 analyses the impact of the macroeconomic factors on the term structure of freight rates. Chapter 4 investigates the nature of the risk and return relationship in the shipping freight market. Finally, Chapter 5 concludes by summarising the most important theoretical and empirical findings of the thesis, whilst also outlining the limitations and propose future research around the main topic.

Chapter 2
Investigating the Profitability of Ship Chartering Strategies in the Dry-Bulk Shipping Market using Market Timing Rules

The existence of freight contracts with different maturities in the shipping freight market offers flexibility in terms of decisions regarding chartering activities to both ship-owners and charterers. Operating in the freight market poses significant price risks to participants who often mitigate these risks by operating under short- or long-term contracts. This highlights the need to identify an approach that can be used to predict the market timing at which ship-owners should commit their vessels to short- or long-term contracts. This chapter focuses on the difference between *active* (vessel allocation to the best performing contracts and avoidance of worst performing ones) and *passive* (vessel allocation to a single contract type) chartering strategies in terms of profitability. A *chartering strategy* is defined as the sequence of contracts that shipping companies select in order to maximise their operating revenues. A chartering decision is made considering the current and the expected value of the spread between the spot and period rates. An extended universe of technical trading rules is used to predict the market timing at which ship-owners should sign either a short- or long-term contract. The examination of several parameterisations of active trading strategies show that active strategies can be applied to the physical market in order to increase the profitability of the chartering operations.

2.1 Introduction

The focus of this study is on the optimal chartering decision problem of dry-bulk shipping companies. Shipping companies mainly generate profits from selling and purchasing vessels (asset play) rather than from operating in the physical charter market (Norman, 1982). However, there are several facts that underline the importance of identifying the best timing for chartering decisions in the dry-bulk physical market in order to efficiently manage the freight market risk that results from the increasing volatility of dry-bulk freight markets.

The shipping industry facilitates around 90% of the world's trade (UNCTAD, 2015), which means that the primary task of shipping companies is to transport cargoes around the world. Thus, apart from having a fleet that will cover the demand, it is also crucial to assess how good planning of the chartering operations has the potential to improve the economic performance of shipping companies. Additionally, Tsolakis (2004) and Stopford (2009) state that due to the integration existing between the shipping markets, companies can take advantage of the revenues generated from chartering operations by covering their financial costs (i.e. costs of operating, maintenance, financing fleet, etc.), while an efficient and effective scheduling of chartering operations could also lead to more efficient investment or divestment decision (Christiansen et al, 2007).

The objective of a chartering decision problem, for a company that needs to decide the duration of the charter contract for its vessels in order to mitigate the price risks resulting from operating in the freight market, is to find the right time and rate to charter the vessel by taking into account the spot and period freight rate dynamics. In essence, the aim of a ship-owner or charterer is to select the best performing contract (i.e. either a *short* - or a *long-term* contract) within a given time period in order to reduce the exposure to market highs and lows. During short-term charters[1] (or spot charter), the ship-owner is contracted to carry a specific cargo on a specific ship at a negotiated price per ton, which covers the voyage and operating costs. In long-term charters (or period charter), the ship-owner and charterer agree to hire the ship and crew for a daily fee for a specified period of time (i.e. months or year). In this case the ship-owner is responsible the operating expenses whilst the charter company covers the voyage costs.

Chartering decisions have been analysed in the past using multiple methodological approaches and although some research studies that were based on time series analysis helped identifying and understanding significant characteristics of the chartering decisions and the industry, they also showed that the freight market fails to retain the *Efficient Market Hypothesis* – EMH (Fama, 1965; Binkley and Bessler, 1983; Hale and Vanags, 1989; Beenstock and Vergottis, 1989a,b; Evans, 1994; Kavussanos, 1996a,b; Berg-Andreassen, 1997; Veenstra, 1999; Kavussanos and Alizadeh, 2001, 2002a,b; Adland and Cullinane, 2005; Alizadeh et al, 2007;

[1] The short-term charter usually lasts between ten days to three months.

Alizadeh and Nomikos, 2011 amongst others) and the corresponding *Random Walk Hypothesis* (Tvedt, 2003) for freight rates.

Other scholars such as Mossin (1968), Devanney (1971) and Taylor (1981) used operational research techniques such as linear, integer, dynamic programming and simulation and even though their findings were significant in terms of how to formulate chartering decisions, the empirical analyses proved that optimal chartering strategies cannot be derived when the process of determining the optimal policies is based on a fixed decision rule (Mossin, 1968), the freight rates and risk preferences assumptions of investors need to be estimated (Devanney, 1971) or when the chartering decisions are made based on desired or preferred position within the freight market (Taylor, 1981).

Additionally, Cullinane (1995) and Berg-Andreassen (1998) examined the investments in the dry bulk shipping market using the Markowitz (1952) portfolio analysis. Both studies showed that traditional hedging mix of voyage and time charters on a subset of the industry (e.g. a couple of selected routes) provide ship-owners with a suboptimal risk/return profile on market investment. Also, by using the market conditions and risk attitude of ship-owners as inputs, the analyses were non-dynamic. This is problematic and might lead to sub-optimality since the underlying future market conditions are changing. In addition, Fagerholt and Lindstad (2000), Fagerholt et al (2010); and Alvarez et al (2011) focused on analysing the tramp shipping contracts in order to assess the best mix of long-term and spot contracts for a given fleet and find the optimal fleet size and mix for a set of contracts. Although Laake's and Zhang's (2016) study that focuses on strategic fleet planning is very flexible and can be applied to different fleet scenarios, it is deterministic meaning that the analysis excludes the uncertainty of the shipping market which is highly important in the decision making process.

Other studies used a Real Option Analysis (Bjerksund and Ekern, 1995; Tvedt, 1997,1998; Tigkas et al, 2005; Koekebakker et al, 2007; George and Tunaru, 2008; Sødal et al 2008, 2009; Wang et al, 2009; Rygaard, 2009; Jørgensen and De Giovanni, 2010 amongst others) to price and value the chartering options for a vessel in the dry-bulk market but only focused on one type of contract.

The limitation of using the aforementioned methodological approaches is their inability to capture the volatility and uncertainty of the freight market mainly due to their deterministic nature. Designing chartering strategies in the dry bulk shipping market is a challenging task due to factors such as volatility and uncertainty of the freight market, market conditions, risk preferences, number of available contract options and available vessels that can be contracted as well as their location, condition etc. In other word, the high number of factors that affect strategies and the fact that this can be expanded indefinitely makes it difficult to identify the best option to be signed at the right time.

Although the aforementioned factors are all equally important, some are more subjective and dependent on the investors' characteristics. The exception is the level of freight rates, which depends on the level of supply and demand in the market. Therefore, the expected level of freight rates is the main driver for the selection of the best type of contract. For instance, if the freight market is expected to be in an upward trend, ship-owners may charter their vessels under short-term (spot) charters in order to take advantage of the rising freight rates. Oppositely, if expecting a downward trend, a long-term contract guarantees a fixed freight rate for a determined period (i.e. 6 months Period Time Charter – PTC6m, 12 months – PTC12m or 36 months – PTC36m) and minimises the risk from having vessels chartered in low freight rates. Therefore, the purpose of this study is to investigate whether market-timing rules can provide useful information about the future dry-bulk freight rate fluctuations and can help identifying dynamic strategies depending on expected market conditions.

Technical analysis (or analysis of past price patterns) is a methodology that was designed to identify predictable trends in prices assuming that the trends will continue in the future. Additionally, the technique assesses technical trading rules and uses them to determine whether they can be used to provide a better analysis of performance. The robustness of these rules has been questioned in the literature by Fama and Blume (1966) as well as Jensen and Benington (1970) because they argued that if the series support the Random Walk Hypothesis, then historical rates cannot be used to accurately predict future changes. On the other hand, Treynor and Ferguson (1985) and Brown and Jennings (1989) demonstrated the usefulness of technical analysis to practitioners in the market. Treynor and Ferguson (1985) showed that when past prices are combined with other information, this could help achieving unusual profits whilst Brown and Jennings (1989) underlined the usefulness of historical and current prices in estimating accurate inferences about past and present signals.

Technical analysis is widely used in the stock, exchange and future markets (Park and Irwin (2007); Hsu et al (2016) etc.), however when it comes to the shipping freight market its application is very limited. Previous attempts to apply technical analysis in the freight markets were generally either restricted to the forward freight agreement markets (Goulas and Skiadopoulos, 2012 and Nomikos and Doctor, 2013) or focused on determining the optimal investment decisions in the sale and purchase of vessels (Norman, 1982; Adland, 2000; Adland and Koekebbaker, 2004 and Alizadeh and Nomikos, 2007). Apart from Adland and Strandenes (2006) and Alizadeh et al (2007) who focused on the physical shipping markets. The aforementioned empirical studies showed that technical trading could beat the freight market. Based on this and in the wake of the global financial crisis, a greater understanding of the economic fundamentals of the freight market is of high interest.

Most of the aforementioned studies tend to only consider a small number of contracts (i.e. exclusively spot or spot and period time charter without specifying the exact duration of a period charter contract when the latter is identified as the most profitable choice), limited sets of technical trading rules, short sample periods, simple performance metrics and basic testing methods which may be subject to data-snooping bias. Therefore, there is an opportunity to develop a comprehensive study of technical analysis in the freight market that will investigate if technical analysis can beat the freight market on a large-scale with an accurate empirical design.

This chapter, comprehensively analyses the technical trading rules in the dry bulk freight market to date in order to assess the profitability and provide further insights on what makes them profitable at times. In addition, the analysis investigates the difference in terms of profitability between *active* and *passive chartering strategies* that affect the optimisation and efficiency of dry-bulk shipping companies. A *chartering strategy* is defined as the sequence of different contracts types that shipping companies select in order to maximise their operating revenues. A *passive* (or buy-and-hold or benchmark) *strategy* is based on the EMH and implies that ship-owners operate their vessels under a single type of contract throughout the planning horizon. An *active strategy* implies that ship-owners only sign the best performing contracts and try to avoid the worst performing ones that pose significant freight rate risks.

The analysis is based on weekly freight rates in the dry bulk freight market over the period from January 1992 to June 2016. Several parameterisations (30,046) of technical trading rules (e.g. trend, momentum, volatility, moving average envelopes and a complex strategy) are applied to the physical market for three vessel categories (i.e. Capesize, Panamax and Handymax vessels) and different contract durations (i.e. spot, 6-, 12- and 36-month contracts) to indicate the best type of contract at each point in time. One important challenge of the analysis is the assessment of the performance of chartering strategies, which is measured, based on the logarithmic differences of the time series. The best chartering strategy is chosen based on the maximum risk-adjusted return and mean returns. Additionally, the active chartering strategies are compared with a passive strategy of physical hedging instruments on the basis of the risk-adjusted and mean returns outperformance.

Additional descriptive and risk-adjusted statistical measures are calculated to assess the distribution of the returns and to summarise the overall performance of the trading rules and strategies. For instance, active strategies transform the distribution of returns by minimising the downside risk and enhancing the upside potential and thus create a distribution with positive skewness to enhance returns. However, some strategies significantly succeed or fail leading to fat tails in the distribution.[2] Additionally, one of the most significant issues that arise when a large set of trading rules is used is "*data snooping*" or *"selection bias"* (Jensen and Bennington, 1970; Lo and MacKinlay, 1990; Brock et al 1992) so the *White's Reality Check p-value* (White, 2000) is used in order to eliminate the data-snooping bias. This testing method is used to accurately identify predictive or profitable technical indicators from a large set of trading rules without data-snooping bias and thus allows the formulation of appropriate statistical inferences.

This study contributes to the existing literature by initially proposing a methodology (i.e. technical trading rules) to construct and evaluate robust chartering strategies. Additionally, analysing the economic significance of an extended universe of ship-chartering trading rules using the spread between spot and period charter rates across various vessel types and contracts with different maturities in the dry-bulk market. Thirdly, unlike existing research (i.e. Adland and Strandenes, 2006 and Alizadeh et al, 2007), this study investigates the inefficiencies in the freight market and whether these can generate economically significant returns. More specifically, the EMH implies that chartering strategies based on available market information do not outperform the buy-and-hold

[2] Positive skewness implies a bias for positive returns and is thus desirable from an investor perspective. In contrast, excess kurtosis is an undesirable statistical attribute as it leads to fat tails and therefore a higher likelihood for extreme adverse outcomes.

(passive) strategy. Therefore, any comparison of risk-adjusted returns between an active and a passive strategy provides a direct test of the EMH as it applies to the freight market. Finally, from a practical perspective, the outcomes of this study increase the understanding and operating performance of the decision making process of ship chartering operators whilst providing assistance in the sale and purchase, shipbuilding and demolition shipping market decisions.

This chapter initially provides description of the chartering strategies incorporated in the analysis and the methodology used to assess them (see Section 2.2). Section 2.3 presents the data and the empirical results, section 2.4 presents additional tests and finally Section 2.5 concludes with the implications of the empirical findings.

2.2 Methodology

This section presents the methodology used to formulate and assess the chartering strategies.

2.2.1 Description of the Chartering Strategies

A *chartering strategy* is defined as the sequence of contracts that shipping companies select in order to maximise their operating revenues. The chartering investment strategies are formulated and defined based on the current and expected level of freight rates as well as the EMH.

The *passive* (or *buy and hold*) *strategies* in the shipping freight market rely on the EMH that implies that ship-owners should be indifferent to whether they will assign their vessels to period time charter contracts or a series of consecutive trip charter ones. In essence, if the EMH is retained, this means that the market cannot generate any profit regardless of the chartering strategy that will be selected. The buy and hold or passive strategy can be considered as a benchmark against which active strategies is tested. Therefore, since ship-owners can operate their vessels in either the spot or one of the three period charter markets, there are four passive strategies available. For example, signing a spot contract (or one of the other 3 options) at the beginning of the period that this study examines means that this will be kept until the end unlike active strategies where a different type could be signed in-between.

Another passive strategy assessed in this study uses the *spread rule* without incorporating any technical trading rule. The spread rule implies that a position is taken in the market based on the value of the spread at time t. For instance, if the spread between spot and 6-month period rates is positive (negative) this means a spot (period) contract should be signed.

As mentioned in section 2.1, various research studies showed that the freight market fails to retain the EMH. In addition, there is considerable empirical evidence supporting the existence of a time varying term premium (Kavussanos and Alizadeh, 2002b), which implies that investors should follow a more *active strategy* and shift their allocations in response to changing term premiums. When a decision on how long to commit a vessel for is made, ship-owners should consider not only the current level of demand for transportation services and the level of freight rates but also the growth prospects of the market. Therefore, the active strategies are formulated using multiple technical trading indicators in order to identify the most profitable contract at each point in time and assesses the growth potential of the market. The spread rule and active strategies are formulated based on the freight rate spread. Section 2.2.3.1 explains why the spread between the freight rates is included in the decision process.

Therefore, this chapter focuses on the difference in terms of profitability between *passive* (vessel allocation to a single contract type), *spread rule* (vessel allocation to the best performing contract at time t based on the current level of freight rates) and *active* (vessel allocation to the best performing contract and avoidance of worst performing ones based on the expected level of freight rates) chartering strategies.

2.2.2 Description of the Technical Trading Rules

Due to the fact that the literature review on trading in physical hedging instruments in the dry-bulk freight market is limited, choosing one technical trading rule may introduce a subjective bias. Sullivan et al (1999) suggested that selecting existing trading that are widely used by market practitioners could minimise the subjective bias of the selection process. This is why the analysis is based on chartering strategies used in existing academic studies on the dry-bulk freight market such as Sullivan et al (1999), Hsu and Kuan (2005), Nomikos and Doctor (2013) and Alizadeh and Nomikos (2007, 2009).

A description of the technical indicators that can be divided into the trend, momentum, volatility and envelope indicators is provided in sub-sections 2*.2.2.1*, 2*.2.2.2*, *2.2.2.3* and *2.2.2.4*. A detailed description of all technical trading rules used is presented in Appendix 2.A.

2.2.2.1 Trend Indicators

Moving Average indicators are amongst the most popular and common trading rules used in the literature when attempting to define trends. The *moving average rule* incorporates the price line and the moving average of price in order to generate signals (Gartley, 1935). The trend strategies incorporated into the analysis are: the *Moving Average Crossover* (MAC), *Triple Moving Average Crossover* (TMAC) and *Moving Average Convergence/ Divergence* (MACD).

More specifically, a *Moving Average Crossover* (MAC) strategy is applied to the spread series to initiate *spot* signals when the short-term moving average (STMA) of the spread crosses the long-term moving average (LTMA) of the spread from below. A *PTC* (Period Time Charter) position is taken if the STMA of the spread is crossing the LTMA of the spread from above. This can be explained as follows: if the STMA crosses the LTMA from below, this confirms an upward momentum for the spread differential (i.e. *spot*-*P6m*) and the *spot* rates are increasing thus a *spot* contract is the most profitable option. Conversely, if the STMA crosses the LTMA from above, this indicates a downward momentum for the spread differential (i.e. *spot*-*P6m*) and the *spot* rates are decreasing so a *PTC* contract would be preferable. Such indicator allows ship-owners to identify whether the *spot* rates cross the *PTC* rates from above/below and when this takes place.

At this point it is important to note that the *Exponential Moving Average Crossover* (EMAC) is also used in order to overcome the limitation of the *Simple Moving Average Crossover* (SMAC) rule related to prices receiving the same weighting throughout the averaging window.

The second strategy is assessed using the *Triple Moving Average Crossover* (TMAC) trading rule that uses a short-term (STMA), a medium-term (MTMA) and a long-term moving average (LTMA). A *spot* signal is generated when the STMA crosses from below the MTMA and LTMA, whereas a *PTC* signal is indicated by the STMA crossing MTMA and LTMA from above. The TMAC rule reduces the number of false signals and can be used to estimate the strength of a trend and the likelihood of continuation.

The third trend strategy is based on the *Moving Average Convergence/ Divergence* (MACD) rule, which was introduced by Appel in 1979. The MACD line ("*oscillator*") oscillates above and below the zero line indicating convergence and divergence signals and is equal to the difference between the STMA and LTMA. A *"signal line"*, which is a moving average of this oscillator, is used to generate a *PTC*/*spot* signal if the oscillator is crossing above/below the signal line. More specifically, a *spot* contract should be signed when the oscillator is positive and crosses the signal line from below. The reason is that a positive oscillator indicates that the STMA crosses the LTMA from below. The positive value of the oscillator increases as the STMA diverges further from the LTMA which means that the upside momentum for the *spot* rates is increasing. A *PTC* contract should be signed when the oscillator is negative and crosses from above the signal line. A negative oscillator indicates that the STMA crosses the LTMA from above. As the STMA diverges further below the LTMA, the negative value of the oscillator increases meaning that the downside momentum is increasing for the *spot* rates and thus, the best option in this case is a *PTC* contract.

The advantage of the moving average rules is the ability to identify crossovers and trends in the time series however they are unable to predict peaks, troughs or "sideways" which is why the momentum indicators are required.

2.2.2.2 Momentum Indicators

A momentum strategy is determined using two momentum oscillators such as the *Stochastic Oscillator* (SO) and the *Relative Strength Index* (RSI).

The *Stochastic Oscillator* (SO) shows where the spread is trading relative to the highest (maximum) and lowest (minimum) spread (Lane, 1984) over a previous look-back period. An upper/lower filter f is required to determine a *spot/PTC* signal. For instance, when the oscillator crosses from above the upper filter band, a *PTC* contract should be signed because the expectation is that the *spot*-*P6m* spread will decrease and the *PTC* rates will increase. On the other hand, when the oscillator is crossing from below the lower filter band then a *spot* would be the best option.

The *Relative Strength Index* (RSI) is a momentum oscillator that measures the speed and change of freight rate movements and fluctuates between zero and 100 (Wilder, 1978). More specifically, when the RSI of the *spot*-*P6m* spread series is crossing from above the upper band (i.e. 50), this would be considered as an overbought and thus suggest a *PTC* contract as the best option. On the other hand, an oversold occurs when the index is crossing from below the lower band (i.e. 50) and in this case, a *spot* contract should be signed.

2.2.2.3 Volatility Indicator

The *Bollinger Bands* (BBs) indicator can be used to capture the volatility of the time series and specify whether a *PTC* or a *spot* signal will be generated. The *Bollinger Bands* (BBs) are created by defining upper and lower bands in spreads over a pre-specified look back period that takes into account the dynamic rather than static volatility (Bollinger, 2002). A *PTC* signal is generated when the spread series crosses from above the lower band and closes when the spread series crosses from below the upper band. A *spot* signal appears when the spread series crosses from below the upper band and close out when it crosses the lower band from above.

2.2.2.4 Moving Average Envelope

According to Alexander (1961, 1964), the use of filters assists in filtering out false trading signals (i.e. resulting in losses) while providing information used to take actions. A *spot* signal is generated when the spread (i.e. *spot*-*P6m*) crossing from below the upper envelope (i.e. this shows significant strength for the *spot* rates) and the position closes when the spread series crosses from above the upper band. Oppositely, a *PTC* signal is initiated when the spread (i.e. *spot*-*P6m*) crosses from above the lower envelope (i.e. this indicates important weakness of the *spot* rates) and that position closes when the spread series crosses from below the upper band.

2.2.2.5 Voting Strategies

In practice, investors may rely on information generated from more than one technical trading rule in order to make a decision. Therefore, considering the aforementioned strategies a new complex strategy can be formulated in order for ship-owners to be able to evaluate potential actions.

The *"voting strategy"* (Hsu and Kuan, 2005) generates a signal based on the majority amongst all the parameterisations of a specific rule. For instance, if the majority of the 1,058 parameterisations of the MAC rule at time step t generate a *spot* signal and the other contracts are either a *P6m*, or *P12m* or *P36m*, then the voting strategy will follow the majority position. Since there are 12 independent simple strategies this means there are also 12 voting strategies.

Multiple trading rules are examined using various variants for each one and a range of different plausible parameterisations of each variant (e.g., Sullivan et al, 1999; White, 2000 amongst others), all presented in Appendix 2.A. This generated a total of 30,046 distinct technical trading rules, including 16,470 trend rules, 7,332 momentum rules, 2,000 volatility indicators, 4,232 moving average envelopes and 12 complex strategies. The next section presents the methodology used to measure and assess the performance of the chartering strategies.

2.2.3 Assessing the Chartering Strategies

The use of multiple technical trading indicators and a combination of these allow the identification of trend-, momentum- and volatility-based patterns of the freight rates that help a ship-owner evaluate different positions that can be taken in the freight market.

2.2.3.1 The Freight Rates Spread and the Chartering Signals

At this point it is important to explain why the spread between the freight rates is used in the decision process. Ship-owners constantly need to decide whether to sign a spot or a period contract or extend the latter considering the freight rates level. Such decision can be made based on the time-varying spread between the spot and period rates that indicates the operational premium of one market over the other. The spot and period rates should have the same units of measurement in order to be comparable. However, hire rates for vessels on spot charters are usually not expressed as daily numbers, which is why the *Time-Charter Equivalent* (TCE)[3] is used to obtain these figures.

$$Spread_t = ln(TCE_t) - ln(TC_t) \tag{2.1}$$

where TCE_t is the rate of the closest to maturity contract at time *t* and TC_t is the Time-Charter (TC) rate of the distant contract. For instance, a positive (negative) $Spread_t$ indicates that spot (period) contracts have an operational premium compared to period (spot) contracts. The assumption that the freight rates spread is time-varying in the dry-bulk market is aligned with evidence found by Kavussanos and Alizadeh (2001, 2002b) for Capesize, Panamax and Handymax vessels. Similarly, Axarloglou and Zarkos (2007) showed that the spread between 3-year and 6-month period charter rates for all vessel sizes in the dry-bulk market is time-varying and dependent on the market's conditions whilst Axarloglou et al (2013) also demonstrated that the time-varying properties of the spread can be used for strategic chartering decisions.

[3] The TCE calculates the average daily revenues of a vessel in the spot market allowing the comparison with daily earnings generated by vessels on long-term charters.

However, any direct comparison between the two type of contracts using the $Spread_t$, might lead to sub-optimality since the future movement of the freight rates is not taken under consideration. Therefore, the decision of whether or not to charter a vessel under a spot charter or a long-term charter contract should not only depend on the current level of the freight rates but also on the expected future ones. For instance, if the freight market is expected to be in an upward trend, ship-owners may charter their vessels under short-term contracts in order to take advantage of this increase. Oppositely, if expecting a downward trend, a long-term contract guarantees a fixed freight rate for a determined period (i.e. 6 months Period Time Charter – P6m, 12 months – P12m or 36 months – P36m) and minimises the risk of having vessels chartered during low freight rates.

More specifically, the following 6 spreads between the spot and different period time charter rates are being examined: *(i) spot – P6m* which is the spread between spot and 6-month period rates, *(ii) spot – P12m, (iii) spot – P36m, (iv) P6m – P12m (v) P6m – P36m (vi) P12m – P36m* is the spread between 12-month and 36-month period rates.

The value of the time spread equation (2.1) is used in order to identify the sequence of chartering signals at each time point. The first step in identifying the optimal contract is to compare the spot rates to the 3 period time charter rates (spot versus P6m, P12m and P36m) to assess whether the former is the best option if all three spreads are positive. On the other hand, the spot contract is not the best option and one of the 3 period time charter rates should be considered, when the spread is negative.

In order to identify which one, the period charter rates are compared with the other 2. For example, the 6m period time charter rate is compared to the 12m rate and then to the 36m rate. If both spreads are positive this indicates that a 6-month period charter is the most profitable contract between all options since step 1 already excluded the spot contract and step 2 proved that 6m rate is higher than both 12m and 36m period time charter rate.

Similarly, if the results from step 2 are inconclusive (i.e. absence of two positive spread results) then the final step is to assess the last spread combination, which is the 12m rate with the 36m rate to finally identify which of the 2 is higher and thus the best amongst all contracts (as the spot and 6m rates have already been eliminated in steps 1 and 2). To sum-up, the approach followed is:

Step 1: Spot spreads comparison:

If $Spot\ versus\ P6m\ >\ 0, Spot\ versus\ P12m\ >\ 0$ **and** $Spot\ versus\ P36m\ >\ 0$ **then** a **spot** contract should be **signed otherwise** proceed as follows.

Step 2: **P6m** spreads comparison:

If $P6m\ versus\ P12m\ >\ 0$ **and** $P6m\ versus\ P36m\ >\ 0$ **then** a **P6m** contract should be **signed otherwise** proceed as follows.

Step 3: **P12m** spread comparison:

If $P12m\ versus\ P36m\ >\ 0$ **then** a **P12m** should be **signed otherwise** a **P36m** is the best option.

Please note that the last comparison step might be redundant since step 2 could allow drawing conclusion regarding the best contract by comparing the spread results rather than only looking at the sign. At this point it important to mention that the aforementioned process defines the spread rule strategy that only determines the best current level of freight rates, which might lead to sub-optimal chartering strategies since the future movements of freight rates is ignored. Therefore, the use of technical trading rules in this process allows the expected level of freight rates to be considered.

More specifically, the technical trading rules use short-term moving averages, long-term averages, signal lines, etc. of the time spread equation (2.1) in order to identify the sequence of chartering signals at each time point. The chartering signals result in a range of five values: 1 represents a *spot* position, 2, 3 and 4 indicate a *P6m*, *P12m* and *P36m* position respectively. This is the main purpose of this chapter: to determine whether the use of technical trading rules can "beat" the dry bulk freight market and suggest profitable chartering strategies.

2.2.3.2 Returns without and with Transaction Costs

Ship-owners need to select a way to measure the operating performance of chartering operations generated under each technical trading rule during the sample period. New series are constructed for each technical trading rule considering the generated signals. Using the new freight rate series, the method that calculates the returns is the logarithmic difference of the freight rates at time t.

$$R_t = log(FR_t) - log(FR_{t-1}) \tag{2.2}$$

In order to calculate the returns of the passive and active strategies the following assumptions are made:

1. The duration of a spot contract is equal to the length of a single voyage (i.e. 6 weeks[4]). As a year consists of 52 weeks, the duration of the *P6m*, *P12m* and *P36m* is equal to 26, 52 and 156 weeks respectively.
2. Throughout the planning horizon, ship-owners do not have the option to lay-up the vessel.
3. A vessel is chartered at rate of the week during which the contract is signed.
4. There are no delays in the agreement of a contract.
5. There is no default risk.

It is very important to adjust the returns and include transaction costs since rules and strategies may appear to be profitable when such costs are ignored but then become less attractive when these are added (Timmermann and Granger, 2004). The impact of transaction costs depends both on their magnitude and on the frequency the positions are changed. The analysis will include transactions costs of 2.5%, which is the typical commission. The expected findings are that the transaction cost-adjusted returns will fail to exceed the returns of the buy-and-hold strategy meaning that the market will be efficient.

2.2.3.3 Performance Metrics

It is crucial to take into account and estimate the risk-adjusted measures since this constitutes a key component in evaluating the usefulness and profitability of trading rules. These measures are also essential when it comes to measure the consistency of results using the market efficiency and the liquidity hypothesis. In addition, risk-adjusting measures are required for comparison purposes since the active strategies might include time out of the market and therefore have less volatile returns than the buy-and-hold returns.

The risk-adjusted returns reveal how much risk was taken to achieve a return by incorporating volatility, sensitivity to overall market moves and other measures. Therefore, multiple risk-adjusted performance metrics are calculated in order to assess and compare the performance of the chartering strategies. One of the metrics is the *Sharpe ratio* (Sharpe, 1966), a common risk-adjusted measure that determines a strategy's return over and above the "risk free rate" (e.g. 1%) and

[4] This assumption is based on an average total voyage time required to complete the spot charter routes included in the data.

divides that figure by the strategy's standard deviation. Strategies with higher Sharpe Ratios are seen as having better risk-adjusted performance. Additionally, the *Sortino ratio* (Sortino and Price, 1994) is a variation of the Sharpe ratio that focuses more on downside volatility rather than the overall volatility. A higher Sortino ratio suggests that the strategy had fewer large declines.

Traditional descriptive measures such as the *mean*, *variance* (volatility), *skewness*, *kurtosis*, *minimum* and *maximum* are also calculated for comparison reasons. The study also measures the *maximum drawdown,* which is the largest decline in the return series after a historical peak. The distribution of the chartering strategy returns is assessed using the following diagnostic tests: the autoregressive conditional heteroscedasticity – ARCH test (Engle, 1982), the Ljung-Box (1978) test for serial correlation and the Jarque-Bera (1987) test for normality. The *ADF* - Augmented Dickey-Fuller (1981), the *PP* – Phillips and Perron (1988) and the *KPSS* – Kwiatkowski, Phillips, Schmidt and Shin (1992) tests are also used in order to evaluate the stationarity of the return series.[5] The distribution of the returns is assessed by combining the results of the diagnostic tests with the traditional measures of skewness and kurtosis.

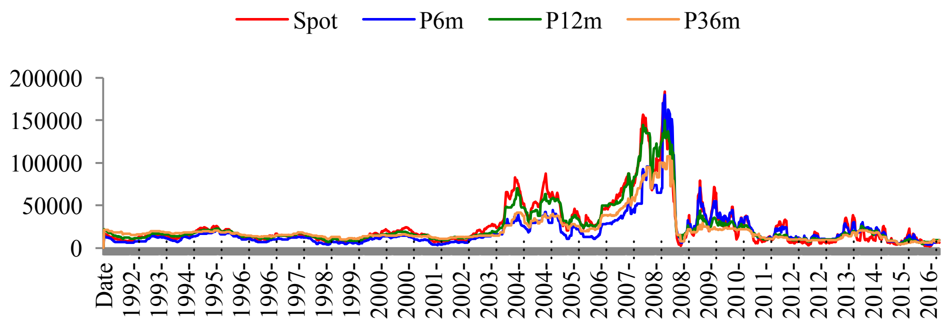

Figure 2.1: Freight Rates for a Capesize vessel

2.2.4 Robustness Checks

Additional analysis that excludes the Credit Crisis period is used as a robustness check to enhance the accuracy of the methodological approach.

2.2.4.1 Elimination of the Crisis Period

During the financial crisis of 2008, there were significant freight rate movements for each vessel size and freight rate series (see Figure 2.1, 2.2 and 2.3), which

[5] The statistics of the PP and KPSS test are not reported but are available upon request.

might affect the trading rules and thus their overall profitability. Figure 2.1, 2.2 and 2.3 present the freight rates for each vessel from January 1992 to June 2016**.**

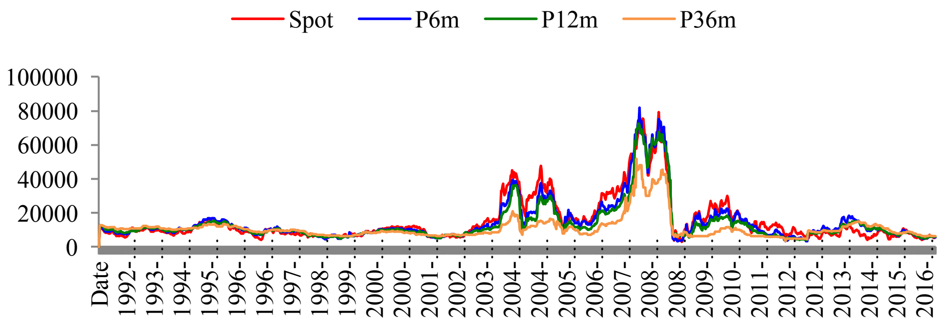

Figure 2.2: Freight Rates for a Panamax vessel

Therefore, in order to test the robustness of the empirical findings, the turbulent period from 31st of August 2007 to 30th of January 2009 is eliminated and the significance and profitability of the chartering strategies is re-estimated.

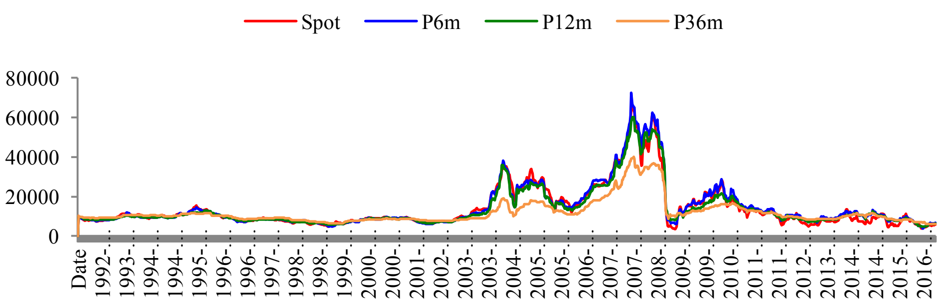

Figure 2.3: Freight Rates for a Handymax vessel

The results of the empirical analysis seem to be robust to the extreme market movements experienced during this turbulent period (see Appendix 2.C).

2.2.4.2 Avoiding Data-Snooping Bias: Bootstrap Methodology

Data-snooping bias arises when a study continuously searches for predictive models or rules but only performs individual tests using the same dataset without considering the fact that all models or rules should be tested together for significance reasons.

To avoid spurious inferences resulting from data snooping, the literature suggests using different tests. Lo and Mackinlay (1990) proposed the use of *"out-of-sample performance tests"* to eliminate the effects of data-snooping bias from an analysis. Additionally, Brock et al (1992) suggested using the *"Bootstrap Approach"* proposed by Efron (1979) in order to evaluate the statistical significance of the findings by fitting several models in the data and re-sampling the residuals.

Sullivan et al (1999) proposed a modified version of the *"Reality Check Bootstrap"* that was initially suggested by White (2000) to test whether a model has predictive superiority over a benchmark model. Hansen (2005) proposed a new *"Superior Predictive Ability"* (SPA) test that overcomes the sensitivity of the White's *Reality Check p-value* that results from the use of a number of irrelevant trading rules. Other tests include the *"False Discovery Rate – FDR"* methodology (Barras, Scaillet and Wermers, 2010) and the *"Wild Bootstrap Reality Check"* proposed by Clark and McCracken (2012).

This chapter uses the *"Reality Check Bootstrap"* approach to address the data-snooping bias. The *"Reality Check Bootstrap"* approach allows the evaluation of the performance of the trading rules by identifying if the superior performance is a result of superior economic content or due to luck (White, 2000). The best performing rule was chosen based on two criteria: the highest risk-adjusted returns and the highest mean returns of all strategies.

The aim is to compare the return of best performing trading rule with the returns of the passive strategies and determine which one is better. Thus, f_r $(r = 1,2,\dots,M)$ denotes the performance measure of the $r - th$ trading rule relative to the benchmark model. Following the methodology proposed by Sullivan et al (1999), the performance is defined as expected loss measuring the difference between the trading rule returns and the benchmark strategy. The following formula is used for $f_{r,t}$ in order to evaluate the trading rules (r):

$$f_{r,t} = ln[1 + R_t P_{rt}] - ln[1 + R_t P_0] \tag{2.3}$$

Where R_t represents the highest risk-adjusted or mean returns of a trading rule at time t. P_r and P_0 are *"signal functions"* of the $r - th$ rule based on the information up to time t and indicate the position held in the market. More specifically, P_r can take three values: 1 if a spot signal is generated, -1 in case of a PTC signal or 0 for no position. P_0 represents the benchmark strategy and is always equal to 1. Thus, the null hypothesis (H_0) is that the performance of the best trading rule r, in the collection of M rules $(r = 1,2,\dots,M)$, is not better than the performance of the benchmark. Therefore, the average of f_r can be used as a test of H_0.

$$H_0: max_{r=1,2,\dots,M}\{\mathcal{E}(f_r)\} \leq 0$$

Rejecting H_0 implies that there is at least one rule that outperforms the benchmark. Using the stationary bootstrap method of Politis and Romano (1994, 2004), the following statistics are calculated to estimate the White's *Reality Check p-value:*

$$\bar{V}_n = max_{r=1,2,\ldots,r}\{\sqrt{n}(\bar{f}_r)\},$$
$$\bar{f}_r(= \sum_{t=1}^{n} f_{r,t}/_n) \text{ with } f_{r,t} \text{ the } t^{th} \text{ observation of } f_r \tag{2.4}$$

Where $n\ (= 10{,}000)$ is the number of bootstrap replications of the model and $\bar{f}_r(n)$ is the average normalised bootstrap sample n. $\bar{f}_r^*(i)$ denotes the maximum i^{th} bootstrapped sample average of f_r and $\bar{f}_r^*(i) = \sum_{t=1}^{n} f_{r,t}^*(i)/_n$. The characteristics of the empirical distribution of $\bar{f}_r$ are calculated as:

$$\bar{V}_n^*(i) = max_{r=1,2,\ldots,r}\{\sqrt{n}(\bar{f}_{r,i}^* - \bar{f}_r)\} \tag{2.5}$$

The White's *Reality Check p-value* for the null hypothesis is obtained by comparing $\bar{V}_n$ and the quartiles of $\bar{V}_{n,i}$. The percentage difference of the best bootstrap return ($\bar{f}_{r,i}^*$) that is greater than the risk-adjusted returns ($\bar{f}_r$) of the trading rule r is called the *p-value* of the best strategy. The null hypothesis is rejected whenever the *p-value* is less than 5% significance level (i.e. *p-value* < 0.05) meaning that the best performing rule outperforms the benchmark strategy.

2.3 Data and Empirical Analysis

The empirical analysis focuses on the dry bulk market and three type of vessels (i.e. Capesize, Panamax and Handymax) that can operate in four type of charter markets (i.e. spot, the 6-, 12 or 36-month period charter market).

2.3.1 Data Description and Descriptive Statistics

The January 1992 to June 2016 (23 years and 6 months) data used for the analysis has been extracted from the Clarkson's Shipping Intelligent Network (SIN) and consists of weekly average spot earnings as well as six-month, one-year and three-year period charter rates. The type of vessels incorporated in the analysis are the ones that are commonly used in the dry bulk shipping market: *Capesize* (more than 100,000 dwt), *Panamax* (60,000 to 75,000 dwt) and *Handymax* (35,000 to 45,000dwt) vessels.

The period charter rates, which are a performance measure for the long-term charters are calculated for a 150,000 dwt Capesize, 65,000 dwt Panamax and 45,000 dwt Handymax vessels. As mentioned previously, TCE (or spot earnings) is used to measure the performance of the spot charters. The average spot earnings of a Capesize vessel are calculated based on coal and ore voyage earnings whilst the Panamax ones are measured based on coal and grain voyage earnings. Although the Clarkson's SIN database does not provide the Handymax voyage earnings, it contains data on weekly trip charter rates from January 1992 onwards. This means that for a Handymax vessel, the average trip-charter[6] rates can be used as an operating performance measure for the spot charters. The use of trip charter rates instead of voyage earnings eliminates the effect of voyage cost fluctuations of trading in spot versus time charter markets (Kavussanos and Alizadeh, 2002b).

Table 2.1 and 2.2 present descriptive statistic measures, such as the mean, standard deviation, skewness, kurtosis, minimum and maximum return values for each vessel size and series (e.g. earnings, ship prices, etc.) in this chapter. Other measures used to provide further insight on the nature of the series include the ARCH test for autoregressive conditional heteroscedasticity (Engle, 1982), the Ljung-Box (1978) test for serial correlation and the Jarque-Bera (1987) test for normality.

Panel A of Tables 2.1 and 2.2 present the descriptive statistics of the freight rates for all vessels (Capesize, Panamax and Handymax). The spot rates of each vessel appear to be higher compared to the period rates. Additionally, the rates for larger vessels are higher compared to smaller ones, which is due to the greater cost of hiring the former. A similar pattern is also observed for the volatility of the freight rates as the existence of a downward sloping volatility term structure is attributed to the fact that contracts such as *P6m*, *P12m* and *P36m* with a maturity of up to three years are less volatile than the ones with shorter maturity dates like *spot* contracts (Kavussanos, 1996a,b and Kavussanos and Alizadeh, 2001, 2002b).

There are similarities in the distributions of the dry bulk freight rates across vessel size and contract durations. For instance, positive coefficients of skewness and kurtosis indicate leptokurtic and right skewed distributions. The diagnostic tests show that all series are autocorrelated and non-normal at 5% conventional significance level whilst the ARCH test at a 5% significance level rejects the no ARCH effects hypothesis for all series. The existence of ARCH effects (conditional heteroscedasticity) in the series is an indication of strong volatility clustering meaning that large (small) shocks in the series are followed by large (small) shocks of either sign (Mandelbrot, 1963). The ADF - Augmented Dickey-Fuller (1981) test for a unit root in the time series showed that all series are non-stationary and non-significant at a 5% level.

[6] The trip-charter earnings of a Handymax vessel are calculated based on four routes: 1. Continent/ Far East, 2. Transpacific round voyage, 3. Far East/ Continent, and 4. Transatlantic round voyage.

Panel B in Tables 2.1 and 2.2 present the descriptive statistics of the spread between freight rates of contracts with different maturities for the three vessels (Capesize, Panamax and Handymax). A positive average spread indicates that the first freight rates in the differential are moving above the second rates, while a negative spread indicates the opposite. For instance, the calculations suggest that on average, the spread differential between *spot* and *P6m* is positive for all vessels meaning that during the sample period, the *spot* rates were usually higher than the *P6m* rates. The volatilities of the spread differential are higher for Capesize vessels compared to Panamax and Handymax implying that the spread differential of the former fluctuates more than the one of smaller vessels. Apart from the vessel size, the downside volatility of the spread series could be a result of the market crash in 2008 that created *"noisy"* spread series.

It is worth noting that a contract portfolio of a Capesize vessel consisting exclusively of time charter contracts (i.e. *P6m*-*P12m* and *P6m*-*P36m*) produces on average negative spread mean. This can be explained by the fact that smaller vessels are mainly used in the spot market whilst larger ones are usually operate under to long-term contracts (Kavussanos and Alizadeh, 2001 and Tamvakis, 2007).

At a 5% significance level, the Jarque and Bera (1987) test show a significant departure from normality for nearly all spreads and types of vessels that is due to the high levels of kurtosis and the negative skewness in the spread series. The exception is the spread between the *spot* and *P36m* and *P6m-P36m* rates for a Capesize vessel and the spread between *spot* and *P12m* for a Panamax vessel for which the null hypothesis of the Jarque-Bera (1987) test was retained.

Examining the timing of spread trading using technical trading rules requires the series used to be stationary. The stationarity of the spread series in this study is highly important since, according to Fama and Blume (1966), if the series support the *Random Walk Hypothesis* then historical rates cannot be used to accurately predict future changes. Tables 2.1 and 2.2 show that the ADF values of the spread series are stationary and significant at a 5% significant level.

Table 2.1: **Descriptive Statistics – Capesize**

	Panel A: Freight Rates				***Panel B: Spread Series***					
	lnSpot	***lnP6m***	***lnP12m***	***lnP36m***	***1***	***2***	***3***	***4***	***5***	***6***
Mean	9.809	9.598	9.836	9.772	0.211	-0.027	0.038	-0.239	-0.176	0.067
Standard Deviation	0.806	0.713	0.681	0.563	0.374	0.288	0.409	0.324	0.406	0.209
Sharpe Ratio	12.178	13.456	14.440	17.371	0.565	-0.092	0.092	-0.737	-0.432	0.319
Skewness	0.486	0.732	1.056	0.929	-0.861	-0.623	-0.032	0.248	0.107	0.124
Kurtosis	2.941	3.597	3.780	4.471	3.579	5.118	2.762	2.375	2.731	2.609
MaxDrawdown	4.746	3.871	3.507	3.141	2.318	2.299	2.736	1.294	1.519	1.004
Drawdown Duration	405	407	361	356	142	31	31	26	352	364
Minimum	7.375	8.161	8.412	8.445	-1.232	-1.520	-1.478	-1.078	-1.190	-0.448
Maximum	12.121	12.101	11.918	11.585	1.086	0.778	1.258	0.611	1.020	0.629
Jarque-Bera	50.600	133.053	269.878	298.808	175.39	321.56	3.227	33.310	5.150	10.429
Q test	16499	18267	21067	20792	14437.3	4815.2	8568.7	16727.3	16687.8	15486.8
ARCH test	1243.4	1251.3	1262.5	1262.6	966.73	828.07	896.74	1108.75	1175.69	1025.39
ADF test	-0.462	-0.313	-0.449	-0.480	-4.608	-7.318	-5.589	-3.560	-3.495	-5.225

Notes: Table 2.1 shows the descriptive statistics for a Capesize vessel across different freight rates (spot, P6m, P12m and P36m) from January 1992 to June 2016. Panel A presents the logarithmic freight rates. In Panel B, the numbers at the top represent logarithmic spreads: *(1) spot – P6m* the spread between spot and 6-month period rates, *(2) spot – P12m*, *(3) spot – P36m*, *(4) P6m – P12m*, *(5) P6m – P36m* and *(6) P12m – P36m*.

The *Skewness* and *Kurtosis* are calculated to assess the distribution of the time series. *Sharpe Ratio* ($SR = \frac{[R-R_f]}{\sigma}$) provides the excess return per unit of deviation in each series. The *Sortino Ratio* is similar to the Sharpe ratio but the volatility measure is calculated exclusively using negative returns. The *Maximum Drawdown* (i.e. duration from peak to trough) measures the largest decline of the series after a historical peak. The *Duration of Drawdown* expresses the largest decline of the series after a historical peak in weeks. The *Jarque and Bera* (1987) *test* examines the normality of the series whilst the *Ljung-Box* (1978) and the *Engle's* (1982) *ARCH tests* analyse the autocorrelation and heteroscedasticity of the series. ADF is the Augmented Dickey and Fuller (1981) test that examines the unit root of the series. The critical values for the JB, LBQ, ARCH, and ADF tests are 5.71, 31.41, 3.84 and -1.94 respectively.

Table 2.2: Descriptive Statistics: Panamax and Handymax Vessels

	Panel A: Freight Rates				***Panel B: Spread Series***					
	lnSpot	***lnP6m***	***lnP12m***	***lnP36m***	***1***	***2***	***3***	***4***	***5***	***6***
Mean	9.378	9.368	9.309	9.199	0.010	0.069	0.179	0.064	0.172	0.113
Standard Deviation	0.646	0.596	0.551	0.418	0.228	0.281	0.458	0.132	0.322	0.246
Sharpe Ratio	14.522	15.719	16.893	22.011	0.043	0.245	0.390	0.480	0.533	0.460
Skewness	0.955	1.009	1.340	1.453	-0.159	-0.044	0.205	-1.193	0.390	0.754
Kurtosis	3.257	4.129	5.114	6.160	3.752	3.126	2.206	9.272	2.334	2.528
MaxDrawdown	3.270	3.228	2.897	2.773	1.430	1.733	2.347	1.223	1.766	1.158
Drawdown Duration	35	58	223	228	125	527	240	185	246	251
Minimum	8.011	8.086	8.294	8.086	-0.792	-0.882	-1.063	-0.799	-0.792	-0.325
Maximum	11.280	11.314	11.191	10.859	0.638	0.851	1.284	0.425	1.151	0.833
Jarque-Bera	197.77	284.73	620.35	981.27	35.770	1.244	42.514	2511.9	58.056	142.803
Q test	19284	18262	19507	19058	13802.7	14417.4	18970.3	6810.6	16826.5	17907.2
ARCH test	1257.5	1256.4	1261.5	1254.8	1062.7	1087.75	1185.2	729.17	1179.3	1166.1
ADF test	-0.379	-0.423	-0.457	-0.452	-5.615	-4.591	-2.994	-7.067	-3.139	-3.817
Handymax: Descriptive Statistics										
Mean	9.347	9.386	9.349	9.298	-0.039	-0.002	0.049	0.041	0.089	0.054
Standard Deviation	0.573	0.558	0.520	0.373	0.125	0.149	0.270	0.079	0.226	0.183
Sharpe Ratio	16.316	16.813	17.994	24.903	-0.313	-0.013	0.182	0.518	0.396	0.294
Skewness	0.955	1.127	1.290	1.531	-1.208	-1.539	0.024	-0.220	0.513	0.945
Kurtosis	3.371	3.721	4.139	5.383	5.202	7.569	3.716	4.488	2.701	3.385
MaxDrawdown	2.943	2.897	2.536	1.856	0.920	1.170	1.950	0.560	1.266	1.045
Drawdown Duration	63	434	431	435	240	245	245	67	248	616
Minimum	8.143	8.294	8.466	8.740	-0.619	-0.845	-1.075	-0.336	-0.536	-0.351
Maximum	11.086	11.191	11.002	10.597	0.301	0.327	0.876	0.291	0.731	0.693
Jarque-Bera	201.79	298.32	423.32	801.81	593.18	1656.50	28.10	156.45	64.52	236.82
Q test	19600	21035	21722	21762	8585.2	7169.6	14274.9	8782.4	17557.8	19997.0
ARCH test	1265.5	1268.2	1270.4	1270.2	986.36	1084.9	1170.0	898.86	1202.4	1223.9
ADF test	-0.343	-0.285	-0.382	-0.542	-6.256	-5.519	-3.223	-6.254	-2.844	-2.505

Notes: Table 2.2 presents the descriptive statistics of a Panamax and a Handymax vessel across different freight rates (spot, P6m, P12m and P36m) from January 1992 to June 2016. For further definitions refer to the notes in Table 2.1.

2.3.2 Performance of Passive Strategies

The assumption behind the *Efficient Market Hypothesis of the Term Structure* (EHTS) is that the market is efficient meaning that no one can beat it since anything knowable is already reflected in the current price. In other words, the EHTS contradicts the notion of technical analysis and therefore, technical trading returns in a market are often compared with returns of a *benchmark strategy* in order to test the efficient markets hypothesis.

The passive (or *Buy-and-Hold* or *benchmark*) strategy implies that a proportion of assets is chosen and held until the end of the time period (Perold and Sharpe, 1995). The benchmark strategy in this study is defined as the strategy under which a ship-owner holds a long-only passive position that equally weights the position taken.

The mean returns of each benchmark strategy are calculated as the annualised logarithmic differences of the freight series (Eq. 2.2) that a trader receives from operating in the spot and the time charter market (see Table 2.3 – Panel A: Freight Rate Returns). In addition, Panel B of Table 2.3 presents the statistics of the spread rule strategy. Using either the maximum mean or the maximum risk-adjusted outperformance criterion, the outperforming passive strategy for a Capesize vessel is the spread rule strategy whilst the P6m strategy was the best for a Handymax vessel. Finally, for a Panamax vessel, the P36m strategy outperforms the other passive strategies in terms of maximum mean returns, whilst the spot strategy presents the maximum risk-adjusted returns. This means that if the shipowner chooses to operate his Capesize vessel under a spot contract throughout the planning horizon, he would receive an annual return of -4.6% with an annual standard deviation 96.8%. On the other hand, if he owns a Panamax vessel he will receive similar returns (i.e. -2.9%) but with less standard deviation (i.e. 58.6%) if the vessel is assigned to a spot contract.

The volatilities are greater for a Capesize vessel compared to the other vessels, which is an established relationship between vessel size and volatility of the freight contracts as mentioned by Kavussanos (1996a,b), Kavussanos and Alizadeh (2001). Additionally, Table 2.3 show the existence of a downward sloping term structure volatility, which is attributed to the fact that contracts such as *P6m*, *P12m* and *P36m* with a maturity of up to three years are less volatile than for example *spot* contracts (Kavussanos and Alizadeh, 2002b). Additionally, the maximum drawdown (i.e. decline of returns after a historical peak) for most benchmark strategies is observed during the 2008 market crash.

The distributions of the return series for the different vessels, contract durations and return measures used are leptokurtic with a positive skewness coefficient. There are cases were the skewness is negative which can lead to erratic future return fluctuations of the series and potentially significant losses. The results of the Ljung-Box and the Jarque-Bera tests indicate that with a few exceptions (see blue values in table) all series are autocorrelated and non-normal at a 5% conventional significance level. The ARCH test at the 5% significance level rejects the no ARCH effects hypothesis for all series, while also as can be seen from the ADF values, all return series appear to be stationary at a 5% significant level.

2.3.3 Performance of Active Strategies

Table 2.4 and 2.5 present the summary statistics of the best active strategies selected based on the maximum risk-adjusted returns (Sharpe Ratio) out of a total of 30,046 chartering strategies that were tested for all three vessel types using transaction costs.

According to Pirrong (1993), due to the characteristics of certain routes, markets, cargoes and ships the transaction costs of spot contracts are higher compared those of forward or term contracting. This is also supported by Kavussanos and Visvikis (2006), Stefanadis (2003) and Szakmary et al (2010). However, as per other studies (e.g. Alizadeh and Nomikos, 2007, Fuertes et al 2010, Szakmary et al 2010) the transaction costs in this analysis are assumed to be the same across all types of contract and vessels. Transaction costs incur every time a *spot* or a *PTC* signal is indicated and refer to brokerage commission of shipbrokers who arrange the deals. The results obtained under the maximum mean criterion are presented in Appendix 2.B.

The scenario tested across every strategy is that a ship-owner holds either a period or a spot position based on the market signal. Table 2.4 and 2.5 presents the best performing technical trading rules of the trend, momentum, volatility and moving average envelope strategy across all vessels. Under the risk-adjusted return criterion, the best performing technical trading rule is the eBB for a Capesize vessel, the sTMA, sBB and eBB for a Panamax vessel, while for a Handymax the best performing trading rule is the sTMA.

Table 2.3: Summary Statistics – Benchmark Strategies

		Panel A: Freight Rates Returns				**Panel B**
		lnSpot	**lnP6m**	**lnP12m**	**lnP36m**	**Spread Rule**
CAPESIZE	**Mean (% Ann)**	-4.598	-2.075	-3.336	-3.336	**1.692**
	Standard Deviation (% Ann)	96.797	70.761	52.156	42.657	**165.093**
	Downside Risk	3.882	4.280	3.667	4.763	**19.898**
	Sharpe Ratio	-0.058	-0.043	-0.083	-0.102	**0.004**
	Sortino Ratio	-1.184	-0.485	-0.910	-0.701	**0.085**
	Skewness	0.307	0.688	-0.296	-0.360	**-0.012**
	Kurtosis	9.257	20.177	21.466	35.736	**1.718**
	MaxDrawdown	1.450	1.760	0.960	1.050	**0.800**
	Drawdown Duration	68	28	15	324	**1**
	Minimum	-0.700	-0.890	-0.610	-0.610	**-0.400**
	Maximum	0.790	0.870	0.610	0.680	**0.400**
	Jarque-Bera	2104.9	15811.8	18177.2	57093.2	8124.4
	Q test	160.990	91.923	86.083	94.669	176.180
	ARCH test	76.600	3.402	22.444	7.431	18.676
	ADF	-29.299	-30.161	-31.402	-32.943	-45.039
PANAMAX	**Mean (% Ann)**	**-2.930**	-3.377	-3.296	**-2.767**	0.000
	Standard Deviation (% Ann)	**58.601**	55.249	43.879	**39.535**	71.329
	Downside Risk	**2.406**	2.842	2.567	**3.409**	9.201
	Sharpe Ratio	**-0.067**	-0.079	-0.098	**-0.095**	0.000
	Sortino Ratio	**-1.217**	-1.188	-1.284	**-0.812**	0.000
	Skewness	**0.222**	0.013	-0.919	**1.022**	0.019
	Kurtosis	**10.990**	22.645	33.074	**50.273**	1.353
	MaxDrawdown	**1.000**	0.960	1.000	**0.920**	0.266
	Drawdown Duration	**9**	207	56	**56**	269
	Minimum	**-0.520**	-0.680	-0.620	**-0.530**	-0.133
	Maximum	**0.680**	0.690	0.610	**0.730**	0.133
	Jarque-Bera	3409.7	20550.4	48342.3	119222.6	7885.2
	Q test	219.270	94.368	108.863	51.969	188.509
	ARCH test	203.705	74.110	7.082	5.105	75.068
	ADF	-24.861	-30.256	-31.421	-36.095	-48.779
HANDYMAX	**Mean (% Ann)**	-2.018	**-1.400**	-1.701	-1.925	-2.783
	Standard Deviation (% Ann)	39.564	**32.784**	26.220	19.171	35.822
	Downside Risk	1.710	**2.130**	2.002	2.731	4.390
	Sharpe Ratio	-0.076	**-0.073**	-0.103	-0.153	-0.106
	Sortino Ratio	-1.180	**-0.657**	-0.849	-0.705	-0.634
	Skewness	0.101	**-0.976**	-1.745	-6.118	-0.069
	Kurtosis	21.409	**24.969**	40.170	117.611	2.674
	MaxDrawdown	0.857	**0.833**	0.794	0.676	0.186
	Drawdown Duration	313	**222**	222	222	8
	Minimum	-0.475	**-0.438**	-0.468	-0.513	-0.093
	Maximum	0.577	**0.395**	0.326	0.163	0.093
	Jarque-Bera	18047.2	25903.2	74219.5	707443.9	23709.8
	Q test	501.718	338.499	389.628	313.620	38.316
	ARCH test	80.649	146.249	189.297	31.353	0.517
	ADF	-21.518	-24.204	-24.282	-26.022	-39.316

Notes: Table 2.3 presents the summary statistics of the passive strategies and the spread rule for three vessel sizes from January 1992 to June 2016. Panel A presents the logarithmic differences of the spot, 6-, 12- and 36- month period contracts. Panel B reports the returns of the spread rule. For further definitions refer to Table 2.1.

As can be seen from Table 2.4 and 2.5, the annualised returns and the annualised volatilities of a Capesize vessel are higher than the ones of a Panamax and Handymax. This is due to the fact that Capesize vessels are subject to size and geographical restrictions, thus are unable to visit all ports. This means that the price signals generated from the underlying commodity markets are less diffused when it comes to smaller vessels that are more flexible in terms of commodities they can carry whilst being subject to less restricted geographically (Nomikos and Doctor, 2013). The relative outperformance of trend-following strategies may also be attributed to the presence of non-linearities and deviations from normality of the spread series (Neftci, 1991).

Comparing the returns and Sharpe ratios with the ones obtained from the benchmark strategies (Table 2.3), it seems that these outperform the benchmark returns. The annualised volatility of the trading strategies based on the spread series is higher than the volatility of the passive strategies (see Table 2.3). Although the best-performing rules bear more risk, they have better Sharpe and Sortino ratios than the benchmark strategies making them more attractive. Additionally, the active strategies are positively skewed and more leptokurtic compared to the benchmark so would be more preferable for traders. For example, the annualised passive return and Sharpe ratio of the spot passive strategy of a Capesize vessel are equal to -4.6% and 96.8% whilst the annualised eBB active return and Sharpe ratio are equal to 2.13% and 78.48%.

Additionally, the profitability of the vote strategies is assessed. A vote strategy generates a signal when the majority of the parameterisations suggest a particular rule (Hsu and Kuan, 2005). For instance, if the majority of the 1,058 parameterisations of the MAC rule at time step t generate a *spot* signal and the other contracts are either a *P6m*, or *P12m* or *P36m*, then the voting strategy will follow the majority. Since there are 12 independent simple strategies this results in 12 voting strategies.

The summary statistics of the vote strategies for all vessels and strategies are presented in Table 2.6 and 2.7. The best performing vote strategy across all vessels is the same (i.e. sMAC) except from the one for a Handymax for which the best performing voting strategy is the eMAE. When comparing the vote strategies with the benchmark strategies (see Table 2.6 and 2.7), the vote strategies seem to be producing better Sharpe ratios (i.e. 0.06 compared to 0.04). In addition, the best-performing rules bear more risk than the passive strategies. The results also suggest that the active strategies are mainly positively skewed and more leptokurtic compared to the passive ones meaning that they will be more attractive from a trader's perspective.

The analysis also showed that some of the active voting strategies are not better than the passive ones either due to their higher standard deviation or because of a lack of returns. For instance, the vote active strategies of a Capesize, Panamax and Handymax vessel did not outperform the passive strategies in terms of standard deviation. Even though the results are mixed, certain parameterisations of these strategies indicate significant outperformance and hence used by practitioners in the industry to support their chartering positions and provide a more detailed way to assess the chartering performance.

The empirical analysis demonstrates that when the chartering decision problem is analysed using technical trading rules, excess risk-adjusted returns can be generated. In other words it can be concluded that technical trading rules can adequately identify the market's highs and lows in order for optimal chartering decisions to be made. A chartering decision is made considering the current and the expected value of the spread between the spot and period rates. More specifically, the value of the spread indicates the operational premium of the spot market over the period market. The examination of several parameterisations of active trading strategies show that active strategies can be applied to the physical market in order to increase the profitability of the chartering operations.

Additionally, the analysis shows that market timing rules provide useful hedging strategies that enable ship owners to operate in a favourable freight rate over a period of time and either maintain that hedge if the market moves in the desired direction or switch if the market moves against them. The results fail to return the EMH since trend, momentum, volatility and complex strategies suggest that a ship-owner can earn on average higher returns compared to the passive strategies or a *"simple spread strategy"*[7] that does not incorporate any technical trading rule.

The next step of the analysis is to investigate the robustness of the empirical findings while also test if the superior performance of the active strategies is due to data snooping bias.

2.3.4 Empirical Finding of the Robustness Tests

Multiple robustness checks are used to enhance the robustness of the empirical findings and assess if the technical trading rules indicate reliable and profitable chartering strategies. Instead of focusing only on Capesize ships, Panamax and Handymax vessels are also analysed in order to show that the findings are the same irrespective of the vessel size, which is expected due to the homogenous nature of shipping assets.

[7] The simple strategy implies that a position is taken in the market based on the value of the spread at time t. For instance, if the spread between spot and 6-month period rates is positive (negative) this means a spot (period) contract is signed.

Table 2.4: **Summary Statistics: Capesize Active Strategies –** ***Risk-adjusted Returns Outperformance Criterion***

	Description of Rules	*sMAC* (15,34)	*sTMA* (14,24,63)	*sMACD* (14,36,4)	*sBB* (14,14,2.6)	*sMAE* (37,0.052)	*RSI* (16,77,36)	*SOD* (33,78,30)	*eMAC* (17,35)	*eTMA* (17,38,52)	*eMACD* (14,36,4)	*eBB* **(26,29,3)**	*eMAE* (41,0.052)
CAPESIZE	**Mean (% Ann)**	2.588	1.999	2.287	2.147	2.279	2.648	2.360	2.465	0.663	2.287	**2.133**	2.216
	Standard Deviation (% Ann)	124.11	93.330	128.95	98.149	138.01	131.90	137.24	117.50	100.09	128.95	**78.483**	146.59
	Downside Risk	5.924	4.837	5.610	4.738	6.593	6.742	6.070	5.552	4.876	5.610	**4.179**	7.016
	Sharpe Ratio	0.013	0.011	0.010	0.012	0.009	0.012	0.010	0.012	-0.003	0.010	**0.014**	0.008
	Sortino Ratio	0.437	0.413	0.408	0.453	0.346	0.393	0.389	0.444	0.136	0.408	**0.511**	0.316
	Skewness	0.245	0.629	0.479	0.596	0.203	0.217	0.419	0.210	0.336	0.479	**0.334**	-0.015
	Kurtosis	8.455	14.958	8.682	9.910	6.102	7.481	7.246	7.856	10.309	8.682	**10.203**	5.550
	MaxDrawdown	1.605	1.804	1.619	1.301	1.578	1.754	1.564	1.397	1.428	1.619	**1.055**	1.456
	Drawdown Duration	257	28	65	268	258	180	408	165	449	65	**160**	159
	Minimum	-0.885	-0.916	-0.916	-0.629	-0.693	-0.742	-0.847	-0.742	-0.859	-0.916	**-0.629**	-0.674
	Maximum	1.011	0.887	0.866	0.693	0.885	1.012	0.897	0.710	0.710	0.866	**0.639**	0.862
	Jarque-Bera	6032.3	35599.0	6746.5	9982.7	1648.2	4739.9	3438.0	4229.9	12221.4	6746.5	13100.3	1030.8
	Q test	33.572	124.693	38.170	41.731	50.572	18.623	39.206	35.893	37.274	38.170	62.626	48.703
	ARCH test	0.933	2.783	7.925	1.461	17.919	1.300	1.342	10.430	17.249	7.925	6.185	4.257
	ADF	-34.090	-31.422	-33.583	-32.722	-40.765	-36.266	-33.380	-37.162	-34.700	-33.583	-30.837	-38.050
	KPSS	0.015	0.039	0.019	0.023	0.011	0.013	0.012	0.015	0.032	0.019	0.031	0.011

Notes: Table 2.4 presents the summary statistics of the active strategies in terms of the maximum risk-adjusted returns (Sharpe ratio) for a Capesize vessel from January 1992 to June 2016. The description of the technical trading rules presents the parameterisations under which the maximum risk-adjusted or mean returns were achieved. More specifically, **MAC** (*Short-Term Moving Average* – STMA, *Long-Term Moving Average* – (LTMA)) presents the length of the short-and long-term MA. **TMA** (STMA, *Medium-Term Moving Average* – (MTMA), LTMA) represents the length of the short-, medium- and long-term MA. **MACD** (STMA, LTMA, *Signal Line Moving Average* – (SLMA)), **SOD** (Stochastic Oscillator, upper filter, lower filter), **RSI** (RSI index, upper filter, lower filter), **BB** (length of the MA series used to estimate the upper and lower bands, length of the MA series used to generate a signal, pre-specified number of standard deviations) and **MAE** (length of the MA series used to estimate the upper and lower bands, pre-specified percentage b). The letters **'*s*'** and **'*e*'** in front of each technical trading rule indicate the use of a simple or exponential moving average respectively. For further explanations regarding the technical trading rules refer to sub-section 2.2.2 and to Appendix 2.A. Additionally, for further definitions, refer to Table 2.1.

Table 2.5: Summary Statistics: Panamax and Handymax Active Strategies – ***Risk-adjusted Returns Outperformance Criterion***

	Description of Rules	***sMAC*** (1,42)	***sTMA*** (10,30,65)	***sMACD*** (30,32,5)	***sBB*** **(11,11,3)**	***MAE*** (41,0.096)	***RSI*** (7,71,36)	***SOD*** (39,76,20)	***eMAC*** (1,44)	***eTMA*** (12,37,51)	***eMACD*** (30,32,5)	***eBB*** **(8,11,2.6)**	***eMAE*** (39,0.058)
PANAMAX	**Mean (% Ann)**	-0.894	**1.150**	-0.875	**1.130**	-0.080	-1.285	-1.506	-0.901	-1.286	-0.875	**1.130**	-0.717
	Standard Deviation (% Ann)	140.841	**83.011**	109.768	**61.305**	125.646	137.492	84.592	132.445	74.170	109.768	**61.305**	141.257
	Downside Risk	6.649	**3.916**	4.672	**4.220**	5.758	6.109	3.893	6.415	3.360	4.672	**4.220**	6.462
	Sharpe Ratio	-0.013	**0.002**	-0.017	**0.002**	-0.009	-0.017	-0.030	-0.014	-0.031	-0.017	**0.002**	-0.012
	Sortino Ratio	-0.135	**0.294**	-0.187	**0.268**	-0.014	-0.210	-0.387	-0.140	-0.383	-0.187	**0.268**	-0.111
	Skewness	-0.307	**2.043**	0.428	**5.016**	-0.114	-0.226	0.033	-0.443	-0.421	0.428	**5.016**	-0.641
	Kurtosis	10.481	**25.684**	12.012	**50.485**	9.826	9.423	19.340	10.565	16.843	12.012	**50.485**	11.842
	MaxDrawdown	2.050	**1.703**	1.810	**0.826**	1.913	1.947	1.719	2.184	1.749	1.810	**0.826**	1.976
	Drawdown Duration	13	**3**	336	**123**	99	20	193	6	65	336	**123**	217
	Minimum	-1.104	**-0.545**	-0.695	**-0.379**	-1.031	-0.985	-0.877	-0.926	-0.716	-0.695	**-0.379**	-1.409
	Maximum	0.972	**1.158**	1.054	**0.747**	0.882	0.946	0.849	0.972	0.693	1.054	**0.747**	0.945
	Jarque-Bera	5677.4	110525.2	7205.4	11905777.8	5781.7	3433.6	3412.2	8058.7	24612.6	7205.4	11905777.8	6350.0
	Q test	85.047	112.589	57.980	31.797	42.236	123.574	59.850	63.325	59.365	57.980	31.797	100.275
	ARCH test	31.659	6.561	2.746	7.732	33.799	14.818	5.890	21.332	2.380	2.746	7.732	22.921
	ADF	-42.273	-30.414	-36.730	-41.378	-39.117	-41.363	-37.678	-39.470	-33.506	-36.730	-41.378	-43.980
	KPSS	0.008	0.034	0.013	0.040	0.009	0.007	0.009	0.007	0.019	0.013	0.040	0.007
	Description of Rules	(23,28)	**(18,27,52)**	(19,31,4)	(26,32,1.8)	(27,0.044)	(20,64,21)	(27,80,22)	(1,27)	(4,31,53)	(19,31,4)	(26,29,1.4)	(27,0.062)
HANDYMAX	**Mean (% Ann)**	-0.582	**0.914**	-0.910	-0.807	-0.590	-0.928	-0.932	-0.605	-1.240	-0.910	-0.762	-0.583
	Standard Deviation (% Ann)	66.941	**47.872**	48.591	56.393	76.139	50.826	65.324	72.872	45.022	48.591	61.627	82.528
	Downside Risk	3.065	**3.022**	2.821	2.850	3.737	2.336	3.117	3.734	2.171	2.821	3.085	4.262
	Sharpe Ratio	-0.024	**-0.002**	-0.039	-0.032	-0.021	-0.038	-0.030	-0.022	-0.050	-0.039	-0.029	-0.019
	Sortino Ratio	-0.190	**0.302**	-0.323	-0.283	-0.158	-0.397	-0.299	-0.162	-0.571	-0.323	-0.247	-0.137
	Skewness	0.051	**0.162**	-1.358	-0.491	0.431	-0.260	-0.479	-0.073	-0.984	-1.358	-0.462	0.062
	Kurtosis	14.977	**18.700**	20.609	31.683	16.588	15.582	21.137	14.153	20.209	20.609	24.562	16.742
	MaxDrawdown	1.334	**0.929**	1.295	1.627	1.393	1.242	1.342	1.112	0.927	1.295	1.163	1.392
	Drawdown Duration	257	**28**	65	268	258	180	408	165	449	65	160	159
	Minimum	-0.560	**-0.449**	-0.627	-0.747	-0.613	-0.526	-0.816	-0.560	-0.582	-0.627	-0.747	-0.747
	Maximum	0.560	**0.480**	0.362	0.780	0.780	0.453	0.588	0.592	0.400	0.362	0.780	0.780
	Jarque-Bera	13606.8	78908.1	16599.1	14500.5	14232.2	11251.9	32669.7	14264.5	33978.3	16599.1	16364.4	17324.0
	Q test	66.865	330.210	40.683	54.580	42.628	89.260	51.832	92.692	50.866	40.683	56.098	128.070
	ARCH test	31.085	97.178	72.292	23.257	28.398	36.149	4.006	62.988	54.848	72.292	10.845	109.772
	ADF	-38.916	-23.708	-39.615	-39.789	-37.825	-39.521	-35.955	-39.458	-35.091	-39.615	-37.464	-42.116
	KPSS	0.020	0.100	0.026	0.018	0.021	0.020	0.025	0.025	0.054	0.026	0.024	0.018

Notes: Table 2.5 presents the summary statistics of the active strategies in terms of the maximum risk-adjusted returns (Sharpe ratio) for a Panamax and a Handymax vessel from January 1992 to June 2016. For further definitions, refer to Tables 2.1 and 2.4.

The only difference observed is that the values of the empirical findings (i.e. mean, standard deviation etc.) decrease as the ship size reduces. For instance, Table 2.3 shows that the volatility of the logarithmic returns (Panel A) is sloping downward across the term for all vessels but also decreasing as the vessel size is also becomes smaller (i.e. the Capesize spot freight rate volatility is 10.08, while for a Panamax and Handymax the volatility is 6.78 and 4.53 respectively).

2.3.4.1 No Financial Crisis Period

Due to the fact that there were significant freight rate movements (see Figure 2.1) during the financial crisis of 2008, the profitability of the trading rules may have been affected and thus had an impact on the overall profitability. Therefore, in order to test the robustness of the empirical findings, the turbulent period from August 2007 to January 2009 is eliminated and the significance of the outperformance is re-evaluated.

The empirical findings are robust meaning that the extreme market movements recorded during this turbulent period do not affect the empirical findings, thus the profitability observed from the use of technical trading rules was not due to extreme freight rate values recorded during the financial crisis period (see Appendix 2.C – Table C.2.17 to C.2.26). The next-section presents another solution to address the data-snooping or over-fitting issue.

2.3.4.2 Data Snooping Bias – White's Reality Check *p*-value

In order to eliminate the data-snooping bias from the analysis, the *White's Reality Check (WRC) p-value* is estimated for 10,000 bootstrap replications of the model by comparing the best performing trading rules (see Table 2.8) to the benchmark passive long-only strategies.

An issue that arises at this point is the choice of the block-length for the stationary bootstrap method that, according to White (2000), depends on the data that is being examined. Politis and White (2004) proposed an algorithm that estimates the optimal block-length based on the spectral estimation via the flat-top lag-windows of Politis and Romano (1994). Thus, in order to estimate the WRC *p-value*, the optimal block length first needs to be estimated.[8]

[8] Dr. Andrew Patton's code was used for the estimation of the optimal block length. The code is available at: http://public.econ.duke.edu/~ap172/code.html.

Table 2.6: **Summary Statistics: Capesize Vote Strategies –** ***Risk-adjusted Returns Outperformance Criterion***

	Description of Rules	*sMAC*	*sTMA*	*sMACD*	*sBB*	*MAE*	*RSI*	*SOD*	*eMAC*	*eTMA*	*eMACD*	*eBB*	*eMAE*
CAPESIZE	**Mean (% Ann)**	**7.170**	-1.387	-8.036	-1.667	-1.519	-1.747	-5.672	1.636	0.620	-8.036	-3.258	-2.073
	Standard Deviation (% Ann)	**110.94**	83.925	103.24	140.58	157.65	139.69	122.28	115.95	105.84	103.24	134.18	160.18
	Downside Risk	**5.545**	3.790	4.836	6.324	7.542	6.525	5.356	5.418	5.222	4.836	5.953	7.582
	Sharpe Ratio	**0.065**	-0.017	-0.078	-0.012	-0.010	-0.013	-0.046	0.014	0.006	-0.078	-0.024	-0.013
	Sortino Ratio	**1.293**	-0.366	-1.662	-0.264	-0.201	-0.268	-1.059	0.302	0.119	-1.662	-0.547	-0.273
	Skewness	**0.191**	0.500	0.974	0.194	-0.156	-0.038	0.359	0.140	0.084	0.974	0.367	-0.056
	Kurtosis	**9.290**	13.814	14.446	6.142	4.997	6.225	6.988	7.622	8.431	14.446	6.501	4.833
	MaxDrawdown	**1.507**	1.516	1.399	1.624	1.663	1.833	1.481	1.474	1.309	1.399	1.454	1.578
	Drawdown Duration	**257**	28	65	268	258	180	408	165	449	65	160	159
	Minimum	**-0.684**	-0.629	-0.693	-0.766	-0.778	-0.939	-0.674	-0.742	-0.693	-0.693	-0.675	-0.693
	Maximum	**0.862**	0.887	1.192	0.878	0.885	0.894	0.808	0.732	0.681	1.192	0.806	0.885
	Jarque-Bera	6617.4	16434.0	22159.9	1540.1	550.1	1659.4	2249.4	3409.5	6291.3	22159.9	2072.2	481.1
	Q test	39.767	64.843	28.166	46.352	100.136	30.630	37.005	20.856	25.147	28.166	40.876	81.153
	ARCH test	1.093	2.433	4.153	52.473	22.163	13.167	11.175	2.875	3.743	4.153	49.879	15.614
	ADF	-33.350	-32.697	-33.950	-40.609	-42.791	-39.153	-34.090	-37.477	-36.132	-33.950	-40.867	-42.765
	KPSS	0.018	0.032	0.038	0.012	0.009	0.012	0.022	0.014	0.025	0.038	0.013	0.009

Notes: Table 2.6 presents the summary statistics of the voting strategies in terms of the maximum risk-adjusted returns (Sharpe ratio) for a Capesize vessel from January 1992 to June 2016. For further definitions, refer to Tables 2.1 and 2.4.

Table 2.7: Summary Statistics: Panamax and Handymax Vote Strategies – *Risk-adjusted Returns Outperformance Criterion*

	Description of Rules	*sMAC*	*sTMA*	*sMACD*	*sBB*	*MAE*	*RSI*	*SOD*	*eMAC*	*eTMA*	*eMACD*	*eBB*	*eMAE*
PANAMAX	**Mean (% Ann)**	**-1.768**	-3.652	-2.309	-3.052	-3.061	-3.875	-3.544	-4.082	-3.470	-2.309	-5.323	-3.662
	Standard Deviation (% Ann)	**99.327**	75.590	74.909	113.65	152.60	111.14	92.734	106.42	87.437	74.909	113.25	146.59
	Downside Risk	**4.215**	3.068	3.293	5.048	7.211	4.987	3.897	4.943	3.719	3.293	5.081	6.999
	Sharpe Ratio	**-0.018**	-0.048	-0.031	-0.027	-0.020	-0.035	-0.038	-0.038	-0.040	-0.031	-0.047	-0.025
	Sortino Ratio	**-0.420**	-1.191	-0.701	-0.605	-0.424	-0.777	-0.909	-0.826	-0.933	-0.701	-1.047	-0.523
	Skewness	**0.476**	1.233	0.426	-0.092	-0.480	0.092	0.853	-0.358	0.344	0.426	-0.156	-0.728
	Kurtosis	**15.471**	16.819	20.785	12.419	8.590	13.872	23.327	16.216	25.409	20.785	16.533	9.950
	MaxDrawdown	**1.792**	1.364	1.521	1.814	1.913	1.852	1.938	1.852	1.985	1.521	2.220	2.102
	Drawdown Duration	**257**	28	65	268	258	180	408	165	449	65	160	159
	Minimum	**-0.824**	-0.539	-0.828	-0.907	-1.031	-0.907	-0.821	-0.907	-1.101	-0.828	-1.104	-1.409
	Maximum	**0.967**	0.825	0.747	0.908	0.974	0.945	1.117	0.945	0.886	0.747	1.117	0.882
	Jarque-Bera	16627.5	21272.4	35602.6	8632.8	2958.1	11387.3	38374.9	17452.9	50854.8	35602.6	19158.8	4404.7
	Q test	80.316	87.797	65.009	58.389	100.05	63.001	75.776	59.495	53.716	65.009	87.910	103.14
	ARCH test	4.144	4.065	1.347	5.142	13.017	16.211	31.289	0.774	0.061	1.347	37.999	12.903
	ADF	-33.467	-30.159	-32.859	-38.575	-41.438	-39.481	-38.952	-34.407	-32.957	-32.859	-41.469	-43.641
	KPSS	0.015	0.035	0.034	0.013	0.007	0.015	0.020	0.022	0.025	0.034	0.014	0.008
HANDYMAX	**Mean (% Ann)**	-1.654	-2.503	-2.221	-2.371	-1.971	-1.703	-2.300	-2.143	-2.362	-2.221	-1.726	**-1.817**
	Standard Deviation (% Ann)	54.371	37.047	46.582	65.724	79.841	72.919	50.106	63.485	40.703	46.582	66.229	**82.187**
	Downside Risk	2.594	1.906	2.525	3.303	4.027	3.656	2.260	3.194	1.910	2.525	3.204	**4.184**
	Sharpe Ratio	-0.031	-0.068	-0.048	-0.036	-0.025	-0.023	-0.046	-0.034	-0.058	-0.048	-0.026	**-0.022**
	Sortino Ratio	-0.638	-1.313	-0.880	-0.718	-0.490	-0.466	-1.018	-0.671	-1.236	-0.880	-0.539	**-0.434**
	Skewness	0.037	-1.344	-1.040	-0.808	-0.152	-0.452	0.046	0.076	0.339	-1.040	-0.140	**0.014**
	Kurtosis	18.630	24.002	21.587	21.309	13.645	20.103	21.482	21.446	25.967	21.587	17.162	**13.264**
	MaxDrawdown	1.009	0.760	0.863	1.306	1.417	1.473	0.886	1.243	0.755	0.863	1.306	**1.392**
	Drawdown Duration	257	28	65	268	258	180	408	165	449	65	160	**159**
	Minimum	-0.501	-0.526	-0.582	-0.747	-0.637	-0.747	-0.627	-0.560	-0.526	-0.582	-0.526	**-0.612**
	Maximum	0.560	0.292	0.437	0.780	0.780	0.780	0.597	0.693	0.569	0.437	0.780	**0.780**
	Jarque-Bera	28359.3	59271.7	49619.3	36293.2	11953.7	29990.8	37094.7	36692.9	62156.6	49619.3	24081.1	10938.2
	Q test	97.405	166.575	156.411	33.962	58.045	76.145	66.652	74.345	107.608	156.411	42.729	68.650
	ARCH test	12.854	11.692	5.547	8.981	25.521	58.671	10.014	50.025	7.668	5.547	16.509	12.767
	ADF	-30.818	-27.547	-27.496	-34.847	-40.621	-38.658	-29.603	-37.287	-29.138	-27.496	-36.184	-38.365
	KPSS	0.061	0.117	0.075	0.030	0.023	0.027	0.059	0.036	0.092	0.075	0.034	0.021

Notes: Table 2.7 presents the summary statistics of the voting strategies in terms of the maximum risk-adjusted returns (Sharpe ratio) for a Panamax and a Handymax vessel from January 1992 to June 2016. For further definitions, refer to Tables 2.1 and 2.4.

This testing method helps confirm the absence of data-snooping bias and thus make statistical inferences accordingly. The empirical analysis highlights the significance of market timing strategies in the dry-bulk physical market since most of the *p*-values are significant at all levels. This means that the active strategies outperform the passive ones and the spread rule whilst not being subject to data snooping bias. Additionally, the fact that the active strategies outperform the passive ones also confirms that the Efficient Market Hypothesis fails to be retained after including the robustness check using the WRC *p*-value.

Table 2.8 presents the WRC *p-values* of the best active and vote trading rules, chosen based on the highest Sharpe Ratio between January 1992 to June 2016. The purpose of the WRC *p-values* is to assess if the superior outperformance of the active strategies is attributed to the data snooping bias. A necessary requirement for the use of stationary bootstrap (Politis and Romano, 1994) is that the series should be stationary. Therefore, as can be seen from Tables 2.4 to 2.7, the best active and vote return series are all stationary at a 5% significance level (see ADF-test and KPSS-test values).

The WRC *p-values* of all vessels and across each active strategy are statistically significant overall at a 5% significant level (Table 2.8). Most of the WRC *p-values* indicate that the vote strategies are not the result of data snooping bias.

However, there are a few exceptions such as the sMACD, eMACD and SOD returns of a Capesize vessel (i.e. non-significant when compared with the spread benchmark strategy) as well as the sMAE, RSI, eBB, eMAE returns of a Panamax vessel that are non-significant when compared with the spot passive strategy. Additionally, the sTMA, MAE, RSI, SOD, eTMA, eBB and eMAE returns of a Panamax are non-significant when compared with the spread benchmark strategy. The MAE vote returns of a Handymax vessel are non-significant when compared with the spot and P6m benchmark strategy, while also the eMAE returns are non-significant when compared with the P6m benchmark strategy. All non-significant cases are highlighted in blue in Table 2.8.

Therefore, using the WRC *p-value* to exclude the non-significant active strategies, the null hypothesis of the remaining strategies can be rejected at conventional significance levels meaning that the proposed trading strategies are profitable. Appendix 2.D presents the WRC *p-values* of the best active and vote-trading rules selected using the maximum mean returns as the performance criterion. Appendix

2.D also presents the WRC *p-values* of the best active and vote strategies for the sample after the elimination of the financial crisis period.

2.3.4.3 Assessing the t – test *p-values*

In addition, the annualised mean values of the active and passive strategies are very close to zero, therefore a t-test is used to evaluate if the mean is statistically different from zero at a 5% significance level. More specifically, the t-test was performed on all maximum mean and Sharpe ratio return series to assess if the series are statistically different from zero. The empirical findings show that all annualised mean values are significantly different from zero. Table 2.9 presents the t – test's *p-values* of the passive strategy returns across the entire timeline (Panel A), as well as after the exclusion of the financial crisis period (Panel B).

As can be seen from Panel A in Table 2.9, the return of most passive strategies are statistically different from zero at any significance level, except from the spot return series for a Capesize and a Panamax vessel (*p-value* = 0.166 and *p-value* = 0.416). Similarly, Panel B (excluding financial crisis period) shows that all *p-values* are statistically significant at any significance level, with an exception being the P36m returns of a Handymax vessel (*p-value* = 0.157). Table 2.10 presents the *p-values* of the t – test for the active and vote strategies for every vessel and performance criterion (i.e. mean or Sharpe Ratio (SR) outperformance).

The results show that the t – test *p-values* are highly significant at a 5% significant level indicating the every value is statistically different from zero. Additionally, the study examines if the difference between the active and passive strategies' returns is statistically different from zero. More specifically, the following hypothesis is tested for each type of vessel and for both samples (i.e. full sample and the full sample excluding the financial crisis):

$$H_0\ (Null\ Hypotheisis): R_{active} - R_{passive} > 0$$

$$H_1 (Alternative\ Hypothesis): R_{active} - R_{passive} = 0$$

where R_{active} $(i.e. R_{sMAC}, R_{sTMA}, etc.)$ is the maximum mean and risk-adjusted return and $R_{passive}$ represents the returns of the spot, P6m, P12m, P36m and the Spread rule return.

Table 2.8: White's Reality Check *p-values* for Active and Vote Strategies

Panel A: Capesize	***sMAC***	***sTMA***	***sMACD***	***sBB***	***MAE***	***RSI***	***SOD***	***eMAC***	***eTMA***	***eMACD***	***eBB***	***eMAE***
Spot	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P6m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P12m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Spread Rule	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel B: Capesize VOTE strategies												
Spot	0.000	0.000	0.000	0.000	0.000	0.000	0.034	0.000	0.000	0.000	0.000	0.000
P6m	0.000	0.000	0.000	0.000	0.000	0.000	0.005	0.000	0.000	0.000	0.000	0.000
P12m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.000	0.000	0.000	0.000	0.620	0.000	0.000	0.001	0.000	0.000
Spread Rule	0.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000
Panel C: Panamax												
Spot	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P6m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P12m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Spread Rule	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel D: Panamax VOTE strategies												
Spot	0.000	0.000	0.000	0.000	0.562	0.206	0.000	0.000	0.000	0.000	0.620	0.527
P6m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P12m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Spread Rule	0.000	0.923	0.000	0.000	1.000	1.000	0.411	0.000	0.366	0.000	1.000	1.000
Panel E: Hanydmax												
Spot	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P6m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P12m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Spread Rule	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel E: Hanydmax VOTE Strategies												
Spot	0.000	0.000	0.000	0.000	0.566	0.000	0.000	0.000	0.000	0.000	0.000	0.014
P6m	0.000	0.001	0.017	0.002	1.000	0.000	0.000	0.000	0.000	0.014	0.000	0.796
P12m	0.000	0.000	0.000	0.000	0.017	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Spread Rule	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table 2.8 presents the *White's Reality Check p-values* of the best active and vote strategies based on the highest Sharpe Ratio criterion, compared against each passive strategy. The analysis includes 30,046 models (r) for the active strategies and 12 models (r) for the vote strategies and 10,000 bootstrap repetitions. For further details regarding the chartering strategies, refer to *sub-section* 2.2.2.

Table 2.9: Passive Strategies: *t* – test's *p-values*

	Panel A: full sample					Panel B: No Crisis sample				
	spot	**P6m**	**P12m**	**P36m**	**Spread Rule**	**spot**	**P6m**	**P12m**	**P36m**	**Spread Rule**
Capesize	0.166	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panamax	0.416	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Handymax	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.157	0.000

Notes: Table 2.9 Panel A presents the *t* – test's *p-values* of the passive strategies for all vessel sizes from January 1992 to June 2016. Panel B present the *t* – test's *p-values* for sample period excluding the financial crisis (31st of August 2007 to 30th of January 2009). The *t* – test examines if the return series of the passive strategies are statistically different from zero.

The empirical findings of the difference in returns between the active and the spot passive strategy are presented in Table 2.11 whilst Appendix 2.E contains the rest of the findings. The results show that, despite a few exceptions highlighted in blue in Table 2.11, most the *t* – test *p-values* are highly significant at a 5% significant level indicating that the value is statistically different from zero.

2.3.5 Considerations of the Returns Assessment Method

The complexity of the shipping freight market and the ship-chartering problem makes it very difficult to tackle the assessment of chartering strategies without making some assumptions. The purpose though is to choose the method that will be less based on assumptions and will not negatively affect the robustness and the accuracy of the empirical finding.

There are several approaches that can be used to assess the profitability of the chartering strategies (i.e. Cullinane 1995; Berg-Andreassen, 1998; Alizadeh and Nomikos, 2007, 2011, Stopford, 2009; Adland and Strandenes, 2006; Alizadeh and Nomikos, 2009 and logarithmic differences). However, some of these are subject to limitations such as operating cost values (i.e. Cullinane's, 1995 method, Alizadeh and Nomikos, 2007, 2011), ship prices and depreciation rate (Alizadeh and Nomikos, 2007, 2011) or only estimated overlapping cumulative earnings resulting from a chartering strategy (i.e. Adland and Strandenes, 2006 and Alizadeh and Nomikos, 2009) hence why it was decided to only keep the logarithmic differences that best measure the way the physical market operates. Empirical findings of the return methods that were excluded are available upon request.

Another important problem is related to the way the returns are calculated (i.e. in a continually compounded way or using holding period horizon). Each vessel contract in the physical market requires a specific amount of time in order to be completed, therefore the choice of holding period return is a better option. For instance, in case of a *spot* signal, if a decision is made at $t = 0$ (week) then the next decisions will be made at $t = 6$, $t = 12$, $t = 18$, …, $t = T$.

Table 2.10: Active and Vote Strategies: *t* – test's *p-values*

	Panel A: Active and Vote Strategies - full sample												
	Capesize												
	Criteria	***sMAC***	***sTMA***	***sMACD***	***sBB***	***MAE***	***RSI***	***SOD***	***eMAC***	***eTMA***	***eMACD***	***eBB***	***eMAE***
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.005	0.000	0.000	0.000	0.100	0.000	0.000	0.005	0.000	0.000
	SR	0.000	0.000	0.005	0.000	0.000	0.000	0.100	0.000	0.000	0.005	0.000	0.000
	Panamax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.018	0.059	0.000	0.000	0.000	0.000	0.005	0.025
	SR	0.000	0.000	0.000	0.000	0.018	0.059	0.000	0.000	0.000	0.000	0.005	0.025
	Handymax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Panel B: Active and Vote Strategies – No Crisis sample												
	Capesize												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Panamax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.643	0.000	0.175	0.000	0.000	0.675	0.000	0.137	0.000	0.000	0.000
	SR	0.000	0.643	0.000	0.175	0.000	0.000	0.675	0.000	0.137	0.000	0.000	0.000
	Handymax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table 2.10 Panel A presents the t – test's p-values of the best active and vote strategies in terms of both the maximum risk-adjusted and mean outperformance criteria for thee vessel sizes from January 1992 to June 2016. Panel B and C present the *t* – test's *p-values* for the sample period excluding the financial crisis (31st of August 2007 to 30th of January 2009). The *t* – test examines if the return series of the best active strategies are statistically different from zero.

Table 2.11: Testing the Difference between $R_{active} - R_{spot}$ using t – test's *p-values*

	Panel A: Active and Vote Strategies - full sample												
	Capesize												
	Criteria	***sMAC***	***sTMA***	***sMACD***	***sBB***	***MAE***	***RSI***	***SOD***	***eMAC***	***eTMA***	***eMACD***	***eBB***	***eMAE***
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.400	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.400	0.000	0.000	0.000	0.000	0.000
	Panamax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.027	0.000	0.000	0.000	0.000	0.000	0.001
	SR	0.000	0.000	0.000	0.000	0.000	0.027	0.000	0.000	0.000	0.000	0.000	0.001
	Handymax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.254
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.254
	Panel B: Active and Vote Strategies – No Crisis sample												
	Capesize												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000
	Panamax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.000	0.000	0.037	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.000	0.000	0.037	0.000
	Handymax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.568
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.568

Notes: Table 2.11 Panel A presents the statistical significance of the difference between the returns of active and passive strategies using t – test's p-values for the period from January 1992 to June 2016. As active returns (R_{active}) are used the best active and vote strategies returns in terms of both the maximum risk-adjusted and mean outperformance criteria. Panel B shows the same statistics however the excludes the financial crisis (31st of August 2007 to 30th of January 2009). The t – test examines if the differences between the active and passive return series is statistically different from zero.

In other words, decisions can only be made at the maturity date of the contracts. Between t and $t + HP$ (where HP is the holding period of the contract), the freight rate remains the same as it was when the contract was signed at $t - HP$, therefore the returns between t and $t + HP$ are equal to zero. A change in returns occurs when a new type of contract is signed which means that the returns should be calculated as non-overlapping returns.

However, an issue that might arise when estimating non-overlapping holding period returns is that the sample might not be large enough to draw reliable conclusions. For instance, estimating non-overlapping returns for a holding period of 52 weeks will result in approximately 20 estimated non-overlapping returns, which is a very small number of observations to allow drawing reliable conclusions. There are techniques in the literature that can increase the number of estimated returns such as bootstrap with replacement (Conrad and Kaul, 1998; Hickman et al, 2001; Mukherji, 2002) but the limitations of this approach is the accuracy of the empirical findings since the new sample will be drawn from a small sample that is unable to accurately capture the return series distribution characteristics.

The focus of this chapter is on the physical freight market and therefore estimating the profitability of the chartering strategies using the continually compounded way (i.e. logarithmic differences of the freight rates – see eq. 2.2) might create concerns since it is an approach mainly found in the financial (i.e. non-physical) markets.

Additionally, estimating the returns using the continually compound method, eliminated the issue related to the use of a holding period returns approach however, it means that a shipowner can only charter vessel every week and then charters it out immediately so the number of ships in the fleet is equal to the number of weeks being analysed. Therefore, in the future, in order for the analysis to reflect the reality more accurately, it will require multiple scenarios regarding the potential number of vessels in a fleet.

Producing empirical findings and draw conclusions based on a method that relies on a series of assumptions, which have also been based on further assumptions, might result in biased or inaccurate conclusions. This is why the continually compounded returns method was selected as it is based on reasonable assumptions that do not affect the robustness of the empirical findings and can therefore be considered as an adequate method to measure the performance of chartering strategies.

Even though the assessment of the chartering strategies needs to be treated cautiously as it does not fully capture the way the chartering market operates, it can be still used as an indication that the technical trading rules can indeed be used in the dry bulk freight market and produce profitable strategies.

2.4 Liquidity Preference Hypothesis and the Monotonicity Test

The use of technical trading rules can be considered as an alternative test of the EMH that, based on the aforementioned empirical findings, rejected the hypothesis. Therefore, it can be concluded that the dry bulk market does not support the EMH for the period from January 1992 to June 2016.

As a result, there is a need to examine whether the freight market supports the *Liquidity Preference Theory* (LPH). The LPH implies that investors require higher interest rates or premiums on securities with long-term maturities since the long-term maturities are less liquid and carry greater risk (McCulloch, 1973). Long-term interest rates not only reflect investors' assumptions about future interest rates but also include a premium for holding long-term bonds (investors prefer short term bonds to long term bonds), called the *term premium* or the *liquidity premium*. This premium compensates investors for the added risk of having their capital tied up for a longer period and the greater price uncertainty.

Similarly, in the shipping freight market, shipowners usually prefer to operate under spot contracts and persuade them to take on a long term ones usually requires an extra premium to offset the loss in liquidity. Kavussanos and Alizadeh (2002b) argue that shipowners are willing to offer a discount in time-charter rates over spot rates because chartering a vessel under a spot contract can lead to risks of: (i) not finding a new contract for the vessel when the contract expires; (ii) freight rates might decrease by the time the next spot contract starts; (iii) vessel relocation to a nearby, but more expensive, port; and (iv) bunker fuel price might increase. Additionally, managers of shipping companies may use time-charter contracts as protection (hedge) against potential freight market decrease. However, according to Kavussanos and Visvikis (2004), this hedging strategy might be inflexible, expensive or non-existent if not scheduled accurately since long-term charters are difficult to find when the market is in decline.

When the LPH is held, due to the term premium, long-term bond yields tend to be higher than short-term ones and the yield curve slopes upward. Therefore, the study tested whether the term premium increases monotonically over time to maturity (i.e. liquidity premium) in order to assess whether the freight market supports the Liquidity Preference Hypothesis – LPH (Hicks, 1946).

Initially, the liquidity spread is defined and then the test used to assess the existence of the liquidity premium is presented.

2.4.1 The Liquidity Spread

The freight spread and the technical trading rules assess if the dry bulk freight market supports the EMH. This sub-section examines whether the freight market supports the LPH.

The LPH implies that the term premium increases monotonically over time to maturity. In other words, based on the LPH ship-owners prefer to operate their vessels using a long-term contract for an extra liquidity premium. This premium compensates investors for the added risk of having their capital tied up for a longer period, including the greater price uncertainty.

There are different measures and methods that can be used to measure the liquidity (Amihud and Mendelson (1991)). For instance, the liquidity premium is measured as the difference in freight rates between fixtures with differing levels of liquidity. Thus, it can be defined as the difference between spot and period rates as per equation (2.1). Many scholars calculated the liquidity premium by comparing the yields in different Treasury bonds (Fama, 1984; McCulloch, 1987; Kamara, 1988; Amihud and Mendelson, 1991; Boudoukh and Whitelaw, 1991; Longstaff, 1992; Richardson et al, 1992; Kamara, 1994; Chalmers and Kadlec, 1998; Boukoukh et al, 1999; Longstaff, 2004; Patton and Timmermann, 2010 amongst others).

Under the liquidity preference hypothesis, the expected returns of freight rates should increase monotonically as they get closer to maturity and therefore a long-term contract is a more profitable choice compared to a shorter one. The Patton and Timmermann (2010) process is followed to investigate the presence or absence of a monotonic pattern in expected returns. The difference between the long-term returns and the spot return $E\left[R_t^{\tau_i} - R_t^{spot}\right]$ is defined as the liquidity premium, where $R_t^{\tau_i}$ is the P36m, P12m and P6m logarithmic difference in returns. The liquidity preference hypothesis implies that the term structure of freight rates increases over time, which mathematically can be expressed as follows:

$$E\left[R_t^{\tau_i} - R_t^{spot}\right] > E\left[R_t^{\tau_j} - R_t^{spot}\right] \text{ for all } \tau_i \geq \tau_j \tag{2.6}$$

Where τ_i represents the 36m or 12m returns at time t and τ_j is the 12m or 6m returns. For instance, the freight rate curve at time t is upward sloping **if** $E\left[R_t^{P12m} - R_t^{spot}\right] > E\left[R_t^{P6m} - R_t^{spot}\right]$ **and** $E\left[R_t^{P36m} - R_t^{spot}\right] > E\left[R_t^{P12m} - R_t^{spot}\right]$. The liquidity premium is defined as follows:

$$\Delta_{\tau_i} = E\left[R_t^{\tau_i} - R_t^{spot}\right] - E\left[R_t^{\tau_j} - R_t^{spot}\right] \tag{2.7}$$

Therefore, the existence of a strictly decreasing pattern is tested under the null hypothesis and a strictly increasing pattern under the alternative:

<u>Null</u> Hypothesis (H_o): $\Delta_{\tau_i} \leq 0$ **and** <u>Alternative</u> Hypothesis (H_1): $\Delta_{\tau_i} > 0$

More specifically, if $\Delta_{P12m} = E\left[R_t^{P12m} - R_t^{spot}\right] - E\left[R_t^{P6m} - R_t^{spot}\right]$ is negative, this implies that the 6m rates are greater than the 12m ones and thus the freight curve cannot be sloping upwards. This approach allows testing if the liquidity premium is monotonically increasing and thus supports the liquidity preference hypothesis.

2.4.2 Monotonicity Test

The Patton's and Timmermann's (2010) test assesses if the return series increase monotonically (see equation 2.7). This approach tests if the liquidity premium is monotonically increases and thus can support the liquidity preference hypothesis. Therefore, there is a need to test the existence of a strictly increasing pattern under the null hypothesis or a strictly decreasing pattern under the alternative:

<u>Null</u> Hypothesis (H_o): $\Delta_i \geq 0$ and <u>Alternative</u> Hypothesis (H_1): $\Delta_i < 0$

Table 2.12: Monotonicity Tests

		Full Sample	No Crisis	sub-samples A	B	C	D	E
Liquidity Premium	**Panel A: Capesize**	0.339	0.341	0.304	0.199	0.267	0.822	0.358
	Panel B: Panamax	0.259	0.258	0.140	0.383	0.176	0.708	0.434
	Panel C: Handymax	0.209	0.230	0.251	0.579	0.242	0.420	0.210

Notes: Table 2.12 presents the p-values of the Patton and Timmermann (2010) monotonicity test for each vessel type and sample.

The monotonicity is analysed across the full sample (January 1992 to June 2016) as well as for the full sample period after excluding the financial crisis period (i.e. 31st of August 2007 to 30th of January 2009). Additionally, a separate analysis is performed for five non-overlapping sub-periods 1992-1995, 1996-01, 2002-08, 2009-11 and 2012-16.

The reason the aforementioned sub-samples were analysed was because they consist of both bullish and bearish periods. For instance, the period from January 1996 to December 2001 is a bearish period since the market collapsed due to the Asia and Dotcom Crisis. After that, from January 2002 to December 2008, the market entered a bullish period again since it recovered from the Asia and Dotcom crisis. Between January 2009 and December 2011 the market went back to a bearish period due to the Credit Crisis. Finally, from January 2012 to June 2016 the market recovered from the financial crisis period. The expectation is that the LPH might hold during the bearish periods when ship-owners prefer period time charter contracts to secure a fixed freight rate for a determined period of time.

The empirical findings show that the *p-values* are greater that 5% for all vessels and samples, thus the null hypothesis is rejected in this case, while also when the monotonicity test is applied to the five subsamples. At this point it is important to mention that although these findings might require further investigation, they still provide a solid indication that the dry bulk market fails to support the LPH.

2.5 Conclusion

The analysis demonstrates how participants in the shipping industry can evaluate chartering decisions under uncertainty by using technical trading indicators to identify an optimal choice between a short- and a long-term contract and appropriately manage the market's highs and lows. A chartering decision is made considering the current and the expected value of the spread between the spot and period rates (i.e. operational premium).

The empirical analysis of several parameterisations of active trading strategies show that these can be applied to the physical market in order to increase the profitability of the chartering operations. Additionally, market timing rules can provide reliable hedging strategies that enable participants to operate in a favourable freight rate over a period of time and they can maintain that hedge if the market moves in the desired direction or switch if the market moves against them. The empirical analysis also highlights the fact that active strategies are less risky compared to passive ones so ship owners can use technical trading rules as a heuristic approach in order to make chartering decisions

The use of multiple robustness tests, such as extending the analysis to alternative vessels types and sizes and excluding the turbulent financial period enhance the accuracy of the empirical findings. All robustness tests conclude that the active strategies present superior performance compared to the passive ones. In addition, the bootstrap analysis and the estimation of the White's Reality Check *p-value* indicated that the empirical findings are not the result of the data-snooping bias effect.

Since the active chartering strategies are more profitable than the passive ones, it can be concluded that the dry bulk freight market rejects the Efficient Market Hypothesis for the period between January 1992 and June 2016. Additionally, during the same period, the freight rates fail to retain the Liquidity Theory Hypothesis since the empirical findings indicated that the liquidity spread does not increase monotonically. Kavussanos and Alizadeh (2002b) suggested that the failure to prove the existence of the EMH is mainly because of the existence of time-varying risk premium. The chartering signals are generated using the spread differential between spot and period rates, which can be considered as a way to model the time-varying risk-premium. Therefore, the chartering strategies cannot rely on the these two term structure theories in order to propose profitable strategies since the trend, momentum, volatility and complex strategies suggest that a ship-owner can earn on average higher returns compared to passive strategies and to a *"simple spread strategy"*.

To sum up, the technical trading rules result in robust and profitable chartering strategies. All of the chartering strategies were constructed based on a shipowner's objective to maximise the revenues and therefore, future research could focus on constructing chartering strategies from a charterer's standpoint. When it comes to charterers, the length of a contract is based on a cost minimisation principle. In a market upturn for instance, charterers tend to commit by signing a long-term contract in order to protect themselves from a future increase in freight rates. Therefore, by assessing the contrarian strategies of the ones identified in this study, the chartering problem can be tackled from a charterer's perspective.

Furthermore, future research could also focus on incorporating multiple vessels in the proposed model as well as additional options, such as the *"lay-up"*, *"wait"*, *"exit"*, and the *"purchase option"* in a period charter (Alizadeh and Nomikos, 2007, 2009). Another aspect that could be included is the willingness of participants to take bigger risks in favour of greater returns during weak market conditions or take less risk during strong market periods.

Finally, due to the fact that the dry bulk freight market failed to retain the Efficient Market Hypothesis and the Liquidity Theory Hypothesis, future research could focus on whether other term structure theories, such as the *Market Segmentation Theory* (Culbertson, 1957) or the *Preferred Habitat Theory* (Modigliani and Sutch, 1966) could explain the way the freight rates are formulated.

Appendices

Appendix 2.A: The Parameter Values of the Chartering Strategies

2.A.1. Trend Indicators

The parameters of the trend indicators are presented below. The Moving Average Crossover – MAC trading rule at time *t* is defined as:

$$\boldsymbol{if}\ STMA_{n_{ST}}(t)\ \boldsymbol{crossing}\ from\ \boldsymbol{below}\ LTMA_{n_{LT}}(t) \xrightarrow{indicates} \boldsymbol{spot}\ signal$$

$$\boldsymbol{if}\ STMA_{n_{ST}}(t)\ \boldsymbol{crossing}\ from\ \boldsymbol{above}\ LTMAC_{n_{LT}}(t) \xrightarrow{indicates} \boldsymbol{PTC}\ signal$$

where n_{ST} and n_{LT} indicate the length of the moving average at time *t*. The parameterisations for the STMA (Short-Term Moving Average) are $n_{ST} = 1, 2, \dots, 23$ weeks, for the LTMA (Long-Term Moving Average) are $n_{LT} = 26, 27, \dots, 48$ weeks and an additional parameter x $(= 0\ or\ 1)$ indicates whether the averaging is arithmetic or exponential. This results in 1,058 $(= n_{ST} \times n_{LT} \times x)$ combinations of the MAC trend trading strategies.

The Triple Moving Average Crossover – TMAC at time *t* is defined as:

$$\boldsymbol{if}\ STMA_{n_{ST}}(t)\ \boldsymbol{crossing}\ from\ \boldsymbol{below}$$

$$MTMA_{n_{MT}}(t)\ \boldsymbol{and}\ LTMA_{n_{LT}}(t) \xrightarrow{indicates} \boldsymbol{spot}\ signal$$

$$\boldsymbol{if}\ STMA_{n_{ST}}(t) \boldsymbol{crossing}\ from\ \boldsymbol{above}$$

$$MTMA_{n_{MT}}(t)\ and\ LTMA_{n_{LT}}(t) \xrightarrow{indicates} \boldsymbol{PTC}\ signal$$

The parameterisations for this trading strategy are: $n_{ST} = 3, 4, \dots, 18$ weeks, $n_{MT} = 23, 24, \dots, 38$ weeks, $n_{LT} = 51, 52, \dots, 66$ weeks and x $(= 0\ or\ 1)$. This results in 8,192 $(= n_{ST} \times n_{MT} \times n_{LT} \times x)$ combinations of trading strategies for the TMAC rule. The Moving Average Convergence and Divergence – MACD at time *t* is defined as:

$$\boldsymbol{if}\ Oscillator(t) > 0$$

$$\boldsymbol{and}\ Oscillator(t)\ \boldsymbol{crossing}\ from\ \boldsymbol{below}\ signal\ line\ (t)$$

$$\xrightarrow{indicates} \boldsymbol{spot}\ signal$$

$$\boldsymbol{if}\ Oscillator(t) < 0$$

$$\boldsymbol{and}\ Oscillator(t)\ \boldsymbol{crossing}\ from\ \boldsymbol{above}\ signal\ line\ (t) \xrightarrow{indicates} \boldsymbol{PTC}\ signal$$

The parameterisations for this trading strategy are: $n_{ST} = 12, 13, \dots, 30$ weeks, $n_{LT} = 31, 32, \dots, 49$ weeks, $n_{SL} = 4, 5, \dots, 13$ weeks and x $(= \ 0\ or\ 1)$. This results in 7,220 $(= n_{ST} \times n_{LT} \times n_{SL} \times x)$ combinations of the *MACD* trading strategies.

2.A.2. Momentum Indicators

The *Stochastic Oscillator* (SO) shows where the spread is trading relative to the highest (maximum) and lowest (minimum) spreads (Lane, 1984) over a previous look-back period ($n = 10, 15, \dots, 40\ weeks$) in order to compute the oscillator, *K*. The oscillator, *K* is given by the following formula:

$$K = \left({}^{Spread_t - Lowest} \big/ {}_{Highest - Lowest} \right) \times 100$$

The moving average of the stochastic *K* ($n_K = 3, 9, \dots, 39\ weeks$) is called smoothed oscillator, SOD. The *spot/PTC* signals are generated using the smoothened oscillator SOD by defining a filter f ($f \ = \ 20, 22, \dots, 32$) and the upper filter bands are given by $U = \ 100 - f$ whilst the lower filter bands (L) are equal to f. The SOD at time t is defined as:

$$\boldsymbol{if}\ SOD_n(t)\ \boldsymbol{crossing}\ from\ \boldsymbol{below}\ U(t) \xrightarrow{indicates} \boldsymbol{spot}\ signal$$
$$\boldsymbol{if}\ SOD_n(t)\ \boldsymbol{crossing}\ from\ \boldsymbol{above}\ L(t) \xrightarrow{indicates} \boldsymbol{PTC}\ signal$$

The total number of parameterisations for the SO strategy are 2,401 $(= n \times n_{MAK} \times f \times L)$. The Relative Strength Index – RSI index is calculated using the following formula:

$$RSI_{t+1} = 100 - \left[100 \Big/ 1 + \left({}^{\frac{1}{n}\sum_{t=1}^{n} u_t} \Big/ {}_{\frac{1}{n}\sum_{t=1}^{n} d_t} \right) \right]$$

Where u_t and d_t are weekly gain and losses over the previous n days (look back period). Additionally, a pre-specified filter f is defined in order to determine the upper ($U \ = \ 100 - f$) and lower filter bands ($L \ = \ f$). If the number of upward movements is equal to the number of downward movements, the RSI will take a value of 50 which indicates no momentum in rates. The parameterisations are: $n = 3, 4, \dots, 19$ weeks, $L = 20, 21, \dots, 36$. The RSI at time t is defined as:

$$\boldsymbol{if}\ RSI_n(t)\ \boldsymbol{crossing}\ from\ \boldsymbol{below}\ U(t) \xrightarrow{indicates} \boldsymbol{spot}\ signal$$
$$\boldsymbol{if}\ RSI_n(t)\ \boldsymbol{crossing}\ from\ \boldsymbol{above}\ L(t) \xrightarrow{indicates} \boldsymbol{PTC}\ signal$$

This results in 4,913 ($= n \times L \times U$) combinations of trading strategies for the RSI trading rule.

2.A.3. Volatility Indicator

The Bollinger Bands – BBs increase or decrease in width with the increase or decrease in the volatility over the look-back period ($n_{BB} = 5, 8, \dots, 32\ weeks$). The bands are then applied to a smoothed price series ($n = 5, 8, \dots, 32\ weeks$) and a trading signal is generated the former cross these bands. The upper band is calculated by adding a pre-specified number of standard deviations ($d = 1.2, 0.2, \dots, 3$) to the n period moving average of the freight rate series, whereas the lower band is calculated by subtracting $d\sigma_t$ from the n period moving average. For instance, the upper and lower bands of the *spot* series are obtained as follows: $UpperBand(t) = MA_{nt} + d\sigma_t$ and $LowerBand(t) = MA_{nt} - d\sigma_t$. The BBs at time t is defined as:

$$\begin{aligned} &\boldsymbol{if}\ MA_n(t)\ \boldsymbol{crossing}\ from\ \boldsymbol{below}\ UpperBand(t) \xrightarrow{indicates} \boldsymbol{spot}\ signal \\ &\boldsymbol{if}\ MA_n(t)\ \boldsymbol{crossing}\ from\ \boldsymbol{above}\ LowerBand(t) \xrightarrow{indicates} \boldsymbol{PTC}\ signal \end{aligned}$$

This results in 2,000 ($= n_{BB} \times x \times d$) parameterisations for the BBs strategy.

2.A.4. Moving Average Envelope

In other words, the *Moving Average Envelope* (MAE) is constructed by adding and subtracting a pre-specified percentage b ($b = 0.01, 0.002, \dots, 0.10$) to a moving average time series ($n = 4, 5\ \dots, 49\ weeks$). For instance, the upper and lower bands of the *spot* series are obtained as follows: $UpperBand(t) = MA_{nt} + bMA_{nt}$ and $LowerBand(t) = MA_{nt} - dMA_{nt}$. The MAE at time t is defined as:

$$\begin{aligned} &\boldsymbol{if}\ Spread(t)\ \boldsymbol{crossing}\ from\ \boldsymbol{below}\ UpperBand(t) \xrightarrow{indicates} \boldsymbol{spot}\ signal \\ &\boldsymbol{if}\ Spread(t)\ \boldsymbol{crossing}\ from\ \boldsymbol{above}\ LowerBand(t) \xrightarrow{indicates} \boldsymbol{PTC}\ signal \end{aligned}$$

This results in 4,232 ($= n \times b \times x$) parameterisations for the MAE strategy.

Appendix 2.B: Empirical Findings of the Mean Outperformance Criterion

Table B.2.13 and B.2.16 present the summary statistics of the active and vote strategies based on the maximum mean outperformance criterion from January 1992 to June 2016.

Table B.2.13: Summary Statistics: Capesize Active strategies – Mean Outperformance Criterion

	Description of Rules	*sMAC* (18,40)	*sTMA* (14,24,63)	*sMACD* (13,33,6)	*sBB* (14,14,2.6)	*MAE* (37,0.052)	***RSI*** **(16,77,36)**	*SOD* (33,78,32)	*eMAC* (17,35)	*eTMA* (17,38,52)	*eMACD* (13,33,6)	*eBB* (26,29,3)	*eMAE* (40,0.068)
CAPESIZE	**Mean (% Ann)**	2.560	1.999	2.197	2.147	2.279	**2.648**	2.343	2.465	0.663	2.197	2.133	2.183
	Standard Deviation (% Ann)	117.687	93.330	114.269	98.149	138.014	**131.904**	133.691	117.503	100.092	114.269	78.483	137.202
	Downside Risk	5.564	4.837	5.251	4.738	6.593	**6.742**	5.988	5.552	4.876	5.251	4.179	6.570
	Sharpe Ratio	0.013	0.011	0.010	0.012	0.009	**0.012**	0.010	0.012	-0.003	0.010	0.014	0.009
	Sortino Ratio	0.460	0.413	0.418	0.453	0.346	**0.393**	0.391	0.444	0.136	0.418	0.511	0.332
	Skewness	0.200	0.629	0.386	0.596	0.203	**0.217**	0.372	0.210	0.336	0.386	0.334	-0.061
	Kurtosis	8.842	14.958	9.096	9.910	6.102	**7.481**	7.476	7.856	10.309	9.096	10.203	5.517
	MaxDrawdown	1.639	1.804	1.775	1.301	1.578	**1.754**	1.564	1.397	1.428	1.775	1.055	1.536
	Drawdown Duration	257	28	65	268	258	**180**	408	165	449	65	160	159
	Minimum	-0.811	-0.916	-0.916	-0.629	-0.693	**-0.742**	-0.847	-0.742	-0.859	-0.916	-0.629	-0.674
	Maximum	0.875	0.887	0.796	0.693	0.885	**1.012**	0.950	0.710	0.710	0.796	0.639	0.805
	Jarque-Bera	5825.4	35599.0	5361.6	9982.7	1648.2	4739.9	3229.9	4229.9	12221.4	5361.6	13100.3	1104.2
	Q test	28.787	124.693	39.542	41.731	50.572	18.623	49.877	35.893	37.274	39.542	62.626	61.855
	ARCH test	2.602	2.783	8.813	1.461	17.919	1.300	1.247	10.430	17.249	8.813	6.185	2.592
	ADF	-36.896	-31.422	-34.825	-32.722	-40.765	-36.266	-33.606	-37.162	-34.700	-34.825	-30.837	-38.577
	KPSS	0.015	0.039	0.015	0.023	0.011	0.013	0.012	0.015	0.032	0.015	0.031	0.010

Notes: Table B.2.13 presents the summary statistics of the active strategies in terms of the maximum mean outperformance criterion for all vessel sizes from January 1992 to June 2016. For further definitions refer to Tables 2.1 and 2.4.

Table B.2.14: Summary Statistics: Panamax and Handymax Active strategies – Mean Outperformance Criterion

	Description of Rules	*sMAC* (1,42)	*sTMA* **(10,30,65)**	*sMACD* (29,31,5)	*sBB* (11,11,3)	*MAE* (39,0.076)	*RSI* (7,72,34)	*SOD* (17,80,28)	*eMAC* (2,27)	*eTMA* (5,38,55)	*eMACD* (29,31,5)	*eBB* (8,11,2.6)	*eMAE* (40,0.072)
PANAMAX	**Mean (% Ann)**	-0.894	**1.150**	-0.893	1.130	-0.081	-1.302	-1.780	-0.996	-2.024	-0.893	1.130	-0.725
	Standard Deviation (% Ann)	140.841	**83.011**	111.888	61.305	133.165	147.862	126.525	143.862	98.910	111.888	61.305	147.445
	Downside Risk	6.649	**3.916**	4.780	4.220	6.230	6.643	5.480	6.661	4.329	4.780	4.220	6.877
	Sharpe Ratio	-0.013	**0.002**	-0.017	0.002	-0.008	-0.016	-0.022	-0.014	-0.031	-0.017	0.002	-0.012
	Sortino Ratio	-0.135	**0.294**	-0.187	0.268	-0.013	-0.196	-0.325	-0.150	-0.468	-0.187	0.268	-0.105
	Skewness	-0.307	**2.043**	0.394	5.016	-0.297	-0.009	0.116	-0.224	0.228	0.394	5.016	-0.577
	Kurtosis	10.481	**25.684**	11.045	50.485	10.389	8.907	8.763	11.989	17.632	11.045	50.485	11.037
	MaxDrawdown	2.050	**1.703**	1.749	0.826	1.913	1.882	1.688	1.897	1.254	1.749	0.826	1.976
	Drawdown Duration	257	**28**	65	268	258	180	408	165	449	65	160	159
	Minimum	-1.104	**-0.545**	-0.848	-0.379	-1.031	-0.985	-0.907	-1.409	-1.037	-0.848	-0.379	-1.409
	Maximum	0.972	**1.158**	0.962	0.747	0.974	1.012	0.812	0.974	0.807	0.962	0.747	0.945
	Jarque-Bera	5677.4	110525.2	8442.0	1190577.8	4779.6	3883.1	29888.8	5927.2	19997.3	8442.0	11905777.8	7390.8
	Q test	85.047	112.589	52.399	31.797	91.255	102.847	22.631	61.973	34.922	52.399	31.797	85.299
	ARCH test	31.659	6.561	3.439	7.732	25.149	17.574	0.002	30.084	16.385	3.439	7.732	16.319
	ADF	-42.273	-30.414	-38.559	-41.378	-39.128	-39.778	-34.466	-41.709	-34.022	-38.559	-41.378	-41.194
	KPSS	0.008	0.034	0.013	0.040	0.009	0.008	0.023	0.009	0.031	0.013	0.040	0.008
	Description of Rules	(1,27)	**(18,27,52)**	(30,31,4)	(8,11,1.2)	(27,0.01)	(10,66,36)	(27,80,28)	(1,27)	(4,36,51)	(30,31,4)	(29,8,1.2)	(27,0.066)
HANDYMAX	**Mean (% Ann)**	-0.601	**0.914**	-1.206	-1.093	-0.593	-1.258	-0.946	-0.605	-1.297	-1.206	-0.942	-0.588
	Standard Deviation (% Ann)	79.998	**47.872**	74.874	85.391	79.658	83.325	72.564	72.872	51.581	74.874	74.753	85.141
	Downside Risk	3.932	**3.022**	3.624	4.200	3.938	4.037	3.506	3.734	2.666	3.624	3.653	4.447
	Sharpe Ratio	-0.020	**-0.002**	-0.029	-0.025	-0.020	-0.027	-0.027	-0.022	-0.045	-0.029	-0.026	-0.019
	Sortino Ratio	-0.153	**0.302**	-0.333	-0.260	-0.151	-0.312	-0.270	-0.162	-0.487	-0.333	-0.258	-0.132
	Skewness	-0.121	**0.162**	-0.396	-0.407	0.119	-0.089	-0.315	-0.073	-1.437	-0.396	-0.214	-0.061
	Kurtosis	13.962	**18.700**	14.802	15.056	14.426	13.075	20.286	14.153	20.262	14.802	15.063	15.818
	MaxDrawdown	1.120	**0.929**	0.914	1.306	1.393	0.980	1.322	1.112	0.881	0.914	1.261	1.392
	Drawdown Duration	257	**28**	65	268	258	180	408	165	449	65	160	159
	Minimum	-0.811	**-0.449**	-0.744	-0.947	-0.613	-0.562	-0.836	-0.560	-0.582	-0.744	-0.747	-0.747
	Maximum	0.613	**0.480**	0.550	0.680	0.780	0.680	0.684	0.592	0.400	0.550	0.620	0.780
	Jarque-Bera	16585.9	78908.1	52392.2	96245.0	19535.2	17116.0	34680.8	14264.5	30217.4	52392.2	48914.6	19341.0
	Q test	36.486	330.210	144.604	65.654	48.094	38.470	62.963	92.692	85.469	144.604	57.077	130.973
	ARCH test	13.360	97.178	38.330	0.322	17.198	33.111	5.108	62.988	112.223	38.330	4.232	77.633
	ADF	-36.362	-23.708	-28.255	-31.036	-38.083	-33.026	-33.341	-39.458	-30.062	-28.255	-33.976	-40.407
	KPSS	0.030	0.100	0.071	0.044	0.023	0.051	0.031	0.025	0.070	0.071	0.035	0.019

Notes: Table B.2.14 presents the summary statistics of the active strategies in terms of the maximum mean outperformance crietrion for a Panamax and a Handymax vessel from January 1992 to June 2016. For further definitions, refer to Tables 2.1 and 2.4.

Table B.2.15: Summary Statistics Capesize Vote Strategies – Mean Outperformance Criterion

CAPESIZE	*sMAC*	*sTMA*	*sMACD*	*sBB*	*MAE*	*RSI*	*SOD*	*eMAC*	*eTMA*	*eMACD*	*eBB*	*eMAE*
Mean (% Ann)	**7.170**	-1.387	-8.036	-1.667	-1.519	-1.747	-5.672	1.636	0.620	-8.036	-3.258	-2.073
Standard Deviation (% Ann)	**110.937**	83.925	103.243	140.584	157.652	139.685	122.275	115.950	105.838	103.243	134.179	160.180
Downside Risk	**5.545**	3.790	4.836	6.324	7.542	6.525	5.356	5.418	5.222	4.836	5.953	7.582
Sharpe Ratio	**0.065**	-0.017	-0.078	-0.012	-0.010	-0.013	-0.046	0.014	0.006	-0.078	-0.024	-0.013
Sortino Ratio	**1.293**	-0.366	-1.662	-0.264	-0.201	-0.268	-1.059	0.302	0.119	-1.662	-0.547	-0.273
Skewness	**0.191**	0.500	0.974	0.194	-0.156	-0.038	0.359	0.140	0.084	0.974	0.367	-0.056
Kurtosis	**9.290**	13.814	14.446	6.142	4.997	6.225	6.988	7.622	8.431	14.446	6.501	4.833
MaxDrawdown	**1.507**	1.516	1.399	1.624	1.663	1.833	1.481	1.474	1.309	1.399	1.454	1.578
Drawdown Duration	**257**	28	65	268	258	180	408	165	449	65	160	159
Minimum	**-0.684**	-0.629	-0.693	-0.766	-0.778	-0.939	-0.674	-0.742	-0.693	-0.693	-0.675	-0.693
Maximum	**0.862**	0.887	1.192	0.878	0.885	0.894	0.808	0.732	0.681	1.192	0.806	0.885
Jarque-Bera	6617.4	16434.0	22159.9	1540.1	550.1	1659.4	2249.4	3409.5	6291.3	22159.9	2072.2	481.1
Q test	39.767	64.843	28.166	46.352	100.136	30.630	37.005	20.856	25.147	28.166	40.876	81.153
ARCH test	1.093	2.433	4.153	52.473	22.163	13.167	11.175	2.875	3.743	4.153	49.879	15.614
ADF	-33.350	-32.697	-33.950	-40.609	-42.791	-39.153	-34.090	-37.477	-36.132	-33.950	-40.867	-42.765
KPSS	0.018	0.032	0.038	0.012	0.009	0.012	0.022	0.014	0.025	0.038	0.013	0.009

Notes: Table B.2.15 presents the summary statistics of the Capesize vote strategies in terms of the maximum mean outperformance criterion from January 1992 to June 2016. For further definitions refer to Tables 2.1 and 2.4.

Table B.2.16 Summary Statistics Panamax and Handymax Vote Strategies – Mean Outperformance Criterion

		sMAC	*sTMA*	*sMACD*	*sBB*	*MAE*	*RSI*	*SOD*	*eMAC*	*eTMA*	*eMACD*	*eBB*	*eMAE*
PANAMAX	**Mean (% Ann)**	**-1.768**	-3.652	-2.309	-3.052	-3.061	-3.875	-3.544	-4.082	-3.470	-2.309	-5.323	-3.662
	Standard Deviation (% Ann)	**99.327**	75.590	74.909	113.645	152.603	111.138	92.734	106.418	87.437	74.909	113.250	146.585
	Downside Risk	**4.215**	3.068	3.293	5.048	7.211	4.987	3.897	4.943	3.719	3.293	5.081	6.999
	Sharpe Ratio	**-0.018**	-0.048	-0.031	-0.027	-0.020	-0.035	-0.038	-0.038	-0.040	-0.031	-0.047	-0.025
	Sortino Ratio	**-0.420**	-1.191	-0.701	-0.605	-0.424	-0.777	-0.909	-0.826	-0.933	-0.701	-1.047	-0.523
	Skewness	**0.476**	1.233	0.426	-0.092	-0.480	0.092	0.853	-0.358	0.344	0.426	-0.156	-0.728
	Kurtosis	**15.471**	16.819	20.785	12.419	8.590	13.872	23.327	16.216	25.409	20.785	16.533	9.950
	MaxDrawdown	**1.792**	1.364	1.521	1.814	1.913	1.852	1.938	1.852	1.985	1.521	2.220	2.102
	Drawdown Duration	**257**	28	65	268	258	180	408	165	449	65	160	159
	Minimum	**-0.824**	-0.539	-0.828	-0.907	-1.031	-0.907	-0.821	-0.907	-1.101	-0.828	-1.104	-1.409
	Maximum	**0.967**	0.825	0.747	0.908	0.974	0.945	1.117	0.945	0.886	0.747	1.117	0.882
	Jarque-Bera	16627.5	21272.4	35602.6	8632.8	2958.1	11387.3	38374.9	17452.9	50854.8	35602.6	19158.8	4404.7
	Q test	80.316	87.797	65.009	58.389	100.047	63.001	75.776	59.495	53.716	65.009	87.910	103.144
	ARCH test	4.144	4.065	1.347	5.142	13.017	16.211	31.289	0.774	0.061	1.347	37.999	12.903
	ADF	-33.467	-30.159	-32.859	-38.575	-41.438	-39.481	-38.952	-34.407	-32.957	-32.859	-41.469	-43.641
	KPSS	0.015	0.035	0.034	0.013	0.007	0.015	0.020	0.022	0.025	0.034	0.014	0.008
HANDYMAX	**Mean (% Ann)**	**-1.654**	-2.503	-2.221	-2.371	-1.971	-1.703	-2.300	-2.143	-2.362	-2.221	-1.726	-1.817
	Standard Deviation (% Ann)	**54.371**	37.047	46.582	65.724	79.841	72.919	50.106	63.485	40.703	46.582	66.229	82.187
	Downside Risk	**2.594**	1.906	2.525	3.303	4.027	3.656	2.260	3.194	1.910	2.525	3.204	4.184
	Sharpe Ratio	**-0.031**	-0.068	-0.048	-0.036	-0.025	-0.023	-0.046	-0.034	-0.058	-0.048	-0.026	-0.022
	Sortino Ratio	**-0.638**	-1.313	-0.880	-0.718	-0.490	-0.466	-1.018	-0.671	-1.236	-0.880	-0.539	-0.434
	Skewness	**0.037**	-1.344	-1.040	-0.808	-0.152	-0.452	0.046	0.076	0.339	-1.040	-0.140	0.014
	Kurtosis	**18.630**	24.002	21.587	21.309	13.645	20.103	21.482	21.446	25.967	21.587	17.162	13.264
	MaxDrawdown	**1.009**	0.760	0.863	1.306	1.417	1.473	0.886	1.243	0.755	0.863	1.306	1.392
	Drawdown Duration	**257**	28	65	268	258	180	408	165	449	65	160	159
	Minimum	**-0.501**	-0.526	-0.582	-0.747	-0.637	-0.747	-0.627	-0.560	-0.526	-0.582	-0.526	-0.612
	Maximum	**0.560**	0.292	0.437	0.780	0.780	0.780	0.597	0.693	0.569	0.437	0.780	0.780
	Jarque-Bera	28359.3	59271.7	49619.3	36293.2	11953.7	29990.8	37094.7	36692.9	62156.6	49619.3	24081.1	10938.2
	Q test	97.405	166.575	156.411	33.962	58.045	76.145	66.652	74.345	107.608	156.411	42.729	68.650
	ARCH test	12.854	11.692	5.547	8.981	25.521	58.671	10.014	50.025	7.668	5.547	16.509	12.767
	ADF	-30.818	-27.547	-27.496	-34.847	-40.621	-38.658	-29.603	-37.287	-29.138	-27.496	-36.184	-38.365
	KPSS	0.061	0.117	0.075	0.030	0.023	0.027	0.059	0.036	0.092	0.075	0.034	0.021

Notes: Table B.2.16 presents the summary statistics of the Panamax and Handymax vote strategies in terms of the maximum mean outperformance criterion from January 1992 to June 2016. For further definitions refer to Tables 2.1 and 2.4.

Appendix 2.C: Empirical Findings of the no Financial Crisis Period

Table C.2.17 – C.2.26 present the summary statistics of the active and vote strategies based on the maximum Sharpe ratio and mean outperformance criteria for the in-sample period January 1992 to June 2016 after eliminating the financial crisis period (i.e. from 31st August 2007 to 30th of January 2009). Table C.2.26 presents the same statistics for the benchmark strategies.

The purpose of this analysis is to assess if the turbulent period of the financial crisis affects the profitability of the chartering strategies.

Table C.2.17: Summary Statistics of Capesize Active Strategies: No Crisis Period – Risk-adjusted Returns Outperformance Criterion

	Description of Rules	***sMAC*** (15,34)	***sTMA*** **(14,24,63)**	***sMACD*** (14,36,4)	***sBB*** (14,14,2.6)	***MAE*** (37,0.052)	***RSI*** (16,77,36)	***SOD*** (33,78,30)	***eMAC*** (17,35)	***eTMA*** (17,38,53)	***eMACD*** (14,36,4)	***eBB*** (26,29,3)	***eMAE*** (41,0.05)
CAPESIZE	**Mean (% Ann)**	2.759	**2.216**	2.474	2.226	2.411	2.859	2.517	2.630	0.729	2.474	2.183	2.364
	Standard Deviation (% Ann)	122.702	**75.986**	124.985	91.318	136.521	128.352	137.861	118.410	101.650	124.985	82.976	150.060
	Downside Risk	6.103	**4.145**	5.574	4.580	6.704	6.800	6.494	5.897	5.436	5.574	4.457	7.341
	Sharpe Ratio	0.014	**0.016**	0.012	0.013	0.010	0.014	0.011	0.014	-0.003	0.012	0.014	0.009
	Sortino Ratio	0.452	**0.535**	0.444	0.486	0.360	0.420	0.388	0.446	0.134	0.444	0.490	0.322
	Skewness	0.119	**0.532**	0.623	0.341	0.211	0.269	0.026	-0.097	-0.173	0.623	0.100	-0.094
	Kurtosis	9.596	**7.971**	8.582	10.722	6.449	8.269	9.345	9.530	14.789	8.582	9.253	6.093
	MaxDrawdown	1.627	**0.999**	1.614	1.424	1.637	1.764	2.175	1.739	1.751	1.614	1.075	1.720
	Drawdown Duration	426	**102**	12	203	202	475	76	460	94	12	150	33
	Minimum	-0.885	**-0.455**	-0.716	-0.752	-0.752	-0.752	-1.284	-1.083	-1.083	-0.716	-0.752	-1.083
	Maximum	1.011	**0.545**	0.866	0.672	0.885	1.012	0.897	0.710	0.710	0.866	0.639	0.862
	Jarque-Bera	6557.8	8610.2	7904.0	10618.1	1811.2	6040.0	6663.3	6623.7	28676.4	7904.0	8868.9	1459.1
	Q test	58.190	103.302	72.372	37.322	47.287	32.288	55.350	43.754	40.954	72.372	73.917	75.462
	ARCH test	2.530	8.544	24.392	0.403	18.004	0.265	0.110	8.598	16.210	24.392	16.710	4.706
	ADF	-32.370	-28.779	-32.473	-31.702	-40.042	-34.777	-32.543	-35.439	-33.780	-32.473	-29.824	-37.139
	KPSS	0.013	0.046	0.019	0.022	0.010	0.011	0.010	0.012	0.024	0.019	0.024	0.009

Notes: Table C.2.17 presents the summary statistics of the Capesize active strategies in terms of the maximum Sharpe ratio outperformance criterion for all vessel sizes from January 1992 to June 2016. The period from 31st of August 2007 to 30th of January 2009 is eliminated in order to assess if the financial crisis affects the profitability of the chartering strategies. For further definitions refer to Tables 2.1 and 2.4.

Table C.2.18: Summary Statistics of Panamax and Handymax Active Strategies: No Crisis Period – Risk-adjusted Returns Outperformance Criterion

	Description of Rules	***sMAC***	***sTMA***	***sMACD***	***sBB***	***MAE***	***RSI***	***SOD***	***eMAC***	***eTMA***	***eMACD***	***eBB***	***eMAE***
		(1,42)	**(10,30,65)**	(30,32,5)	(11,11,3)	(41,0.096)	(7,71,36)	(39,76,20)	(1,44)	(12,37,51)	(30,32,5)	(8,11,2.6)	(40,0.084)
PANAMAX	**Mean (% Ann)**	-0.957	**1.255**	-0.947	1.130	-0.085	-1.371	-1.612	-0.968	-1.375	-0.947	1.130	-0.768
	Standard Deviation (% Ann)	145.814	**93.756**	115.067	61.305	129.344	138.631	94.103	141.553	77.728	115.067	61.305	139.372
	Downside Risk	7.408	**5.479**	5.411	4.220	6.374	6.473	4.939	7.175	3.929	5.411	4.220	6.995
	Sharpe Ratio	-0.013	**0.003**	-0.017	0.002	-0.008	-0.017	-0.028	-0.014	-0.031	-0.017	0.002	-0.013
	Sortino Ratio	-0.129	**0.229**	-0.175	0.268	-0.013	-0.212	-0.326	-0.135	-0.350	-0.175	0.268	-0.110
	Skewness	-1.025	**-3.447**	-1.068	5.016	-1.013	-0.445	-2.860	-1.035	-3.257	-1.068	5.016	-1.371
	Kurtosis	16.234	**88.419**	26.911	50.485	18.975	10.772	53.746	17.017	51.358	26.911	50.485	18.539
	MaxDrawdown	2.791	**3.060**	2.846	0.826	2.702	2.150	2.641	2.791	1.927	2.846	0.826	2.765
	Drawdown Duration	137	**172**	150	123	43	154	38	137	77	150	123	161
	Minimum	-1.820	**-1.902**	-1.792	-0.379	-1.820	-1.204	-1.792	-1.820	-1.469	-1.792	-0.379	-1.820
	Maximum	0.972	**1.158**	1.054	0.747	0.882	0.946	0.849	0.972	0.629	1.054	0.747	0.945
	Jarque-Bera	16071.1	1409848	53244.4	9924948	21061.9	5018.1	9653.8	18041.7	803891.9	53244.4	9924948	13379.4
	Q test	86.569	55.144	60.856	29.936	113.228	127.718	81.839	98.858	37.216	60.856	29.936	142.233
	ARCH test	12.703	0.165	0.006	7.255	17.170	5.211	1.397	7.393	0.166	0.006	7.255	18.779
	ADF	-40.973	-33.173	-37.691	-40.144	-41.123	-38.399	-36.252	-39.956	-34.468	-37.691	-40.144	-43.723
	KPSS	0.005	0.022	0.009	0.043	0.006	0.005	0.007	0.005	0.019	0.009	0.043	0.005
	Description of Rules	(23,28)	**(18,27,52)**	(19,31,4)	(26,32,1.8)	(27,0.044)	(20,64,21)	(27,80,22)	(1,27)	(4,31,52)	(19,31,4)	(26,29,1.4)	(27,0.062)
HANDYMAX	**Mean (% Ann)**	-0.624	**1.024**	-0.990	-0.869	-0.631	-1.001	-1.004	-0.650	-1.341	-0.990	-0.828	-0.624
	Standard Deviation (% Ann)	71.044	**51.865**	58.474	63.780	80.142	59.594	68.911	78.429	49.095	58.474	65.443	88.913
	Downside Risk	3.795	**4.021**	4.095	3.791	4.565	3.249	3.780	4.783	2.688	4.095	3.807	5.263
	Sharpe Ratio	-0.023	**0.000**	-0.034	-0.029	-0.020	-0.034	-0.029	-0.021	-0.048	-0.034	-0.028	-0.018
	Sortino Ratio	-0.164	**0.255**	-0.242	-0.229	-0.138	-0.308	-0.266	-0.136	-0.499	-0.242	-0.217	-0.119
	Skewness	-4.064	**-5.909**	-8.210	-6.073	-3.123	-5.737	-3.482	-4.544	-4.771	-8.210	-5.284	-2.780
	Kurtosis	73.372	**100.198**	145.365	121.059	63.567	109.425	61.792	78.707	78.638	145.365	105.698	52.849
	MaxDrawdown	2.250	**1.515**	2.268	2.113	2.417	2.419	2.048	2.279	2.108	2.268	2.053	2.499
	Drawdown Duration	163	**223**	148	183	164	186	143	154	138	148	149	164
	Minimum	-1.515	**-1.069**	-1.433	-1.515	-1.637	-1.433	-1.364	-1.719	-1.069	-1.433	-1.515	-1.719
	Maximum	0.560	**0.446**	0.362	0.780	0.780	0.453	0.588	0.560	0.382	0.362	0.780	0.780
	Jarque-Bera	320800	2700848	430770	85432.6	275940	228665	183779	567236	2657236	430770.8	176473.0	199853
	Q test	85.712	33.803	73.388	66.185	63.497	108.120	67.576	60.411	22.776	73.388	91.726	98.676
	ARCH test	0.656	0.000	0.799	0.685	1.277	7.404	0.119	1.729	0.278	0.799	0.223	7.209
	ADF	-38.601	-30.554	-38.235	-38.939	-38.037	-39.706	-35.324	-39.423	-35.388	-38.235	-38.040	-42.336
	KPSS	0.015	0.065	0.017	0.013	0.015	0.013	0.017	0.017	0.028	0.017	0.017	0.012

Notes: Table C.2.18 presents the summary statistics of the active strategies in terms of the maximum risk-adjusted returns (Sharpe ratio) for a Panamax and a Handymax vessel from January 1992 to June 2016. The period from 31st of August 2007 to 30th of January 2009 is eliminated in order to assess if the financial crisis affects the profitability of the chartering strategies. For further definitions, refer to Tables 2.1 and 2.4.

Table C.2.19: Summary Statistics of Capesize Vote Strategies: No Crisis Period – Risk-adjusted Returns Outperformance Criterion

		sMAC	*sTMA*	*sMACD*	*sBB*	*MAE*	*RSI*	*SOD*	*eMAC*	*eTMA*	*eMACD*	*eBB*	*eMAE*
CAPESIZE	**Mean (% Ann)**	**11.038**	-1.516	-8.485	0.774	-1.604	-1.842	-5.305	2.020	-1.260	-8.485	-3.413	-1.608
	Std Deviation (% Ann)	**116.507**	77.375	95.962	135.298	158.150	138.333	118.004	117.365	105.594	95.962	130.892	162.619
	Downside Risk	**6.193**	3.686	4.745	6.492	7.871	6.687	5.474	5.791	5.569	4.745	6.157	7.788
	Sharpe Ratio	**0.095**	-0.020	-0.089	0.006	-0.010	-0.013	-0.045	0.017	-0.012	-0.089	-0.026	-0.010
	Sortino Ratio	**1.782**	-0.411	-1.788	0.119	-0.204	-0.275	-0.969	0.349	-0.226	-1.788	-0.554	-0.206
	Skewness	**-0.467**	-0.456	0.729	-0.079	-0.275	-0.191	-0.082	-0.147	-0.301	0.729	0.054	-0.083
	Kurtosis	**13.259**	21.159	14.967	6.987	5.412	7.256	11.444	10.245	11.834	14.967	7.541	5.156
	MaxDrawdown	**2.139**	1.787	1.399	1.961	1.947	1.977	2.085	1.890	1.764	1.399	1.889	1.947
	Drawdown Duration	**189**	82	8	194	202	476	81	459	264	8	189	202
	Minimum	**-1.277**	-1.062	-0.693	-1.083	-1.062	-1.083	-1.277	-1.157	-1.083	-0.693	-1.083	-1.062
	Maximum	**0.862**	0.725	1.192	0.878	0.885	0.894	0.808	0.732	0.681	1.192	0.806	0.885
	Jarque-Bera	14983.3	43232.8	22164.8	2090.5	694.3	2418.6	8223.8	7128.0	15357.6	22164.8	2819.5	570.6
	Q test	57.567	72.097	31.447	40.780	119.788	37.809	46.638	34.370	30.836	31.447	52.465	101.563
	ARCH test	2.597	1.033	3.088	26.400	11.571	4.633	2.165	3.904	0.986	3.088	31.961	6.101
	ADF	-34.626	-31.400	-32.891	-39.220	-41.942	-38.026	-33.128	-36.658	-34.774	-32.891	-40.101	-41.150
	KPSS	0.013	0.032	0.035	0.009	0.007	0.010	0.019	0.011	0.021	0.035	0.010	0.007

Notes: Table C.2.19 presents the summary statistics of the vote strategies in terms of the maximum risk-adjusted returns (Sharpe ratio) for a Capesize vessel from January 1992 to June 2016. The period from 31st of August 2007 to 30th of January 2009 is eliminated in order to assess if the financial crisis affects the profitability of the chartering strategies. For further definitions refer to Tables 2.1 and 2.4.

Table C.2.20: Summary Statistics of Panamax and Handymax Vote Strategies: No Crisis Period – Risk-adjusted Returns Outperformance Criterion

		sMAC	*sTMA*	*sMACD*	*sBB*	*MAE*	*RSI*	*SOD*	*eMAC*	*eTMA*	*eMACD*	*eBB*	*eMAE*
PANAMAX	**Mean (% Ann)**	**-0.593**	-3.896	-2.468	-4.779	-3.258	-4.125	-3.766	-4.338	-3.169	-2.468	-4.383	-3.912
	Standard Deviation (% Ann)	**102.670**	71.435	74.551	118.147	154.829	115.346	102.264	99.663	86.186	74.551	120.457	148.157
	Downside Risk	**4.793**	3.212	3.700	5.633	7.772	5.646	4.813	4.916	4.107	3.700	5.783	7.390
	Sharpe Ratio	**-0.006**	-0.055	-0.033	-0.041	-0.021	-0.036	-0.037	-0.044	-0.037	-0.033	-0.036	-0.026
	Sortino Ratio	**-0.124**	-1.213	-0.667	-0.848	-0.419	-0.731	-0.783	-0.882	-0.772	-0.667	-0.758	-0.529
	Skewness	**-1.507**	-0.686	-1.837	-1.425	-0.955	-1.319	-1.511	-1.249	-1.577	-1.837	-1.433	-1.171
	Kurtosis	**39.459**	41.682	39.363	26.245	12.756	28.302	44.099	27.178	40.002	39.363	29.044	15.000
	MaxDrawdown	**2.739**	2.057	1.638	2.648	2.702	2.737	2.908	2.414	2.180	1.638	2.937	2.702
	Drawdown Duration	**153**	189	107	148	43	161	144	161	9	107	144	43
	Minimum	**-1.772**	-1.232	-1.232	-1.820	-1.820	-1.792	-1.792	-1.469	-1.469	-1.232	-1.820	-1.820
	Maximum	**0.967**	0.825	0.747	0.908	0.974	0.945	1.117	0.945	0.816	0.747	1.117	0.882
	Jarque-Bera	125828.5	144831.3	136212.9	47337.9	7979.9	55149.7	143125.0	52883.1	129920.1	136212.9	65220.2	11794.6
	Q test	92.144	106.992	48.283	70.243	96.472	45.099	56.450	68.371	128.643	48.283	111.283	101.803
	ARCH test	0.546	5.069	2.650	3.791	9.851	3.556	6.293	4.617	8.989	2.650	8.985	10.135
	ADF	-32.714	-29.153	-30.645	-39.439	-40.696	-37.044	-36.573	-32.099	-30.719	-30.645	-40.357	-42.186
	KPSS	0.011	0.032	0.028	0.010	0.005	0.011	0.013	0.022	0.020	0.028	0.009	0.006
HANDYMAX	**Mean (% Ann)**	-1.758	-2.636	-2.380	**-1.093**	-2.113	-1.843	-2.536	-2.295	-2.461	-2.380	-1.876	-1.955
	Standard Deviation (% Ann)	63.641	47.843	56.617	**69.156**	79.650	79.614	62.602	69.836	48.962	56.617	69.026	86.292
	Downside Risk	3.731	2.974	3.644	**3.895**	4.416	4.392	3.414	4.001	2.865	3.644	3.849	5.039
	Sharpe Ratio	-0.028	-0.055	-0.042	**-0.016**	-0.027	-0.023	-0.041	-0.033	-0.050	-0.042	-0.027	-0.023
	Sortino Ratio	-0.471	-0.886	-0.653	**-0.280**	-0.478	-0.420	-0.743	-0.574	-0.859	-0.653	-0.487	-0.388
	Skewness	-8.602	-10.759	-8.166	**-4.652**	-1.840	-2.663	-7.574	-4.179	-9.260	-8.166	-4.413	-3.098
	Kurtosis	176.081	223.993	150.138	**86.358**	34.083	47.393	157.438	80.580	192.277	150.138	86.466	55.703
	MaxDrawdown	2.286	1.597	1.769	**2.295**	2.122	2.226	2.062	2.208	1.592	1.769	2.295	2.499
	Drawdown Duration	149	81	13	**164**	164	164	77	163	164	13	164	164
	Minimum	-1.726	-1.364	-1.433	**-1.515**	-1.341	-1.446	-1.656	-1.515	-1.364	-1.433	-1.515	-1.719
	Maximum	0.560	0.234	0.336	**0.780**	0.780	0.780	0.597	0.693	0.340	0.336	0.780	0.780
	Jarque-Bera	2996367	5555930	2704045	695235	90657	189329	2243551	587461	3597582	2704045	752332	253320
	Q test	22.457	29.086	75.547	34.612	58.042	69.918	26.331	53.207	42.682	75.547	40.983	72.647
	ARCH test	0.213	0.002	0.001	0.000	16.738	3.134	0.088	1.271	0.001	0.001	0.052	0.633
	ADF	-35.315	-30.983	-30.607	-34.815	-40.147	-38.674	-33.290	-36.746	-31.219	-30.607	-36.507	-38.300
	KPSS	0.036	0.058	0.039	0.021	0.018	0.017	0.029	0.024	0.052	0.039	0.024	0.015

Notes: Table C.2.20 presents the summary statistics of the vote strategies in terms of the maximum risk-adjusted returns (Sharpe ratio) for a Panamax and a Handymax vessel from January 1992 to June 2016. The period from 31st of August 2007 to 30th of January 2009 is eliminated in order to assess if the financial crisis affects the profitability of the chartering strategies. For further definitions, refer to Tables 2.1 and 2.4.

Table C.2.21: Summary Statistics of Capesize Active Strategies: No Crisis Period – Mean Outperformance Criterion

	Description of Rules	***sMAC*** (18,40)	***sTMA*** (14,24,63)	***sMACD*** (13,35,7)	***sBB*** (14,14,2.6)	***MAE*** (37,0.052)	***RSI*** **(16,77,36)**	***SOD*** (33,78,32)	***eMAC*** (17,35)	***eTMA*** (17,38,53)	***eMACD*** (13,35,7)	***eBB*** (26,29,3)	***eMAE*** (41,0.072)
CAPESIZE	**Mean (% Ann)**	2.735	2.216	2.340	2.226	2.411	**2.859**	2.477	2.630	0.729	2.340	2.183	2.340
	Std Deviation (% Ann)	116.350	75.986	105.818	91.318	136.521	**128.352**	133.276	118.410	101.650	105.818	82.976	141.685
	Downside Risk	5.745	4.145	5.058	4.580	6.704	**6.800**	6.381	5.897	5.436	5.058	4.457	7.110
	Sharpe Ratio	0.015	0.016	0.013	0.013	0.010	**0.014**	0.011	0.014	-0.003	0.013	0.014	0.009
	Sortino Ratio	0.476	0.535	0.463	0.486	0.360	**0.420**	0.388	0.446	0.134	0.463	0.490	0.329
	Skewness	0.084	0.532	0.457	0.341	0.211	**0.269**	-0.072	-0.097	-0.173	0.457	0.100	-0.222
	Kurtosis	9.312	7.971	9.896	10.722	6.449	**8.269**	9.940	9.530	14.789	9.896	9.253	6.186
	MaxDrawdown	1.798	0.999	1.579	1.424	1.637	**1.764**	2.175	1.739	1.751	1.579	1.075	1.945
	Drawdown Duration	98	102	11	203	202	**475**	76	460	94	11	150	189
	Minimum	-0.811	-0.455	-0.761	-0.752	-0.752	**-0.752**	-1.284	-1.083	-1.083	-0.761	-0.752	-1.062
	Maximum	0.875	0.545	0.901	0.672	0.885	**1.012**	0.950	0.710	0.710	0.901	0.639	0.805
	Jarque-Bera	7602.4	8610.2	5187.5	10618.1	1811.2	6040.0	5932.0	6623.7	28676.4	5187.5	8868.9	1426.1
	Q test	53.506	103.302	44.930	37.322	47.287	32.288	51.197	43.754	40.954	44.930	73.917	88.339
	ARCH test	2.916	8.544	12.941	0.403	18.004	0.265	0.121	8.598	16.210	12.941	16.710	1.717
	ADF	-35.863	-28.779	-33.237	-31.702	-40.042	-34.777	-32.868	-35.439	-33.780	-33.237	-29.824	-37.670
	KPSS	0.012	0.046	0.013	0.022	0.010	0.011	0.010	0.012	0.024	0.013	0.024	0.008

Notes: Table C.2.21 presents the summary statistics of the active strategies in terms of the maximum mean outperformance criterion for a Capesize vessel from January 1992 to June 2016. The period from 31st of August 2007 to 30th of January 2009 is eliminated in order to assess if the financial crisis affects the profitability of the chartering strategies. For further definitions refer to Tables 2.1 and 2.4.

Table C.2.22: Summary Statistics of Panamax and Handymax Active Strategies: No Crisis Period – Mean Outperformance Criterion

	Description of Rules	*sMAC* (1,42)	***sTMA*** **(10,30,65)**	*sMACD* (30,32,5)	*sBB* (11,11,3)	*MAE* (39,0.096)	*RSI* (7,72,35)	*SOD* (17,80,28)	*eMAC* (1,33)	*eTMA* (12,37,53)	*eMACD* (30,32,5)	*eBB* (8,11,2.6)	*eMAE* (40,0.072)
PANAMAX	**Mean (% Ann)**	-0.957	**1.255**	-0.947	1.130	-0.087	-1.391	-1.896	-1.064	-1.427	-0.947	1.130	-0.770
	Standard Deviation (% Ann)	145.814	**93.756**	115.067	61.305	137.211	145.798	125.419	151.201	83.745	115.067	61.305	152.129
	Downside Risk	7.408	**5.479**	5.411	4.220	6.782	6.752	5.712	7.753	4.449	5.411	4.220	7.473
	Sharpe Ratio	-0.013	**0.003**	-0.017	0.002	-0.008	-0.016	-0.023	-0.014	-0.029	-0.017	0.002	-0.012
	Sortino Ratio	-0.129	**0.229**	-0.175	0.268	-0.013	-0.206	-0.332	-0.137	-0.321	-0.175	0.268	-0.103
	Skewness	-1.025	**-3.447**	-1.068	5.016	-0.895	-0.185	-0.391	-1.040	-5.381	-1.068	5.016	-0.960
	Kurtosis	16.234	**88.419**	26.911	50.485	17.970	10.436	13.390	17.016	93.067	26.911	50.485	15.302
	MaxDrawdown	2.791	**3.060**	2.846	0.826	2.702	2.171	2.253	2.791	2.360	2.846	0.826	2.765
	Drawdown Duration	137	**172**	150	123	43	153	49	137	77	150	123	161
	Minimum	-1.820	**-1.902**	-1.792	-0.379	-1.820	-1.204	-1.440	-1.820	-1.902	-1.792	-0.379	-1.820
	Maximum	0.972	**1.158**	1.054	0.747	0.974	1.012	0.812	0.972	0.629	1.054	0.747	0.945
	Jarque-Bera	16071.1	1409848.4	53244.4	9924948.6	22806.1	5287.7	260386.3	18354.2	218436.9	53244.4	9924948.6	20892.5
	Q test	86.569	55.144	60.856	29.936	134.901	100.935	40.271	75.134	64.820	60.856	29.936	102.747
	ARCH test	12.703	0.165	0.006	7.255	10.260	9.628	0.434	11.899	6.263	0.006	7.255	11.166
	ADF	-40.973	-33.173	-37.691	-40.144	-39.862	-37.852	-32.382	-41.023	-29.983	-37.691	-40.144	-41.543
	KPSS	0.005	0.022	0.009	0.043	0.007	0.006	0.014	0.005	0.022	0.009	0.043	0.006
	Description of Rules	(1,27)	**(18,27,52)**	(30,31,5)	(8,11,1.2)	(27,0.026)	(10,72,36)	(27,80,28)	(1,27)	(3,38,51)	(30,31,5)	(29,8,1.2)	(27,0.066)
HANDYMAX	**Mean (% Ann)**	-0.644	**1.024**	-1.325	-1.174	-0.634	-1.409	-1.020	-0.650	-1.392	-1.325	-1.014	-0.631
	Standard Deviation (% Ann)	81.274	**51.865**	80.331	87.378	82.660	91.551	77.336	78.429	64.447	80.331	78.721	91.067
	Downside Risk	4.608	**4.021**	4.438	4.721	4.855	5.188	4.232	4.783	3.654	4.438	4.316	5.460
	Sharpe Ratio	-0.020	**0.000**	-0.029	-0.025	-0.020	-0.026	-0.026	-0.021	-0.037	-0.029	-0.026	-0.018
	Sortino Ratio	-0.140	**0.255**	-0.299	-0.249	-0.131	-0.272	-0.241	-0.136	-0.381	-0.299	-0.235	-0.116
	Skewness	-3.555	**-5.909**	-3.749	-2.081	-3.181	-2.766	-2.564	-4.544	-8.164	-3.749	-2.558	-2.748
	Kurtosis	60.256	**100.198**	66.113	33.652	56.962	49.667	45.525	78.707	166.328	66.113	44.906	49.021
	MaxDrawdown	2.074	**1.515**	1.720	2.295	2.417	1.886	1.952	2.279	1.450	1.720	2.295	2.499
	Drawdown Duration	197	**223**	202	164	164	120	159	154	138	202	164	164
	Minimum	-1.637	**-1.069**	-1.656	-1.433	-1.637	-1.726	-1.364	-1.719	-1.726	-1.656	-1.433	-1.719
	Maximum	0.613	**0.446**	0.612	0.680	0.780	0.693	0.684	0.560	0.512	0.612	0.620	0.780
	Jarque-Bera	496376.3	2700848.3	2999893.6	1513040.3	343355.8	1078920.0	336127.3	567236.6	536300.6	2999893.6	1040040.0	228265.7
	Q test	34.593	33.803	19.235	40.410	52.825	17.658	51.751	60.411	55.929	19.235	46.953	107.751
	ARCH test	0.072	0.000	0.000	0.005	1.237	0.051	0.015	1.729	21.831	0.000	0.003	5.250
	ADF	-38.230	-30.554	-33.034	-32.793	-38.836	-34.316	-33.834	-39.423	-30.222	-33.034	-33.425	-41.257
	KPSS	0.021	0.065	0.036	0.027	0.016	0.029	0.022	0.017	0.046	0.036	0.024	0.013

Notes: Table C.2.22 presents the summary statistics of the active strategies in terms of the maximum mean outperformance criterion for a Panamax and a Handymax vessel from January 1992 to June 2016. The period from 31st of August 2007 to 30th of January 2009 is eliminated in order to assess if the financial crisis affects the profitability of the chartering strategies. For further definitions, refer to Tables 2.1 and 2.4.

Table C.2.23: Summary Statistics of Capesize Vote Strategies: No Crisis Period – Mean Outperformance Criterion

CAPESIZE	*sMAC*	*sTMA*	*sMACD*	*sBB*	*MAE*	*RSI*	*SOD*	*eMAC*	*eTMA*	*eMACD*	*eBB*	*eMAE*
Mean (% Ann)	**11.038**	-1.516	-8.485	0.774	-1.604	-1.842	-5.305	2.020	-1.260	-8.485	-3.413	-1.608
Std Deviation (% Ann)	**116.507**	77.375	95.962	135.298	158.150	138.333	118.004	117.365	105.594	95.962	130.892	162.619
Downside Risk	**6.193**	3.686	4.745	6.492	7.871	6.687	5.474	5.791	5.569	4.745	6.157	7.788
Sharpe Ratio	**0.095**	-0.020	-0.089	0.006	-0.010	-0.013	-0.045	0.017	-0.012	-0.089	-0.026	-0.010
Sortino Ratio	**1.782**	-0.411	-1.788	0.119	-0.204	-0.275	-0.969	0.349	-0.226	-1.788	-0.554	-0.206
Skewness	**-0.467**	-0.456	0.729	-0.079	-0.275	-0.191	-0.082	-0.147	-0.301	0.729	0.054	-0.083
Kurtosis	**13.259**	21.159	14.967	6.987	5.412	7.256	11.444	10.245	11.834	14.967	7.541	5.156
MaxDrawdown	**2.139**	1.787	1.399	1.961	1.947	1.977	2.085	1.890	1.764	1.399	1.889	1.947
Drawdown Duration	**189**	82	8	194	202	476	81	459	264	8	189	202
Minimum	**-1.277**	-1.062	-0.693	-1.083	-1.062	-1.083	-1.277	-1.157	-1.083	-0.693	-1.083	-1.062
Maximum	**0.862**	0.725	1.192	0.878	0.885	0.894	0.808	0.732	0.681	1.192	0.806	0.885
Jarque-Bera	14983.3	43232.8	22164.8	2090.5	694.3	2418.6	8223.8	7128.0	15357.6	22164.8	2819.5	570.6
Q test	57.567	72.097	31.447	40.780	119.788	37.809	46.638	34.370	30.836	31.447	52.465	101.563
ARCH test	2.597	1.033	3.088	26.400	11.571	4.633	2.165	3.904	0.986	3.088	31.961	6.101
ADF	-34.626	-31.400	-32.891	-39.220	-41.942	-38.026	-33.128	-36.658	-34.774	-32.891	-40.101	-41.150
KPSS	0.013	0.032	0.035	0.009	0.007	0.010	0.019	0.011	0.021	0.035	0.010	0.007

Notes: Table C.2.23 presents the summary statistics of the vote strategies in terms of the maximum mean outperformance criterion for a Capesize vessel from January 1992 to June 2016. The period from 31st of August 2007 to 30th of January 2009 is eliminated in order to assess if the financial crisis affects the profitability of the chartering strategies. For further definitions refer to Tables 2.1 and 2.4.

Table C.2.24: Summary Statistics of Panamax and Handymax Vote Strategies: No Crisis Period – Mean Outperformance Criterion

		sMAC	*sTMA*	*sMACD*	*sBB*	*MAE*	*RSI*	*SOD*	*eMAC*	*eTMA*	*eMACD*	*eBB*	*eMAE*
PANAMAX	**Mean (% Ann)**	**-0.593**	-3.896	-2.468	-4.779	-3.258	-4.125	-3.766	-4.338	-3.169	-2.468	-4.383	-3.912
	Standard Deviation (% Ann)	**102.670**	71.435	74.551	118.147	154.829	115.346	102.264	99.663	86.186	74.551	120.457	148.157
	Downside Risk	**4.793**	3.212	3.700	5.633	7.772	5.646	4.813	4.916	4.107	3.700	5.783	7.390
	Sharpe Ratio	**-0.006**	-0.055	-0.033	-0.041	-0.021	-0.036	-0.037	-0.044	-0.037	-0.033	-0.036	-0.026
	Sortino Ratio	**-0.124**	-1.213	-0.667	-0.848	-0.419	-0.731	-0.783	-0.882	-0.772	-0.667	-0.758	-0.529
	Skewness	**-1.507**	-0.686	-1.837	-1.425	-0.955	-1.319	-1.511	-1.249	-1.577	-1.837	-1.433	-1.171
	Kurtosis	**39.459**	41.682	39.363	26.245	12.756	28.302	44.099	27.178	40.002	39.363	29.044	15.000
	MaxDrawdown	**2.739**	2.057	1.638	2.648	2.702	2.737	2.908	2.414	2.180	1.638	2.937	2.702
	Drawdown Duration	**153**	189	107	148	43	161	144	161	9	107	144	43
	Minimum	**-1.772**	-1.232	-1.232	-1.820	-1.820	-1.792	-1.792	-1.469	-1.469	-1.232	-1.820	-1.820
	Maximum	**0.967**	0.825	0.747	0.908	0.974	0.945	1.117	0.945	0.816	0.747	1.117	0.882
	Jarque-Bera	125828	144831	136212	47337	7979.9	55149.7	143125	52883.1	129920	136212	65220	11794.6
	Q test	92.144	106.992	48.283	70.243	96.472	45.099	56.450	68.371	128.643	48.283	111.283	101.803
	ARCH test	0.546	5.069	2.650	3.791	9.851	3.556	6.293	4.617	8.989	2.650	8.985	10.135
	ADF	-32.714	-29.153	-30.645	-39.439	-40.696	-37.044	-36.573	-32.099	-30.719	-30.645	-40.357	-42.186
	KPSS	0.011	0.032	0.028	0.010	0.005	0.011	0.013	0.022	0.020	0.028	0.009	0.006
HANDYMAX	**Mean (% Ann)**	-1.758	-2.636	-2.380	**-1.093**	-2.113	-1.843	-2.536	-2.295	-2.461	-2.380	-1.876	-1.955
	Standard Deviation (% Ann)	63.641	47.843	56.617	**69.156**	79.650	79.614	62.602	69.836	48.962	56.617	69.026	86.292
	Downside Risk	3.731	2.974	3.644	**3.895**	4.416	4.392	3.414	4.001	2.865	3.644	3.849	5.039
	Sharpe Ratio	-0.028	-0.055	-0.042	**-0.016**	-0.027	-0.023	-0.041	-0.033	-0.050	-0.042	-0.027	-0.023
	Sortino Ratio	-0.471	-0.886	-0.653	**-0.280**	-0.478	-0.420	-0.743	-0.574	-0.859	-0.653	-0.487	-0.388
	Skewness	-8.602	-10.759	-8.166	**-4.652**	-1.840	-2.663	-7.574	-4.179	-9.260	-8.166	-4.413	-3.098
	Kurtosis	176.081	223.993	150.138	**86.358**	34.083	47.393	157.438	80.580	192.277	150.138	86.466	55.703
	MaxDrawdown	2.286	1.597	1.769	**2.295**	2.122	2.226	2.062	2.208	1.592	1.769	2.295	2.499
	Drawdown Duration	149	81	13	**164**	164	164	77	163	164	13	164	164
	Minimum	-1.726	-1.364	-1.433	**-1.515**	-1.341	-1.446	-1.656	-1.515	-1.364	-1.433	-1.515	-1.719
	Maximum	0.560	0.234	0.336	**0.780**	0.780	0.780	0.597	0.693	0.340	0.336	0.780	0.780
	Jarque-Bera	2996367	5555930	2704045	695235	90657	189329	2243551	587461	3597582	2704045	752332	253320
	Q test	22.457	29.086	75.547	34.612	58.042	69.918	26.331	53.207	42.682	75.547	40.983	72.647
	ARCH test	0.213	0.002	0.001	0.000	16.738	3.134	0.088	1.271	0.001	0.001	0.052	0.633
	ADF	-35.315	-30.983	-30.607	-34.815	-40.147	-38.674	-33.290	-36.746	-31.219	-30.607	-36.507	-38.300
	KPSS	0.036	0.058	0.039	0.021	0.018	0.017	0.029	0.024	0.052	0.039	0.024	0.015

Notes: Table C.2.24 presents the summary statistics of the vote strategies in terms of the maximum mean outperformance criterion for a Panamax and a Handymax vessel from January 1992 to June 2016. The period from 31st of August 2007 to 30th of January 2009 is eliminated in order to assess if the financial crisis affects the profitability of the chartering strategies. For further definitions refer to Tables 2.1 and 2.4.

Table C.2.25: Descriptive Statistics: No Crisis Period

		Panel A: Freight Rates				Panel B: Spread Series					
		lnSpot	**lnP6m**	**lnP12m**	**lnP36m**	**1**	**2**	**3**	**4**	**5**	**6**
CAPESIZE	**Mean**	9.734	9.514	9.752	9.700	0.220	-0.018	0.034	-0.239	-0.187	0.054
	Std Deviation	0.715	0.605	0.568	0.454	0.365	0.284	0.408	0.323	0.408	0.204
	Sharpe Ratio	13.621	15.728	17.157	21.345	0.604	-0.063	0.083	-0.740	-0.459	0.263
	Skewness	0.273	0.245	0.747	0.280	-0.870	-0.531	0.065	0.268	0.132	0.135
	Kurtosis	2.742	2.451	3.170	3.622	3.573	4.945	2.631	2.428	2.745	2.645
	MaxDrawdown	4.091	2.936	3.076	2.712	2.206	2.299	2.736	1.294	1.519	0.961
	Drawdown Duration	371	353	327	330	356	31	31	26	352	560
	Minimum	7.375	8.161	8.412	8.445	-1.120	-1.520	-1.478	-1.078	-1.190	-0.448
	Maximum	11.466	11.165	11.488	11.156	1.086	0.778	1.258	0.611	1.020	0.586
	Jarque-Bera	18.252	27.125	113.213	35.140	167.66	246.29	7.651	30.252	6.275	9.035
	ADF	-0.465	-0.310	-0.464	-0.505	-4.278	-7.083	-5.294	-3.213	-3.173	-4.803
PANAMAX	**Mean**	9.312	9.304	9.235	9.141	0.009	0.078	0.172	0.074	0.166	0.097
	Std Deviation	0.554	0.478	0.424	0.308	0.230	0.283	0.464	0.114	0.314	0.240
	Sharpe Ratio	16.803	19.477	21.791	29.648	0.039	0.275	0.370	0.649	0.528	0.404
	Skewness	0.834	0.619	0.661	0.429	-0.221	-0.046	0.266	-0.027	0.598	0.897
	Kurtosis	3.010	3.315	3.555	3.937	3.685	3.005	2.187	5.476	2.349	2.900
	MaxDrawdown	2.575	2.786	2.339	2.405	1.430	1.733	2.347	1.223	1.544	1.158
	Drawdown Duration	286	158	157	158	125	452	240	185	163	176
	Minimum	8.340	8.124	8.294	8.086	-0.792	-0.882	-1.063	-0.799	-0.393	-0.325
	Maximum	10.916	10.911	10.633	10.491	0.638	0.851	1.284	0.425	1.151	0.833
	Jarque-Bera	139.423	81.861	103.042	80.891	33.51	0.42	47.304	333.637	96.911	176.211
	ADF	-0.379	-0.419	-0.446	-0.449	-4.984	-3.896	-2.718	-7.029	-3.032	-3.756
HANDYMAX	**Mean**	9.290	9.320	9.282	9.244	-0.031	0.007	0.046	0.042	0.078	0.041
	Std Deviation	0.484	0.463	0.424	0.285	0.118	0.133	0.253	0.074	0.212	0.174
	Sharpe Ratio	19.184	20.137	21.910	32.441	-0.261	0.055	0.183	0.569	0.367	0.236
	Skewness	0.816	0.873	1.041	1.034	-1.101	-0.986	0.460	0.318	0.724	1.158
	Kurtosis	3.030	3.140	3.585	4.285	4.843	5.167	3.159	3.206	2.997	4.196
	MaxDrawdown	2.498	2.480	2.226	1.656	0.823	0.913	1.552	0.462	1.254	1.045
	Drawdown Duration	367	367	367	371	483	272	488	300	541	541
	Min	8.221	8.294	8.466	8.740	-0.522	-0.586	-0.676	-0.211	-0.523	-0.351
	Max	10.719	10.774	10.692	10.397	0.301	0.327	0.876	0.291	0.731	0.693
	Jarque-Bera	133.541	153.819	234.358	297.327	432.71	441.55	44.205	58.751	112.610	409.908
	ADF	-0.330	-0.267	-0.328	-0.445	-6.083	-5.584	-3.231	-6.112	-3.063	-2.602

Notes: Table C.2.25: presents the descriptive statistics of the freight rate and the spreads series for all vessels sizes from January 1992 to June 2016 after eliminating the financial crisis period from 31st of August 2007 to 30th of January 2009. See Table 2.1 for further definitions.

Table C.2.26: Summary Statistics of Benchmark Strategies: No Crisis Period

		Panel A: Freight Rates Returns				Panel B
		lnSpot	**lnP6m**	**lnP12m**	**lnP36m**	**Spread Rule**
CAPESIZE	**Mean (% Ann)**	-4.884	-2.161	-3.501	-3.631	**1.875**
	Standard Deviation (% Ann)	96.120	60.878	50.845	40.733	**161.811**
	Downside Risk	4.053	3.844	3.935	5.283	**20.649**
	Sharpe Ratio	-0.061	-0.052	-0.089	-0.114	**0.005**
	Sortino Ratio	-1.205	-0.562	-0.890	-0.687	**0.091**
	Skewness	-0.250	0.560	-4.034	-6.630	**-0.032**
	Kurtosis	14.698	9.522	89.626	140.817	**1.723**
	MaxDrawdown	1.520	0.970	1.570	1.390	**0.800**
	Drawdown Duration	80	102	150	58	**3**
	Minimum	-1.250	-0.440	-1.250	-1.130	**-0.400**
	Maximum	0.790	0.530	0.510	0.300	**0.400**
	Jarque-Bera	6871.7	2195.2	379404.5	960859.0	8561.8
	Q test	134.64	87.489	66.352	34.749	187.208
	ARCH test	16.977	5.602	0.347	0.000	20.468
	ADF	-29.495	-28.092	-31.325	-33.856	-44.750
PANAMAX	**Mean (% Ann)**	**-3.069**	-3.717	-3.544	**-2.983**	0.000
	Standard Deviation (% Ann)	**63.749**	60.489	48.542	**41.731**	70.476
	Downside Risk	**3.136**	3.636	3.258	**4.158**	9.954
	Sharpe Ratio	**-0.064**	-0.078	-0.094	**-0.095**	0.000
	Sortino Ratio	**-0.979**	-1.022	-1.088	**-0.717**	0.000
	Skewness	**-7.415**	-6.852	-7.456	**-5.075**	0.024
	Kurtosis	**161.506**	164.760	179.594	**169.872**	1.419
	MaxDrawdown	**2.130**	2.030	1.770	**1.530**	0.266
	Drawdown Duration	**203**	148	148	**14**	269
	Minimum	**-1.850**	-1.750	-1.430	**-1.170**	-0.133
	Maximum	**0.310**	0.690	0.610	**0.730**	0.133
	Jarque-Bera	1270377.4	1320998.5	1574318.9	1400961.4	11518.9
	Q test	73.66	79.839	73.331	49.540	178.526
	ARCH test	0.173	1.275	2.155	0.972	55.824
	ADF	-29.275	-29.682	-28.843	-32.894	-45.731
HANDYMAX	**Mean (% Ann)**	-2.148	**-1.478**	-1.807	-2.053	-2.927
	Standard Deviation (% Ann)	47.565	**45.104**	36.495	25.906	36.538
	Downside Risk	2.569	**3.694**	3.523	4.510	4.545
	Sharpe Ratio	-0.066	**-0.055**	-0.077	-0.118	-0.107
	Sortino Ratio	-0.836	**-0.400**	-0.513	-0.455	-0.644
	Skewness	-12.115	**-16.044**	-17.197	-20.325	-0.051
	Kurtosis	300.993	**439.011**	485.882	590.221	2.615
	MaxDrawdown	1.838	**2.078**	1.723	1.205	0.186
	Drawdown Duration	164	**164**	164	164	8
	Minimum	-1.615	**-1.683**	-1.397	-1.042	-0.093
	Maximum	0.260	**0.395**	0.326	0.163	0.093
	Jarque-Bera	4480515.7	9580641.6	11747214.0	17367334.4	20705.3
	Q test	72.73	15.63	38.50	24.36	34.087
	ARCH test	0.125	0.215	0.001	0.001	0.276
	ADF	-29.741	-33.773	-32.227	-32.835	-37.826

Notes: Table C.2.26 presents the summary statistics of the passive strategies and the spread rule for three vessel sizes from January 1992 to June 2016, after eliminating the financial crisis period from 31st of August 2007 to 30th of January 2009. Panel A presents the logarithmic differences of the spot, 6-, 12- and 36- month period contracts. Panel B reports the returns of the spread rule. For further definitions refer to Table 2.1.

Appendix 2.D: Additional White Reality Check *p-values*

Table D.2.27 and D.2.29 present the White Reality Check (WRC) *p-values* using the maximum mean return outperformance criterion for the entire sample period (i.e. January 1992 to June 2016) and for the sample period after eliminating the financial crisis period (from 31^{st} of August 2007 to 30^{th} of January 2009), respectively.

Table D.2.28 present the WRC *p-values* using the maximum risk-adjusted for the sample period after eliminating the financial crisis period (from 31^{st} of August 2007 to 30^{th} of January 2009).

Table D.2.27: White's Reality Check *p-values* for Active and Vote Strategies – Mean Return Outperformance Criterion

Panel A: Capesize	***sMAC***	***sTMA***	***sMACD***	***sBB***	***MAE***	***RSI***	***SOD***	***eMAC***	***eTMA***	***eMACD***	***eBB***	***eMAE***
Spot	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P6m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P12m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Spread Rule	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel B: Capesize VOTE strategies												
Spot	0.000	0.000	0.000	0.000	0.000	0.000	0.034	0.000	0.000	0.000	0.000	0.000
P6m	0.000	0.000	0.000	0.000	0.000	0.000	0.006	0.000	0.000	0.000	0.000	0.000
P12m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.002	0.000	0.000	0.000	0.642	0.000	0.000	0.002	0.000	0.000
Spread Rule	0.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000
Panel C: Panamax												
Spot	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P6m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P12m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Spread Rule	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel D: Panamax VOTE strategies												
Spot	0.000	0.000	0.000	0.000	0.558	0.212	0.000	0.000	0.000	0.000	0.628	0.530
P6m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P12m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Spread Rule	0.000	0.920	0.000	0.000	1.000	1.000	0.414	0.000	0.371	0.000	1.000	1.000
Panel E: Hanydmax												
Spot	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P6m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P12m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Spread Rule	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel E: Hanydmax VOTE Strategies												
Spot	0.000	0.000	0.000	0.000	0.568	0.000	0.000	0.000	0.000	0.000	0.000	0.014
P6m	0.000	0.000	0.020	0.003	0.999	0.000	0.000	0.000	0.000	0.017	0.000	0.806
P12m	0.000	0.000	0.000	0.000	0.015	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Spread Rule	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table D.2.27 presents the *White's Reality Check p-values* of the best active and vote strategies based on the highest mean return criterion, compared against each passive strategy. The analysis includes 30,046 models (r) for the active strategies and 12 models (r) for the vote strategies and 10,000 bootstrap repetitions. For further details regarding the chartering strategies, refer to *sub-section* 2.2.2.

Table D.2.28: White's Reality Check *p-values* for Active and Vote Strategies: No Crisis – Risk-adjusted Returns Outperformance Criterion

Panel A: Capesize	***sMAC***	***sTMA***	***sMACD***	***sBB***	***MAE***	***RSI***	***SOD***	***eMAC***	***eTMA***	***eMACD***	***eBB***	***eMAE***
Spot	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P6m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P12m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Spread Rule	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel B: Capesize VOTE strategies												
Spot	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P6m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P12m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Spread Rule	0.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000	0.000	1.000	0.010	0.000
Panel C: Panamax												
Spot	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P6m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P12m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Spread Rule	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel D: Panamax VOTE strategies												
Spot	0.000	0.000	0.000	0.000	0.755	0.491	0.000	0.000	0.000	0.000	0.000	0.775
P6m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P12m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Spread Rule	0.000	1.000	0.000	1.000	1.000	1.000	0.977	0.000	0.992	0.000	1.000	1.000
Panel E: Hanydmax												
Spot	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P6m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P12m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Spread Rule	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel E: Hanydmax VOTE Strategies												
Spot	0.000	0.000	0.000	0.000	0.778	0.000	0.000	0.000	0.000	0.000	0.000	0.058
P6m	0.000	0.000	0.016	0.000	0.999	0.000	0.000	0.000	0.000	0.019	0.000	0.733
P12m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Spread Rule	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table D.2.28 presents the *White's Reality Check p-values* of the best active and vote strategies based on the highest risk-adjusted return criterion, compared against each passive strategy. For the period from January 1992 to June 2016, after the elimination of the financial crisis period. The analysis includes 30,046 models (r) for the active strategies and 12 models (r) for the vote strategies and 10,000 bootstrap repetitions. For further details regarding the chartering strategies, refer to *sub-section* 2.2.2.

Table D.2.29: White's Reality Check *p-values* for Active and Vote Strategies: No Crisis – Mean Return Outperformance Criterion

Panel A: Capesize	*sMAC*	*sTMA*	*sMACD*	*sBB*	*MAE*	*RSI*	*SOD*	*eMAC*	*eTMA*	*eMACD*	*eBB*	*eMAE*
Spot	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P6m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P12m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Spread Rule	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel B: Capesize VOTE strategies												
Spot	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P6m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P12m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Spread Rule	0.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000	0.000	1.000	0.009	0.000
Panel C: Panamax												
Spot	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P6m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P12m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Spread Rule	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel D: Panamax VOTE strategies												
Spot	0.000	0.000	0.000	0.000	0.768	0.490	0.000	0.000	0.000	0.000	0.000	0.771
P6m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P12m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Spread Rule	0.000	1.000	0.000	1.000	1.000	1.000	0.975	0.000	0.993	0.000	1.000	1.000
Panel E: Hanydmax												
Spot	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P6m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P12m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Spread Rule	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel E: Hanydmax VOTE Strategies												
Spot	0.000	0.000	0.000	0.000	0.776	0.000	0.000	0.000	0.000	0.000	0.000	0.059
P6m	0.000	0.000	0.019	0.000	0.998	0.000	0.000	0.000	0.000	0.020	0.000	0.734
P12m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P36m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Spread Rule	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table D.2.29 presents the *White's Reality Check p-values* of the best active and vote strategies based on the highest mean return criterion, compared against each passive strategy. For the period from January 1992 to June 2016, after the elimination of the financial crisis period. The analysis includes 30,046 models (r) for the active strategies and 12 models (r) for the vote strategies and 10,000 bootstrap repetitions. For further details regarding the chartering strategies, refer to *sub-section* 2.2.2.

Appendix 2.E: Additional t-tests

As mentioned in section 2.3.4.3, the study examines if the difference between the active and the passive returns is statistically different from zero.

Table E.2.30 presents the *p*-values of the difference in returns between the active and the P6m strategy. Table E.2.31 reports the same statistics for the difference between the active and the P12m returns, while Tables E.2.32 and E.2.33 present the results for the difference between the active and the P36m and the spread rule returns respectively.

Table E.2.30: Testing the Difference between $R_{active} - R_{P6m}$

	Panel A: Active and Vote Strategies - full sample												
	Capesize												
	Criteria	***sMAC***	***sTMA***	***sMACD***	***sBB***	***MAE***	***RSI***	***SOD***	***eMAC***	***eTMA***	***eMACD***	***eBB***	***eMAE***
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.892	0.000	0.000	0.000	0.021	0.000	0.000	0.892	0.000	0.000
	SR	0.000	0.000	0.892	0.000	0.000	0.000	0.021	0.000	0.000	0.892	0.000	0.000
	Panamax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Handymax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Panel B: Active and Vote Strategies – No Crisis sample												
	Capesize												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.400	0.000	0.000	0.000	0.000	0.000	0.000	0.400	0.000	0.000
	SR	0.000	0.000	0.400	0.000	0.000	0.000	0.000	0.000	0.000	0.400	0.000	0.000
	Panamax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Handymax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table E.2.30 Panel A presents the statistical significance of the difference between the returns of active and passive strategies using t – test's p-values for the period from January 1992 to June 2016. As active returns (R_{active}) are used the best active and vote strategies returns in terms of both the maximum risk-adjusted and mean outperformance criteria. Panel B shows the same statistics however the excludes the financial crisis (31^{st} of August 2007 to 30^{th} of January 2009). The t – test examines if the differences between the active and passive return series is statistically different from zero.

Table E.2.31: Testing the Difference between $R_{active} - R_{P12m}$

	Panel A: Active and Vote Strategies – full sample												
	Capesize												
	Criteria	***sMAC***	***sTMA***	***sMACD***	***sBB***	***MAE***	***RSI***	***SOD***	***eMAC***	***eTMA***	***eMACD***	***eBB***	***eMAE***
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Panamax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Handymax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Panel B: Active and Vote Strategies – No Crisis sample												
	Capesize												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Panamax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Handymax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table E.2.31 presents the statistical significance of the difference between the returns of active and passive strategies using t – test's p-values. For further definitions refer to Table E.2.30.

Table E.2.32: Testing the Difference between $R_{active} - R_{P36m}$

	Panel A: Active and Vote Strategies - full sample												
	Capesize												
	Criteria	***sMAC***	***sTMA***	***sMACD***	***sBB***	***MAE***	***RSI***	***SOD***	***eMAC***	***eTMA***	***eMACD***	***eBB***	***eMAE***
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Panamax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Handymax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Panel B: Active and Vote Strategies – No Crisis sample												
	Capesize												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Panamax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Handymax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table E.2.32 presents the statistical significance of the difference between the returns of active and passive strategies using t – test's p-values. For further definitions refer to Table E.2.30.

Table E.2.33: Testing the Difference between $R_{active} - R_{Spread\_Rule}$

	Criteria	*sMAC*	*sTMA*	*sMACD*	*sBB*	*MAE*	*RSI*	*SOD*	*eMAC*	*eTMA*	*eMACD*	*eBB*	*eMAE*
	Panel A: Active and Vote Strategies - full sample												
	Capesize												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.136	0.000	0.000	0.000	0.004	0.000	0.000	0.136	0.000	0.000
	SR	0.000	0.000	0.136	0.000	0.000	0.000	0.004	0.000	0.000	0.136	0.000	0.000
	Panamax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.137	0.046	0.000	0.000	0.000	0.000	0.234	0.119
	SR	0.000	0.000	0.000	0.000	0.137	0.046	0.000	0.000	0.000	0.000	0.234	0.119
	Handymax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Panel B: Active and Vote Strategies – No Crisis sample												
	Capesize												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.014	0.000	0.000	0.000	0.223	0.000	0.000	0.014	0.000	0.000
	SR	0.000	0.000	0.014	0.000	0.000	0.000	0.223	0.000	0.000	0.014	0.000	0.000
	Panamax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.006	0.028	0.000	0.000	0.000	0.000	0.504	0.003
	SR	0.000	0.000	0.000	0.000	0.006	0.028	0.000	0.000	0.000	0.000	0.504	0.003
	Handymax												
	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
VOTE	**Mean**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table E.2.33 presents the statistical significance of the difference between the returns of active and passive strategies using t – test's p-values. For further definitions refer to Table E.2.30.

Chapter 3

The Effects of Macroeconomic Variables on the Term Structure of Freight Rates

The understanding and modelling of the term structure of freight rates is highly important in the shipping industry. Although there are various studies that focus on the characteristics of the freight market, only a few concentrate on the term structure of freight rates in bulk shipping. The proposed model includes common components of a large number of macroeconomic and latent variables as factors in order to understand and model the term structure of freight rates. The term structure of freight rates is modelled and assessed within a Vector Autoregression (VAR) – framework that includes a Factor Augmented Vector Autoregression ($FAVAR$) model and a latent factor freight rate model. The VAR framework assesses the dynamics between the term structure of freight rates and the macroeconomic datasets. The empirical findings indicate that the supply macroeconomic factors explain a larger variation of the freight rates across the maturity spectrum compared to the demand macroeconomic factors. In addition, the latent freight rates (i.e. level, slope and curvature) model also adequately explains a large proportion of the freight rate variability across all examined scenarios.

3.1 Introduction

The modelling and forecasting of the yield curve is important when formulating investment strategies and asset pricing in the financial markets. The main problem investors face is how to model the yield curve in order to predict future interest rates and analyse the dynamics between interest rates with different maturities. This problem can be explained by some of the most widely known term structure theories such as the *Expectation Theory* (Muth (1961, 1985), Mankiw and Miron (1986), Campbell and Shiller (1987,1991) amongst others), the *Pure Expectation Theory* (Lovell, 1986), the *Liquidity Preference Theory* (Hicks, 1946), the *Market Segmentation Theory* (Culbertson, 1957) and the *Preferred Habitat Theory* (Modigliani and Sutch, 1966).

Various studies in the shipping industry such as Glen et al (1981), Binkley and Bessler (1983), Strandenes (1984), Hale and Vanags (1989), Beenstock and Vergottis (1989a, 1989b), Evans (1994), Berg-Andreassen (1997), Veenstra (1999), Kavussanos and Alizadeh (2002b), Alizadeh et al (2007) have analysed the term structure of freight rates based on the expectation theory. More specifically, these studies focused on how to express time charter rates as an average of expected future trip charter rates. The empirical tests of the expectation hypothesis either rejected the hypothesis or were inconclusive mainly because of the existing time-varying risk premium (Kavussanos and Alizadeh, 2002b).

Due to the failure in proving the validity of the expectations hypothesis, some researchers such as Kavussanos and Nomikos (1999) and Kavussanos et al (2004) focused on the validity of the *pure expectations hypothesis* or *unbiasedness hypothesis*. The approach used in both studies vary in terms of methodology and shipping sector, ship size, trade route, etc. however both found evidence of the unbiasedness of freight derivatives across one and two months before maturities whereas a bias appeared in the three-month futures prices.

Many scholars, based on the expectation theory, expanded the theoretical frameworks and explained the relationship between the yield and maturity using empirical yield models consisting of factor models that are widely used in the literature on interest rates and bond market (Merton, 1973; Vasicek, 1977; Cox et al, 1985; Ho and Lee, 1986; Nelson and Siegel, 1987; Hull and White, 1990a,b; Black and Karasinki, 1991; Heath et al, 1992; Dai and Singleton, 2003 amongst others). The Nelson-Siegel (1987) approach has been used to model interest rates and bond curves however one of its most important shortcomings is that the factors (level, slope and curvature) are stable. Therefore, Diebold et al (2006) extended the Nelson and Siegel model to make it dynamic and include time-varying level, slope and the curvature.

However, capturing the movements in the yield curve based solely on unobservable or latent factors might not be sufficient so some studies focused on affine term structure models that use well-defined macroeconomic factors. More specifically, Ang and Piazzesi (2003) found that macroeconomic factors could explain a large part of the variation in interest rates and also improve yield forecasts. More studies have since attempted to explore different approaches and jointly model the term structure and the macroeconomy (Hördahl et al, 2006; Diebold et al, 2006; Dewachter and Lyrio, 2006;

Rudebusch and Wu, 2008; Exterkate et al, 2013). These studies consistently showed that macroeconomic variables can be useful when explaining and forecasting government bond yields however the macroeconomic information sets were small. Möench (2008) analysed larger macroeconomic information sets and attempted to identify other macroeconomic information that had being neglected. Even though multiple studies focus on applying macro-finance models of the term structure in the bond and interest rates market, no research used this approach for shipping freight market.

Chapter 2 showed that the evolution of freight rates is the key factor when attempting to make an optimal decision, which also underlines the importance to identify the macroeconomic variables affect the level of freight rates, since the literature shows that the long-term rates and short-term rates are determined by the demand for trade, the supply of ships and other macro-economic factors of the freight market (Hawdon, 1978; Beenstock and Vergottis, 1989a,b; Evans and Marlow, 1990; Beenstock and Vergottis, 1993).

Multiple studies focus on modelling the demand and supply for transportation using different methodological approaches (e.g. static supply/ demand models, stochastic models, econometric models amongst others) that only focused on the dynamic interactions between shipping markets (Koopmans, 1939; Zannetos, 1966; Hawdon, 1978; Charemza and Gronicki, 1981; Strandenes, 1984; Beenstock, 1985; Beenstock and Vergottis, 1989a,b, 1993, Tvedt, 2003, Tsolakis, 2005 and Adland and Strandenes, 2007) or between the shipping stock market and a limited number of macroeconomic variables (Grammenos and Arkoulis, 2002, Drobetz et al, 2010, 2012; Kalouptsidi, 2013; Greenwood and Hanson, 2014).

More specifically, after the seminal work of Tinbergen (1931, 1934) and Koopmans (1939), research on maritime economics has focused on integrating the various markets into a dynamic system. One well known macroeconomic or system approach is the Beenstock–Vergottis (BV) model (1993) which is the first systematic approach to explain the interaction of the freight, time charter, secondhand, newbuilding and scrap markets under the twin assumptions of rational expectations and market efficiency. Since the publication of the BV model, research in maritime economics has been mainly of empirical nature and concentrated for example on the efficiency of individual shipping markets except from numerous research studies that focus on how returns on shipping stocks react to contemporaneous changes in macroeconomic risk factors (Kavussanos and Marcoulis, 1997a, 1997b, 1998, 2000a, 2000b, 2001, 2005; Grammenos and Arkoulis, 2002, Drobetz et al., 2010, 2012, 2016).

For instance, Kavussanos and Marcoulis (1997a, 1998 and 2005) showed that the risk associated with water transportation companies is smaller, but not significantly different, than the risk of the average company across industries and also found evidence that the market return is changing over bear and bull market conditions. In addition, Kavussanos and Marcoulis (2000b) examined the relationship between macro- and micro-factors and the cross-section of US transport industry returns and found that rising levels of industrial production and changes in oil prices were associated with higher stock returns whilst consumption levels were negatively correlated with the returns. Similarly, Grammenos and Arkoulis (2002) analysed the relationship between shipping stock returns and a set of macroeconomic factors and found that the oil prices and laid up tonnage are negatively associated with shipping stocks and that the exchange rate variable displayed a positive relationship.

Drobetz et al. (2010) investigated the impact of multiple macroeconomic risk factors (such as world stock market index, currency fluctuations, changes in industrial production, changes in oil prices, etc.) that drive the expected stock returns on the 3 sectors of the shipping industry: container, tanker and bulker shipping. Furthermore, Drobetz et al. (2012) examined whether shocks in macroeconomic variables are able to explain the time-varying volatility of freight rates while Drobetz et al. (2016) studied the impact of macroeconomic and industry-level effects on the corporate systematic risk of the international shipping industry.

All these studies found dynamic interactions between shipping markets, while also they found that macroeconomic variables can explain the movements in the shipping stock market, however they did not assess how the macroeconomic variables relate to the freight rate curve. Therefore, Chapter 3 attempts to grow the literature by investigating the impact of a large number of macroeconomic variables on the term structure of freight rates and the potential existence of dynamic interactions between them.

Until now, although research studies that focused on the shipping industry attempted to analyse how the freight rates' movements are affected by demand and supply factors, the scope was quite narrow since the number of variables used was small. For example, when it comes to the demand factors, researchers have usually included the Oil Prices, Inflation Indicator and Industrial Production (Kavussanos and Marcoulis, 2000a,b; Grammenos and Arkoulis, 2002 and Drobetz et al 2010, 2012) – but omitted others such as aluminium, steel production, international seaborne trade, commodity prices, and exchange rates amongst others that could potentially have affected the proposed results had they been part of the analysis.

Attempting to provide a holistic picture of what affects the freight rates, this study exclusively incorporates a significant number of demand and supply variables that are all directly related to the shipping industry. These variables are listed in Table 3.2 and 3.4 producing a total of 59 variables (34 demand and 25 supply variables). This number is significantly higher than the ten variables included in the study by Drobetz et al (2010) meaning that the current results provide a more robust and accurate view of the freight rates' behaviour.

In addition, rather than consider term structure models from a more technical and finance perspective, the aim is to focus on the interactions between macroeconomics, monetary policy, and the term structure. Therefore, the freight rates are fitted to existing macro-finance models and their forecasting performance is compared within a VAR framework. The VAR framework contains two existing VAR term structure models from the literature (i.e. the latent factor freight rate model without macroeconomic variables and the $FAVAR$ model). The purpose of the VAR framework is to identify the impact of macroeconomic factors across the term structure and recognise which ones are more important in terms of explaining freight rates variations across the maturity spectrum.

The large dataset mentioned above is then reduced to 10 main factors (4 demand and 6 supply factors). The goal is to be able to apply for the first time the FAVAR and dynamic latent factor models to the shipping industry in order to accurately analyse the reasons behind the freight rates movements since these two models (which have been proven to be accurate tools for assessing the dynamic interactions between the macroeconomic variables and the freight rates) have only been used in the financial sector.

Multiple robustness tests are used to enhance the accuracy of the proposed VAR framework. First of all, the financial crisis period is eliminated to assess whether the empirical findings remain significant and unaffected by this turbulent period. Additionally, various regression models are used to assess the use of factors into the $FAVAR$ model. These are unrestricted regressions between the freight rates and the extracted factors, while also extracted factors regressed against the level, slope and curvature. Cubic spline interpolation and the introduction of different values for the factors slope and curvature as well as multiple values of the fixed loading factor lambda are used to enhance the performance of the latent freight rate model without macroeconomic variables.

Therefore, the contributions of this research study can be divided into theoretical, methodological and practical. From a theoretical perspective, this study contributed to the literature by proposing a FAVAR model that compares and assesses the relevance and the forecasting performance of the term structure of freight rates. In addition, the construction of a large macroeconomic dataset facilitates the analysis of the impact from macroeconomic factors on the term structure whilst identifies the ones are more important when explaining freight rates variations across the maturity spectrum.

From a methodological perspective, the main contributions of this study to the literature is that it proposes a model which, for the first time, includes a very large dataset consisting of both demand and supply variables whose influence is then assessed using two methodological approaches that have not previously been applied to the shipping industry.

Finally, from a practical perspective, the proposed framework can serve as a forecasting and trading tool which means that it can provide useful insights to ship-owners regarding the evolution of the term structure of freight rates. Precisely, understanding the evolution of the term structure of freight rates is important when predicting "asset" returns and determining the portfolio allocation choices of investors and their strategies for hedging freight rate risk. Precisely, forecasting future freight rates ex ante can bring extensive economical benefits if determined accurately. For instance, it could allow investors to determine the best moment to invest in new/second hand vessel, sell an existing one or demolishing a vessel. From a risk management perspective, being able to determine future freight rate levels would allow drawing the best chartering strategy and minimise any potential risk. Furthermore, identifying the economic forces behind the movements of freight rates is very importance since the latter are mainly determined by the interaction between supply and demand. As a result, the inclusion of macroeconomic factors into the term structure models is expected to explain a large portion of the variation in freight rates.

This study initially defines the methodology used to analyse the term structure of freight rates (see Section 3.2). Section 3.3 presents the empirical findings while section 3.4 shows the tests performed to enhance the robustness. Section 3.5 sums-up the study and presents the implications of the empirical findings.

3.2 Methodology

This section presents the benchmark model used to estimate the term structure of freight rates as well as the VAR framework that will be used to compare the performance of macro-finance freight rates models. Precisely, a $FAVAR$ model with macroeconomic variables is set as a benchmark model and then compared with an alternative VAR term structure model in terms of their performance across different freight rates. The VAR framework identifies the model that can explain a larger variation of the term structure of freight rates. Additionally, the study attempts to identify the most important macroeconomic factors that affect the behaviour of term structure of freight rates.

3.2.1 Defining the VAR Framework

The VAR framework consists of two models that attempt to model and estimate the term structure of freight rates. The VAR models are the $FAVAR$ freight rate model and the latent factor freight rate model without macroeconomic variables. The first step consists in defining each model that will be used in the analysis. The finally step will be to identify the macroeconomic variables that affect and explain the behaviour of the term structure of freight rates.

3.2.1.1 The Latent Factor Freight Rate Model

The term structure of freight rates is modelled using the traditional approach where the term structure of freight rates is decomposed into a set of latent factors. This approach, also known as the factor model approach, expresses a potentially large set of freight rates curves of various maturities as a function of a small set of unobserved factors.

The term structure freight rate curve is fitted based on the three-factor model proposed by Nelson and Siegel (1987) and the dynamic version of the model is similar to the one used by Diebold and Li (2006). More specifically, the freight rate curve is fitted using the following three-factor model:

$$FR(t,\tau) = \beta_{1t} + \beta_{2t}\left(\frac{1-e^{-\lambda_t\tau}}{\lambda_t\tau}\right) + \beta_{3t}\left(\frac{1-e^{-\lambda_t\tau}}{\lambda_t\tau} - e^{-\lambda_t\tau}\right) \tag{3.1}$$

where β_{1t}, β_{2t}, and β_{3t} are the time-varying level, slope and curvature. The $FR(t,\tau)$ expresses the freight curve at time t with τ representing the time to maturity. There are three factors for each freight rate with τ maturity: $\mathrm{B}_t = [\beta_{1t}, \beta_{2t}, \beta_{3t}]$ with the factor loadings of $\left[1, \left(\frac{1-e^{-\lambda_t\tau}}{\lambda_t\tau}\right), \left(\frac{1-e^{-\lambda_t\tau}}{\lambda_t\tau} - e^{-\lambda_t\tau}\right)\right]$. According to Diebold and Li (2006), the loading on β_{1t} is 1, β_{1t} can be viewed as a long term factor since it is a constant that does not decay to zero in the limit. The loading on β_{2t} is $\left(\frac{1-e^{-\lambda_t\tau}}{\lambda_t\tau}\right)$ a function that starts at 1 but decays monotonically and quickly to 0; hence it may be considered as a short-term factor. The loading on β_{3t} is $\left(\frac{1-e^{-\lambda_t\tau}}{\lambda_t\tau} - e^{-\lambda_t\tau}\right)$ which starts at 0 (i.e. not short-term) increases and then decays to zero (thus is not long-term); hence can be viewed as a medium-term factor. The exponential decay parameter λ_t indicates the maturity at which the curvature factor achieves its maximum value. More specifically, small values of λ_t produce a slow decay and are a better fit to the curve at long maturities while large values of λ_t lead to a fast decay and are best for the curve at short maturities.

However, since there is no standard reference for the formulation of the level, slope and curvature, in the dry bulk shipping market all available combinations need to be examined. The list with all of the available combinations of level, slope and curvature in the dry bulk freight market are presented in Appendix B.

The determination of the best slope, level and curvature is made based on a loss function such as the Root Mean Squared Error (RMSE) while also on the correlation coefficient. The short-term factor β_{2t} is closely related to the freight curve slope and consists of the 3-year minus the spot freight rates. The long-term factor β_{1t} refers to the freight rate level and is defined as 3-year period rates. Finally, the medium-term factor β_{3t} is related to the freight curvature and is defined as twice the 6-month freight rates minus the sum of the spot and 36-month freight rates.

Additionally, model (3.1) can be represented as a state-space system as per Diebold et al (2006) meaning that the dynamic movements of β_{1t}, β_{2t}, and β_{3t} follow a vector autoregressive process of first order. The transition equation, which governs the dynamics of the state vector, is:

$$\begin{pmatrix} \beta_{1t} - m_{\beta_1} \\ \beta_{2t} - m_{\beta_2} \\ \beta_{3t} - m_{\beta_3} \end{pmatrix} = \begin{pmatrix} \phi_{11} & \phi_{12} & \phi_{13} \\ \phi_{21} & \phi_{22} & \phi_{23} \\ \phi_{31} & \phi_{32} & \phi_{33} \end{pmatrix} \begin{pmatrix} \beta_{1t-1} - m_{\beta_1} \\ \beta_{2t-1} - m_{\beta_2} \\ \beta_{3t-1} - m_{\beta_3} \end{pmatrix} + \begin{pmatrix} \varepsilon_t(\beta_1) \\ \varepsilon_t(\beta_2) \\ \varepsilon_t(\beta_3) \end{pmatrix} \tag{3.2}$$

where m_{β_1}, m_{β_2} and m_{β_3} represent the mean level, slope and curvature. For a set of N freight rates with maturities τ, $\tau = \tau_1, \dots, \tau_N$, the measurement equations which relate to the three unobservable factors are:

$$\begin{pmatrix} F_t(\tau_1) \\ F_t(\tau_2) \\ \vdots \\ F_t(\tau_N) \end{pmatrix} = \begin{pmatrix} 1 & \frac{1-e^{-\lambda_t\tau_1}}{\lambda_t\tau_1} & \frac{1-e^{-\lambda_t\tau_1}}{\lambda_t\tau_1} - e^{-\lambda_t\tau_1} \\ 1 & \frac{1-e^{-\lambda_t\tau_2}}{\lambda_t\tau_2} & \frac{1-e^{-\lambda_t\tau_2}}{\lambda_t\tau_2} - e^{-\lambda_t\tau_2} \\ \vdots & \vdots & \vdots \\ 1 & \frac{1-e^{-\lambda_t\tau_N}}{\lambda_t\tau_N} & \frac{1-e^{-\lambda_t\tau_N}}{\lambda_t\tau_N} - e^{-\lambda_t\tau_N} \end{pmatrix} \begin{pmatrix} \beta_{1t} \\ \beta_{2t} \\ \beta_{3t} \end{pmatrix} + \begin{pmatrix} \eta_t(\tau_1) \\ \eta_t(\tau_2) \\ \vdots \\ \eta_t(\tau_N) \end{pmatrix} \tag{3.3}$$

In a vector/matrix notation, the state-space system can be calculated as follows:

$$(\beta_t - m) = \Phi_{LF}(\beta_{t-1} - m) + \varepsilon_t \tag{3.4}$$

$$\mathrm{B}_t = \mu + \Phi_{LF}\mathrm{B}_{t-1} + \eta_t \tag{3.5}$$

Equation (3.5) can be calculated using two methodological approaches proposed in the literature:

- the two-step Ordinary Least Square (OLS) approach by Diebold and Li (2006),

Given λ_t the Nelson-Siegel factor loadings need to be calculated using the following equation $\left[1, \left(\frac{1-e^{-\lambda_t\tau}}{\lambda_t\tau}\right), \left(\frac{1-e^{-\lambda_t\tau}}{\lambda_t\tau} - e^{-\lambda_t\tau}\right)\right]$. Following this, β_{1t}, β_{2t}, and β_{3t} are estimated as parameters in a cross-section of freight rates, allowing for the time to maturity (τ) to vary. Using the freight rates F_t, the VAR coefficients (μ, Φ_{LF}) are estimated by OLS regression using a two-step process. Since B_t is estimated independently from the state dynamics, the in-sample fit of the freight rate curve is not affected by the state equation specification and only the forecast resulting from different specification will differ. By fixing λ_t the non-linear least square estimation (Eq. 3.1) is replaced by a relatively simple ordinary least squares estimation. The Nelson-Siegel framework requires setting $\lambda_t = 0.609$, which implies that the value at which the loading of the curvature (medium-term factor) is maximised is 30 months. In the current analysis, the value of λ_t is set at 0.226 based on a maximisation process of the loading of the curvature factor and also on a loss function such as the Root Mean Squared Error (RMSE). In other words, the purpose is to minimise the measurement errors and increase the correlation levels between the empirical and the implied estimate curvature using the same OLS model (Eq. 3.5). More specifically, multiple values of λ_t were tested in order to find the one that minimises the RMSE of equation 3.1 and maximises the loading factor of the curvature factor. The value of $\lambda_t = 0.226$ means that the curvature loading is maximised during month 8.

- the State-Space Model (SSM) approach proposed by Diebold et al (2006)

The two-step OLS procedure helps obtaining an estimate and forecast however if the assumption is that this state-space form mainly captures the data generating process, estimating the measurement and state equations separately will not be fully accurate. A one-step maximum likelihood estimation using the Kalman Filter might resolve this problem since the Nelson-Siegel factors are treated as latent and the factors and state equation coefficients are estimated together. This approach means that the specification of the state equation as either AR or VAR with a lag 1 or lag p (> 1) makes a difference in the estimated Nelson-Siegel factors.

While the proposed model provides a good in-sample fit to the data, its economic significance is limited since it disregards the relationship between macroeconomic variables and freight rates. Therefore, there is a need to model the term structure of freight rates based on the $FAVAR$ model with macroeconomic variables.

3.2.1.2 The FAVAR Freight Rate Model – Benchmark Model

Macroeconomic factors are largely responsible for the variation in interest rates but also improve yield forecasts and help explaining and forecasting the evolution of short-term interest rates (Ang and Piazzesi, 2003; Bernanke and Boivin, 2003; Giannone et al, 2004; Bernanke et al, 2005; Favero et al, 2005; Hordahl et al, 2006; Diebold et al, 2006; Dewachter and Lyrio, 2006; Möench, 2008; Rudebusch and Wu, 2008 and Exterkate et al, 2013). Bernanke et al (2005) and Möench (2008) argued that there are advantages in combining factor modelling and structural VAR analysis and this approach is identified as *"Factor Augmented Vector AutoRegression"* – $FAVAR$ approach.

The level of freight rates is determined based on the demand and supply levels of shipping transport and therefore it is highly important to identify variables that can capture the main demand and supply drivers as well as investigate their dynamic interactions with the freight rate curve using a $FAVAR$ model. Following the method proposed by Bernanke et al (2005) and Möench (2008), the $FAVAR$ model can be calculated using the following equations:

$$X_t = \Lambda_F F_t + \Lambda_r FR_t + \varepsilon_t \tag{3.6}$$

$$\begin{pmatrix} F_t \\ FR_t \end{pmatrix} = \mu + \Phi_F(L) \begin{pmatrix} F_{t-1} \\ FR_{t-1} \end{pmatrix} + \omega_t \tag{3.7}$$

Where X_t denotes an $M \times 1$ vector of the observed macroeconomic variables at period - t. Λ_F and Λ_r are the $M \times k$ and $M \times 1$ matrices of factor loadings, FR_t denotes the freight rate at time t, F_t is the $k \times 1$ vector of the common factors at time - t and ε_t is an $M \times 1$ vector of idiosyncratic components. Moreover, $\mu = \left(\mu_f', \mu_r\right)'$ is a $(k+1) \times 1$ vector of constants, $\Phi_F(L)$ denotes the $(k+1) \times (k+1)$ matrix of order p -lag polynomials and ω_t is a $(k+1) \times 1$ vector of reduced form shocks with variance covariance matrix Ω. Where k is the number of factors extracted from the demand and supply dataset. Affine term structure models are usually formulated in state-space form and therefore equation (3.7) can be formulated as follows:

$$Z_t = \mu + \Phi_F Z_{t-1} + \omega_t \tag{3.8}$$

Where $Z_t = (F_t', FR_t, F_{t-1}', FR_{t-1}, \cdots, F_{t-p+1}', FR_{t-p+1})'$ and where μ, Φ_F, ω and Ω denote the companion form equivalents of μ, Φ_F, ω and Ω respectively.

According to Bernanke et al (2005) and Möench (2008), the Factor-Augmented VAR model can be estimated using several approaches. The first one is based on estimating the $FAVAR$ model using the Kalman filter and maximum likelihood however this approach becomes computationally infeasible when the number or macroeconomic variables is very large. The second one is based on two alternative estimation methods proposed by Bernanke et al (2005), which are the single-step approach and the two-step approach. The single-step approach uses Markov Chain Monte Carlo methods whilst the two-step approach uses principal component techniques to estimate the common factors F and then the parameters governing the dynamics of the state equation are obtained via standard classical methods of VAR estimation. This study uses the two-step approach since this approach yields more plausible results according to Bernanke et al (2005).

3.2.2 Macroeconomic Dataset

The focus of the study is to describe the joint behaviour of the freight rate curve and macroeconomic variables in the dry bulk-shipping sector. The fluctuations in freight rates values are usually due to changes in the demand and supply levels. The fleet supply function works by moving ships in and out of service in response to freight rates meaning that it is elastic when the freight rates are low and inelastic when these are high (Stopford, 2009). On the other hand, the fleet demand function is almost vertical and shows how charterers react to changes in freight rate. Some of the main drivers affect the supply and demand levels are listed below in Table 3.1 (Stopford, 2009). Since there are no theoretical a priori expectations currently as to what the effect of macroeconomic demand and supply variables are on the freight rates dynamics, the empirical analysis should be able to assess these interactions which are of great importance in the shipping freight investments.

Table 3.1: Demand and Supply drivers

Demand Drivers	Supply Drivers
• World economic activity	• Stock of fleet available for trading
• International seaborne trade	• The shipbuilding production
• Average haul	• Scrapping rate and losses
• Random shocks	• Fleet productivity
• Transport costs	• The level of freight rates in the market (freight revenue)

In order to generate a representative macroeconomic dataset of the shipping industry, existing studies and available data are used to collect a maximum number of variables (e.g. demand, supply etc.) related to the shipping industry. These are then used to create a macroeconomic dataset of 59 time series, 34 demand and 25 supply macroeconomic variables. At this point it is important to note that some of the demand and supply drivers listed above cannot be measured directly either due to the frequency of the series or because of the lack of detailed information on the demand or supply drivers. As a result, proxy variables are used to capture their impact on the term structure of freight rates. The next sub-sections present in detail the variables used to measure the demand and the supply drivers.

3.2.2.1 Demand Drivers

Table 3.2 presents the demand drivers and the variables used to proxy them for the dry bulk freight market. One variable that strongly affects the level of demand is the *world economy*. Two aspects of the world economy (i.e. business and trade development cycle) lead to changes in the demand for sea transport (Stopford, 2009). To help predict business cycles, statisticians have developed leading indicators that provide advance warning of turning points in the economy. The dataset of the current study uses the world *Gross Domestic Product* (GDP) and the *OECD* (Organisation for Economic Co-operation and Development) *Industrial Production* as representative variables of the economy. The OECD Industrial Production is a measure of gross output compared to the GDP that can be considered as a measure of the value added in the economy (Herrera et al, 2011).

Additionally, the Baltic Dry Index (BDI), published by The Baltic Exchange in London, provides an assessment of the price (cost) of transporting major dry-bulk raw commodities (i.e. coal, iron ore and grain) by ocean-going (Capesize, Panamax, Supramax and Handysize) vessels. Therefore, the BDI can be used as proxy for the industry cycle since it accurately reflects the stages of the maritime industry (Klovland, 2002).

One of the problems of the OECD Industrial Production indicator is that it excludes emerging economies in Asia such as China and India, whose demand for industrial raw materials is considered to be driving industrial commodity and oil prices since 2002 (Kilian, 2009; Hamilton, 2013 and Kilian and Hicks, 2013). Therefore, to overcome these issues, Kilian (2009) developed an index of global real economic activity (also included in this study's dataset) using data from dry cargo single voyage ocean freight rates.

Additionally, *Inflation* indicators, *Global Oil Production* and *Steel* and *Aluminium Production* can also be considered as additional variables that affect the dry bulk freight market because of the effect they have on the world economy and international trade. For instance, high inflation is a signal of world economy uncertainty affecting consumers and consequently the international trade. Steel and aluminium are basic materials for sustained developments in a modern industrial society and therefore investigating their impact on freight rates is highly important since for instance, Chinese steel production accounts for more than 50% of the world's steel production and therefore any changes are expected to affect the level of freight rates. The dataset includes the top countries in steel and aluminium production in order to investigate their dynamic interactions with the freight rates.

Table 3.2: Demand Drivers and Variables

		Unit of measurement
A. World Economic Activity		
	GDP	% Yr/Yr
	Baltic Dry Index	Index
	Kilian's Index	Index
Inflation	Inflation OECD	% Yr/Yr
	Inflation OECD EU (excluding Turkey)	% Yr/Yr
	Inflation USA	% Yr/Yr
	Inflation Japan	% Yr/Yr
	Industrial Production OECD	% Yr/Yr
	Global Oil Production	M bpd
Steel Production	World Steel Production	,000 tonnes
	USA Steel Production	,000 tonnes
	China Steel Production	,000 tonnes
	Japan Steel Production	,000 tonnes
	Russia Steel Production	,000 tonnes
	S. Korea Steel Production	,000 tonnes
	India Steel Production	,000 tonnes
Aluminium Production	Africa Aluminium Production	,000 tonnes
	N. America Aluminium Production	,000 tonnes
	S. America Aluminium Production	,000 tonnes
	Asia (ex China) Aluminium Production	,000 tonnes
	W. Europe Aluminium Production	,000 tonnes
	E.Europe Aluminium Production	,000 tonnes
	Oceania Aluminium Production	,000 tonnes
B. International Seaborne Trade		
	Seaborne Trade Iron Ore	million tonnes
	Seaborne Trade Coking Coal	million tonnes
	Seaborne Trade Steam Coal	million tonnes
	Seaborne Trade Grains	million tonnes
C. Random Shocks		
Interest Rates	LIBOR Interest Rates	%
Exchange Rates	Exchange Rates Japan	¥/$
	Exchange Rates Euro	$/€
Commodity Prices	US Gulf Wheat Price	$/Tonne
	Thermal Coal Price	$/Tonne
	US Gulf Corn Price	$/Tonne
	Brent Crude Oil Price	$/bbl

Notes: Table 3.2 presents all demand variables included in the demand dataset and their unit of measurement. Price changes of all series were taken so that all of the series are stationary. All variables cover the period from January 1996 to June 2016.

Although *seaborne trade* is reported for the major dry bulk commodities only on an annual basis, monthly data is available for the main importers and exporters so the seaborne trade of each commodity is estimated by taking the average of all main imports and exports of Iron Ore, Steam and Coking Coal. The main importers and exporters of the main bulk commodities extracted from the Dry bulk Outlook from Clarkson's are presented in Table 3.3.

Table 3.3: Main Importers and Exporters of Bulk Commodities

Bulk Commodity	Imports	Exports
Iron Ore	China Japan South Korea Germany	Australia Brazil South Africa Canada
Coking Coal	Japan India South Korea	Australia Canada USA
Steam/ Thermal Coal	India China Japan South Korea Taiwan	Indonesia Australia Russia South Africa
Grain	Japan China South Korea Indonesia	Australia Argentina USA Canada

Notes: Table 3.3 presents the main importers and exporters of each commodity used to estimate the overall seaborne trade of iron ore, coking coal, steam/thermal coal and grains. For instance, the seaborne trade of coking coal is the sum of the exports of Australia, Canada and the USA.

Random shocks can be either economical or political, with their main characteristic being that their time is unpredictable and they bring a sudden and unexpected change in ship demand. Examples of economic shocks are the US financial crisis of the early 1990s, the Asian crisis of 1997, the stock market crash in 2000 and the financial credit crisis in 2008. In addition to economic shocks, political events such as local wars (i.e. Korean War, 1950, Six day War in 1967 between Israel and Egypt, etc.), revolution (i.e. the 1979 Iran Revolution), political nationalisation of foreign assets or strikes (i.e. oil assets in Libya in 1973) can also disrupt trade. Even though these are unpredictable there is a series of variables that can be used to capture their effects like for instance *exchange rates*, *interest rates* and *commodity prices*.

London InterBank Offered Rate (LIBOR) *interest rate* is used as a base rate (benchmark) by banks and other financial institutions. Rises and falls in the LIBOR interest rates can therefore have an impact on the interest rates of various banking products such as savings accounts, mortgages and loans. The level of interest rates indicates when the political uncertainty is high and the risk of disruption in the global financial system increases. More specifically, the level of interest rates decreases during phases of economic recession and increases during expansion periods. Additionally, the level of interest rates also affects the inflation rate which subsequently, as mentioned previously, has an impact on consumers and the international trade.

The *exchange rates* between the Yen and US dollar and between the euro and US dollar can have a strong impact on shipping returns since markets are heavily oriented toward international trade. Monthly changes in these currencies mirror fluctuations in the external value of the US dollar which is the main currency of the shipping industry. When the exchange rates decrease, this means that the exports of the corresponding country are weak, whilst higher exchange rates make exports strong increasing inflation in other countries because of the rising imported inflation. Therefore, operating profits in the shipping industry can increase or decrease dramatically depending on exchange rate movements.

The demand dataset also includes *commodity prices* of major dry bulk commodities. The level of commodity prices indicates if the market is in contango or backwardation depending on whether consumers are more risk averse than producers. When the market is in contango, spot rates tend to move below period rates while during backwardation, the period rates cross the spot rates from above. All demand variables are measured using aggregate variables or statistics of key countries.

Unfortunately, information and data related to the *average haul* and *transport costs* is not available as a monthly frequency and thus the macroeconomic dataset does not include variables on these two drivers (see Table 3.1). Nevertheless, these drivers are directly correlated with the variables in Table 3.2 and thus their impact would have been captured by these.

3.2.2.2 Supply Drivers

Table 3.4 presents the supply variables included in the macroeconomic time series. These are grouped into five main supply drivers (see Table 3.1).

The merchant *fleet* ($Fleet_t$) affects the supply level of freight rates. For instance, when the number of vessels in the market is too high then the freight rates are low because there is a surplus of ships to cover the demand. On the other hand, when the number of vessels is low then the freight rates are high since there is a lack of vessels to cover the demand. More specifically, the fleet ($Fleet_t$) is calculated as follows: net number of ships available in the market ($Fleet_t$) results from the current number of ships in the market ($Fleet_{t-1}$) added to the number of new ships delivered ($Deliveries_{t-1}$) minus the number of scrapped vessels ($Demolitions_{t-1}$) and those lost ($Losses_{t-1}$). More specifically, the fleet changes are measured as follows:

$$Fleet_t = Fleet_{t-1} + Deliveries_{t-1} - Demolitions_{t-1} - Losses_{t-1} \qquad (3.9)$$

Additionally, the *shipbuilding production* refers to the number of orders placed in the market. More specifically, the number of orders around the world and the order book is defined as:

$$Orders_t = Orders_{t-1} + Contracting_{t-1} - Deliveries_{t-1} - Cancel_{t-1} \qquad (3.10)$$

Table 3.4: Supply Drivers and Variables

A. Stock of fleet available for trading		
	Capesize Bulkcarrier Deliveries	DWT
Fleet $[(t-(t-h)]$	Fleet $h = 1m$	Million DWT
	Fleet $h = 12m$	Million DWT
	Fleet $h = 36m$	Million DWT
B. Shipbuilding Production		
	Orderbook	Million DWT
Orders/ Fleet $[(t-(t-h)]$	Orders/Fleet $h = 1m$	Million DWT
	Orders/Fleet $h = 12m$	Million DWT
	Orders/Fleet $h = 36m$	Million DWT
C. Scrapping Rate and Losses		
Demolition/ Fleet $[(t-(t-h)]$	Demolition/ Fleet	DWT
	Demolition/ Fleet $h = 1m$	DWT
	Demolition/ Fleet $h = 12m$	DWT
	Demolition/ Fleet $h = 24m$	DWT
	Scrap Prices	$ Million
D. Level of Freight Rates in the market		
Earnings	P12m	$ Million
Price Earning Ratio (PE)	PE (Newbuild/ P12m)	ratio
	PE (Newbuild/ P36m)	ratio
	PE (5SHP/ P12m)	ratio
	PE (5SHP/ P36m)	ratio
Premium or Discount	Spot and P12m rates Changes	$ per day
	Spot and P36m rates Changes	$ per day
E. Asset Prices		
Capesize Ship Prices	176-180K DWT Newbuilding	$ Million
	180K 5 Year Old Secondhand	$ Million
	170K 10 Year Old Secondhand	$ Million
Ship Price Ratio	5SHP/ Newbuild	ratio
	10SHP/ Newbuild	ratio

Notes: Table 3.4 presents all supply variables included in the supply dataset and their unit of measurement. The transformation code differs depending on the holding period horizon (h) selected. All variables cover the period from January 1996 to June 2016.

Orders refer to the number of vessels awaiting construction. The change in the order book in year t is equal to the new orders (Contracting), minus the number of ships delivered during the same year (Deliveries) and previous cancelled orders (Cancel). The number of orders is positively correlated with the market conditions since, for instance, orders increase when the market is strong and remain unchanged when the market is weak. This behaviour affects the market conditions because investors neglect the time required to build a vessel so new vessels often become available when the market is in downward trend (Greenwood and Hanson, 2015; Kalouptsidi, 2014).

The number of *scrapped vessels* also has an impact on the level of freight rates. For instance, when the freight market is strong, shipowners are reluctant to scrap their vessel since they want to take advantage of the freight market boom and be able to charter more vessels. Scrapping though is also highly related to the age, technical obsolescence, scrapping prices and current earnings of the vessel.

Greenwoood and Hanson (2014) and Kalouptsidi (2014) showed that the short-term supply is fixed due to the time-to-build delays but the long-term affects the aggregate level of investment and the level of returns. More specifically, firms over-invest when the market is strong (and under-invest when the market is weak) because they mistakenly believe that current earnings will persist.

At this point it is very important to mention that the market may be affected by changes in the variables over a longer period of time. Therefore, to account for the impact of the time-to-build delays in the term structure of freight rates, the variables *Fleet*, *Orders/ Fleet* and *Demolition/ Fleet* are calculated for the past 12- and 24-months.

Changes in freight rates also affect the ship prices since for instance if the demand for spot contracts is high, this means that the ship prices are also high due to the market being strong. Oppositely, when the freight market is weak, the ship prices decrease and the period charters are the preferable choice as they guarantee a fixed freight rate for a specific period and minimise the risk of having vessels chartered in low freight rates.

The estimation of the premium or discount indicates whether the market is strong or weak. This is calculated as the difference between P12m rates (or P36m rates) and spot rates scaled by the spot rates (i.e. ${(P12m - spot)}/{spot}$). If that rate is positive then this means that the market is in contango (period rates are higher than the spot rates), while a negative rate indicates that the market is in backwardation (spot rates are higher than period rates). Therefore, when the market is in backwardation (or strong), shipowners usually prefer to operate under spot contracts and persuade them to agree to long term ones usually requires an extra premium to offset the loss in liquidity.

Another macroeconomic variable included into the time series is the Price to Earnings ratio (PEs) of vessels that is forward looking and reflects the expected earnings from operating a vessel. For instance, when current vessel prices are high in relation to the one-year forward-looking earnings (i.e., high PE ratio), investors expect vessel prices to drop in the future in anticipation of limited earnings growth. Price to Earnings ratio (PEs) is defined as follows:

$$PE_t = Ship\ Price_t / Earnings_t \tag{3.11}$$

Where $Ship\ Price_t$ is the newbuild and 5-year old vessel prices, and the $Earnings_t$ at time t is measured for the P12m and P36m freight rate series. For example, the earnings of a 12m period charter are $Earnings_t = 365 * P12m$.

The Ship Price Ratio (SPR) is calculated as follows:

$$SPR_t = Second\ hand\ Ship\ Price_t / NewbuildingPrice_t \tag{3.12}$$

the prices of a 5- and a 10-years old vessel were used as well as the price of a second-hand vessel to estimate the ship price ratio. During prosperous freight market conditions and high sentiment periods, investors prefer to immediately take advantage of the prevailing market conditions, and tend to purchase second-hand vessels to avoid the time lag of having a new vessel built. This preference consequently creates an immediate delivery premium that may occasionally drive second-hand vessel prices above newbuilding vessel prices. Therefore, the SPR captures the immediate delivery premium, which is related to the level of optimism or pessimism of the current market conditions (Papapostolou et al, 2014). For instance, the ratio 5SHP/NBP value is greater than one during prosperous market conditions and less than one when the market is decreasing.

Unfortunately data on *fleet productivity* could not be found due to the fact that it is measured in ton of miles per deadweight and depends on four main aspects: speed, port time, deadweight utilisation and loaded days at sea. All these factors are related to the geographical area in which the vessel is sailing, rule of thumbs and factors, which cannot be controlled.

Considering all the aforementioned variables and calculations of holding period changes to take into account the time-to-build delay, a macroeconomic dataset of 59 time series was created and then divided between demand and supply dataset. The next section describes the empirical analysis.

3.3 Empirical Analysis

The first part of this section presents the descriptive statistics of the data. The second part focuses on the principal component analysis and the common factors extracted from the principal component analysis. The third part focuses on the empirical findings of the VAR framework and finally the last part presents the robustness tests used to enhance the robustness of the empirical findings.

3.3.1 Data Description and Descriptive Statistics

The freight rates from the Clarkson's Shipping Intelligent Network (SIN) are expressed in \$ per day and recorded each month starting from January 1996 to June 2016 providing a total of 246 monthly curves of four maturities each. More specifically, the data consists of monthly average spot earnings as well as six-month, one-year and three-year period charter rates. The type of vessel incorporated in the analysis is one of the commonly used in the dry bulk shipping market: *Capesize* (about 150,000 dwt) vessel. At this point it also important to mention that all demand and supply macroeoconomic variables and their units of measurement listed in Tables 3.2 and 3.4 were obtained from the Clarkson's Shipping Intelligent Network (SIN).

Table 3.5: Descriptive Statistics, Term Structure of logarithmic Freight Rates

	Mean	Standard Deviation	Min	Max	Skewness	Kurtosis	$\hat{\rho}(1)$	$\hat{\rho}(12)$	$\hat{\rho}(36)$
Panel A: In-sample Performance									
spot	10.011	0.863	7.735	12.148	0.354	2.614	0.928	0.539	0.304
P6m	9.887	0.806	8.355	11.902	0.676	2.807	0.956	0.561	0.307
P12m	9.862	0.742	8.461	11.829	0.853	3.122	0.971	0.598	0.321
P36m	9.769	0.609	8.471	11.585	0.925	3.829	0.973	0.550	0.295
Panel B: No Crisis Performance									
spot	9.918	0.763	7.735	11.512	0.174	2.504	0.923	0.581	0.286
P6m	9.784	0.685	8.355	11.468	0.455	2.499	0.953	0.572	0.254
P12m	9.756	0.618	8.461	11.328	0.575	2.638	0.964	0.577	0.239
P36m	9.677	0.483	8.471	10.968	0.393	3.077	0.970	0.516	0.213

Notes: Table 3.5 presents the descriptive statistics of monthly logarithmic freight rates at different maturities. The last three columns contain sample autocorrelations at displacements of 1, 12, and 36 months. The top panel presents the in-sample period descriptive statistics that cover the period from January 1996 to June 2016, while the bottom panel shows the descriptive statistics for the same period excluding the financial crisis period from August 2007 to January 2009.

The analysis is performed for the whole period from January 1996 to June 2016 as well as for the same period but excluding the financial crisis period from August 2007 to January 2009.

Table 3.5 presents the descriptive statistics of the term structure of freight rates levels for the two sample periods under examination (i.e. the full sample and the sample after excluding the financial crisis period). When analysing freight contracts with different maturities, it appears that the term structure curve is sloping downwards and the long rates are less volatile than the short ones. The logarithmic freight rates appear to be asymmetrically distributed with positive skewness and kurtosis indicating that the series present a more peaked distribution compared to the Gaussian distribution.

3.3.2 Principal Component Analysis – (PCA)

Using all variables simultaneously will increase the dimensionality of the model significantly so the approach proposed by Stock and Watson (2002a,b) will be followed to reduce this effect.

In order to estimate the common macroeconomic factors all variables need to be stationary. The Augmented Dickey-Fuller (1981) test assesses which one are not stationary and thus need to be transformed[1]. Apart from transforming the variables, these also need to be standardised (zero mean and variance of one) so that the PCA can be performed. After ensuring that all series are stationary and standardised, PCA was performed.

Tables 3.6 and 3.7 summarise the steps that were followed to extract factors from each dataset. More specifically, these present the number of variables, the variables eliminate at each step, the number of factors and the total variance explained in each dataset, while also KMO – Kaiser-Meyer-Olkin is a measure of sampling adequacy used to evaluate the appropriateness of applying factor analysis. The values of KMO vary between 0 and 1 with values closer to 1 being considered as better whilst a 0.6 is a recommended minimum.

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[1] The transformations were performed following the sequence below: (1) denotes no transformation is required, (2) denotes using levels – freight rate changes and (3) denotes taking first differences. A description of the list of macroeconomic variables and their transformations is presented in Appendix A.

The results of PC analysis on the Demand and Supply datasets consisting of 34 and 25 variables, showed that 10 and 7 common factors are required to explain the models variability. Since the number of factors is high, the next step is to create a correlation matrix in order to reduce the dimensionality of the demand dataset and thus decrease the total number of factors. More specifically, using the correlation matrix of the demand dataset, the highly variables were eliminated. If any of the correlations was too high (i.e. above 0.9), one of the variables was excluded as this suggest that both measure the same underlying aspect of a collection of variables.

Table 3.6 presents the variables that were eliminated during each step in order to create the final demand dataset that was used in this chapter. The purpose is to build a dataset that explains a large portion of the variance using a small number of factors in order to use these across multiple methodological approaches and be able to draw reliable conclusions since it will reduce the dimensionality of the model.

The analysis started with the original dataset consisted of 34 variables, which were reduced to 10 factors that explain approximately 70% of the total variance after performing PCA (see Table 3.6 – step 1). Although the variance explained is acceptable, the number of factors was high; therefore, high correlated variables had to be eliminated (see Table 3.6 – step 2). Another PCA was performed on the new demand dataset (i.e. Demand 2) but since the number of factors remained high (i.e. 5 factors that explained approximately 68% of the total variable), more variables were eliminated (see Table 3.6 – step 3) and the dataset consisted of 21 variables that required 4 factors and explained about 68% of the total variance. Finally, two more variables were eliminated (see Table 3.6 – step 4) resulting in a final dataset with 19 demand variables that required 3 factors and explained approximately 67% of the total variance.

Table 3.6 reports the variables eliminated during each step, the number of factors, the total variance explained and the KMO obtained after every elimination. The Demand dataset 5 (see Table 3.6 – step 5) uses only 15 aggregate demand shifters from key countries however the number of factors extracted and the total variance explained are not sufficient for the purposes of this study. This thesis only presents the factors of the Demand dataset 4 however the empirical findings of every step and datasets examined are available from the authors upon request.

Table 3.6: Demand Dataset - steps in Principal Component Analysis

		Number of variables	Number of factors	Total variance explained	KMO
Step 1: Original Dataset		**34**	**10**	**70.50%**	**0.887**
Step 2:		Eliminating the variables: *GDP*, *Inflation OECD*, *Inflation USA*, *Inflation Japan*, *Exchange Rates Japan* and *Euro*, *US Gulf Wheat Price*, *Thermal Coal Price*, *US Gulf Corn Price*, *Global Oil Production* and *Brent Crude Oil Price*.			
	Demand 2	**23**	**5**	**68.91%**	**0.914**
Step 3:		Additional eliminations: *Industrial Production OECD* and *LIBOR Interest Rates*			
	Demand 3	**21**	**4**	**68.52%**	**0.919**
Step 4:		Additional eliminations: *Baltic Dry Index* and *Inflation OECD EU* (excluding Turkey)			
	Demand 4	**19**	**3**	**67.82%**	**0.925**
Step 5:	**Demand 5**	**15**	**6**	**65.75%**	**0.652**

Table 3.7 presents the steps followed to determine the final supply dataset. The process is exactly the same as the one followed for the demand dataset with the only exception being that in this case, the unit of measurement needs to be specified. Using the original Supply dataset for instance, two additional datasets are constructed: (i) with one eliminating the variables measured between t and $t-24$ and thus only containing variables with 1- and 12-month unit of measurement (see Table 3.7 – step 3 and 4), (ii) whilst the second one removed the variables between t and $t-12$ leaving only variables with 1-and 24-month unit of measurement (see Table 3.7 – step 5). It can safely be concluded that the unit of measurement does not affect the number of factors that are extracted to explain the model's variation.

Table 3.7: Supply Dataset – steps in Principal Component Analysis

		Number of variables	Number of factors	Total variance explained	KMO
Step 1: Original Dataset	**Supply 1**	**25**	**7**	**78.52%**	**0.626**
Step 2:		Eliminating the variables: *Orderbook*, *Capesize 170K 10 year old Secondhand Prices*, *P12m earnings, PE (Newbuild/ P12m), PE (Newbuild/ P36m), PE (5SHP/ P36m)*			
	Supply 2	**19**	**6**	**74.81%**	**0.630**
Step 3:		Eliminations from Supply 1 dataset: Fleet 24m, Orders/ Fleet 24m, Demolition/ Fleet 24m			
	Supply 3	**22**	**6**	**76.93%**	**0.602**
Step 4:		Eliminations from Supply 3 dataset: *Capesize 170K 10 year old Secondhand Prices, PE (Newbuild/ P12m), PE (Newbuild/ P36m), PE (5SHP/ P36m)*			
	Supply 4	**18**	**6**	**77.42%**	**0.635**
		Eliminations from Supply 1 dataset: *Fleet 12m*, *Orders/ Fleet 12m*, *Demolition/ Fleet 12m*			
Step 5:	**Supply 5**	**22**	**6**	**76.02%**	**0.586**

The factors used to investigate the impact of macroeconomic variables on the term structure of freight rates are based on the demand and supply dataset in step 4 (see Tables 3.6 and 3.7 highlighted with blue).

The common macroeconomic factors are identified using the asymptotic principal component analysis developed by Connor and Korajczyk (1986) that is also widely used for large macroeconomic panels (Stock and Watson (2002a, 2002b, 2006), Ludvigson and Ng (2007, 2009), among others). The macroeconomic time series model can be represented as follows:

$$y_{it} = f_t' \lambda_i + \varepsilon_{it} \tag{3.13}$$

where y_{it} is the i^{th} cross-sectional unit from the macroeconomic panel at time period t; f_t' represents the n-dimensional vector of latent common factors for all cross-sectional units at t; λ_i is the n-dimensional vector of factor loadings for the cross-sectional unit i; and ε_{it} shows the idiosyncratic independent and identical distributed (i.i.d.) errors, allowed to have limited correlation among them.

This model captures the main sources of variation and covariation amongst N macroeconomic variables with a set of n common factors ($n << N$). The framework is frequently referred to as the approximate factor structure and is usually calculated through principal component analysis, which is an eigen decomposition of the sample covariance matrix. The estimated ($T\ x\ r$) factors matrix, $\hat{f} = (\hat{f}_1, \dots, \hat{f}_2)$ is equal to $\sqrt{T}$ when multiplied by the n eigenvectors corresponding to the first n largest eigenvalues of the TxT matrix, $\frac{yy'}{NT}$ where y is a (TxN) data matrix. The normalisation $\hat{f}'\hat{f} = I_n$ is imposed, where I_n is the n dimensional identity matrix. The factor loadings matrix can be calculated as $\widehat{\Lambda} = y'\hat{f}/T$. For a large number of macroeconomic time series, this methodology can effectively distinguish noise from signal and summarise information into a small number of common factors.

Table 3.8 presents the extracted factors and the total variance explained in the Demand and Supply datasets, as these extracted in step 4 (see Tables 3.6 and 3.7). Table 3.8 suggests the three factors from the Demand dataset explain about 67% of the total variance of all variables in the datasets. More specifically, the Aluminium and Steel Production account for approximately 50% of the total variation of the demand dataset with the Aluminium Production being the most important factor as it is responsible for approximately 39% of the total variance. In the Supply dataset, six factors explain about 77% of the total variance with the three first factors accounting for more than 50% of the total variance. The most important supply factor in explaining the total variance is the asset prices (20.90%) followed by the changes in the orderbook (16%).

3.3.3 Empirical Findings of the Term Structure Models

This section presents the empirical findings of the term structure of freight rates model with latent factors and investigates the incorporation of macroeconomic variables in the latent factor model. The empirical analysis shows that the latent factor model can explain an adequate percentage of the term structure variability however it cannot provide information on the dynamic interactions between the macroeconomic variables and the term structure of freight rates. Therefore, the estimation of the $FAVAR$ freight rate model assesses the impact of the macroeconomic variables on the term structure of freight rates and the potential existence of dynamic interactions between them.

3.3.3.1 Estimating the Latent Freight Rate Model

The traditional term structure model decomposes the term structure into three factors that can explain the cross-sectional variation of interest rates. Based on their impact on the shape of the term structure, these components are commonly labelled level, slope and curvature. This sub-section shows that the dynamic version of the Nelson-Siegel model can adequately explain the variation of the term structure of freight rates.

The one-step Kalman filter estimation approach (Diebold et al, 2006) is preferred compared to the two-step OLS Diebold and Li (2006) method because the simultaneous estimation of all parameters produces a more accurate inference via standard theory. Also, unlike the two-step approach, the SSM approach does not account for the parameter estimation and signal extraction uncertainty. The model in this study is fitted to the data using both methods. Although both approaches were tested, the lack of a significant statistical difference between their empirical findings means that this study will only concentrate on the two-step OLS approach

By first applying OLS to the freight rates for each month and setting λ_t at a prespecified value, a time series of estimates of $\{\hat{\beta}_{1t}, \hat{\beta}_{2t}, \hat{\beta}_{3t}\}$ and a corresponding panel of residuals are generated. Simultaneously, the graphic representation of factors such as the freight rate curve shapes, the estimated and the average freight rate curve, the residual plots, the estimated and empirical factors etc. allows a full assessment of the model's fit to the Nelson-Siegel model.

Table 3.8: Demand and Supply Dataset: Variance Explained by Factors

Demand Factors		**Supply Factors**	
Factor 1 – Aluminium Prod. *(38.41% of total variance)*	R^2	**Factor 1 – Asset Prices** *(20.90% of total variance)*	R^2
E.Europe Aluminium Prod.	79.68%	180K 5 Year Old Prices	86.08%
N. America Aluminium Prod.	77.07%	5SHP/ Newbuild	84.87%
Oceania Aluminium Prod.	76.83%	10SHP/ Newbuild	79.82%
		P12m	60.57%
		Scrap Value	48.31%
		PE (5SHP/ P12m)	7.45%
Factor 2 – Steel Production *(19.24% of total variance)*	R^2	**Factor 2 – Orderbook** *(15.68% of total variance)*	R^2
World Steel Prod.	59.89%	Orderbook	76.01%
China Steel Prod.	51.04%	Orders/ Fleet 1m	71.77%
Kilian's Index	43.42%	Orders/ Fleet 12m	66.08%
		176-180K DWT Newbuilding Prices	29.71%
		Fleet 12m	6.33%
		Fleet 1m	4.93%
Factor 3 – Seaborne Trade *(10.17% of total variance)*	R^2	**Factor 3 – Freight Market Changes** *(11.73% of total variance)*	R^2
Seaborne Trade IRON ORE	66.64%	Spot vs 12m	88.24%
Seaborne Trade STEAM COAL	54.84%	Spot vs P36m	86.37%
Kilian's Index	10.86%	Demolition/ Fleet	9.73%
		Deliveries	4.04%
		PE (5SHP/ P12m)	2.63%
		180K 5 Year Old Prices	2.22%
		Factor 4 – Demolition *(11.13% of total variance)*	R^2
		Demolition/ Fleet 1m	43.39%
		Demolition/ Fleet	40.59%
		Demolition/ Fleet 12m	38.51%
		Spot vs P36m	1.70%
		Spot vs 12m	1.17%
		Deliveries	0.85%
		Factor 5 – Fleet Changes *(11.03% of total variance)*	R^2
		Fleet 1m	83.00%
		Fleet 12m	67.39%
		Deliveries	14.97%
		Orders/ Fleet 1m	10.09%
		PE (5SHP/ P12m)	6.18%
		Orderbook	4.75%
		Factor 6 – Supply Indicators *(6.95% of total variance)*	R^2
		PE (5SHP/ P12m)	53.94%
		Deliveries	39.18%
		P12m	14.16%
		176-180K DWT Newbuilding Prices	2.76%
		Scrap Value	2.31%
		Orderbook	1.67%
Total Variance explained	67.82%	**Total Variance** explained	**77.42%**

Notes: Table 3.8 presents the three and six factors of the *Demand* and *Supply* datasets, which explain in total approximately 65% and 77% of the total variation of the time series in each panel. The R^2 is obtained through univariate regressions of the factors extracted from the panel of macroeconomic variables on all individual variables. The table lists the four (six) most highly correlated variables with each factor. Note that prior to extracting the factors, the series have been transformed in order to be stationary, i.e. for most variables, the regressions correspond to regressions on percentage changes.

The OLS can be applied using a fixed λ_t however a value for λ_t needs to be determined in order for the medium-term (or curvature) factor to achieve its maximum value. As mentioned before, following a simple maximisation process[2], the curvature factor appears to achieve its maximum point when the value of lambda (λ_t) is equal to 0.226.

Additionally, the model fit was assessed under different circumstances in order to enhance the robustness of the model while test if the statistical fitting is good depending on: sample selection and size, number of maturities available, fixed loading factors and volatility. In terms of the sample selection, the study examines whether the inclusion of the turbulent period that followed the Credit Crisis is responsible for a poor fitting. In a second attempt to test the fitting of the proposed model, the number of maturities available was increased using cubic spline interpolation (i.e. freight rates of constant maturities are calculated using a third degree polynomial). This decision is based on the fact that time series of freight rates consist of nonlinear relations and therefore averaging the data using splines methodologies reduces any observational error. To ensure that the results do not show strong oscillating patterns between the observation points, algorithms were used to smoothen the resulting surfaces.

The third attempt is to examine whether the fixed loading factors (i.e. lambda) and the constant volatility are responsible for the poor fitting. Multiple values of the fixed loading factors are examined while also the approach proposed by Diebold and Li (2006) allows the introduction of a time varying volatility. The multiple values of lambda examined did significantly affect the predictability of the latent freight rate model. Using various values for the fixed factors may still produce non-satisfactory results since, according to Koopman et al (2007), keeping lambda fixed over the full sample period may be too restrictive as the data usually spans over a long time period.

Table 3.9 presents descriptive statistics for the sample period between January 1996 and June 2016 after having applied the OLS to the freight rates for each month. More specifically, Table 3.9 shows the estimated means and standard deviations of the measurement errors and demonstrates that the former decrease as the maturities increase whilst the autocorrelations indicate that the residuals are persistent. The

[2] Minimise the measurement errors while also increase the correlation levels between the empirical and implied estimated factors using the same two-step OLS model.

residuals of each model present a good fit since the majority of them are close to zero with only a few exceptions. Additionally, the R^2 value of about 85% indicates an adequate fit of the model to the freight rate market.

There also seems to be a good fit between the actual data and the implied Nelson–Siegel model (Eq. 3.1). *Figure 3.1* plots the estimated level $(\hat{\beta}_{1t})$, slope $(\hat{\beta}_{2t})$ and curvature $(\hat{\beta}_{3t})$ along with the empirical level $(level_t)$, slope $(slope_t)$ and curvature $(curvature_t)$ for comparative assessment. The correlations between the estimated factors and the empirical level, slope and curvature are: $\rho(\hat{\beta}_{1t}, level_t) = 0.982$, $\rho(\hat{\beta}_{2t}, slope_t) = -0.997$, and $\rho(\hat{\beta}_{3t}, curvature_t) = 0.948$.

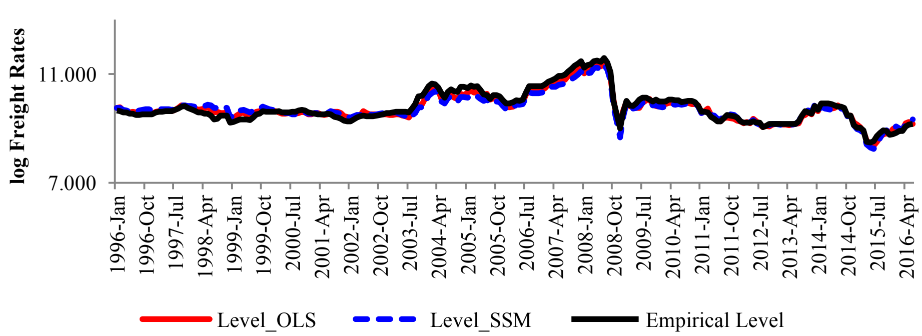
Table 3.9: Descriptive Statistics: Freight Rate Curve Residuals

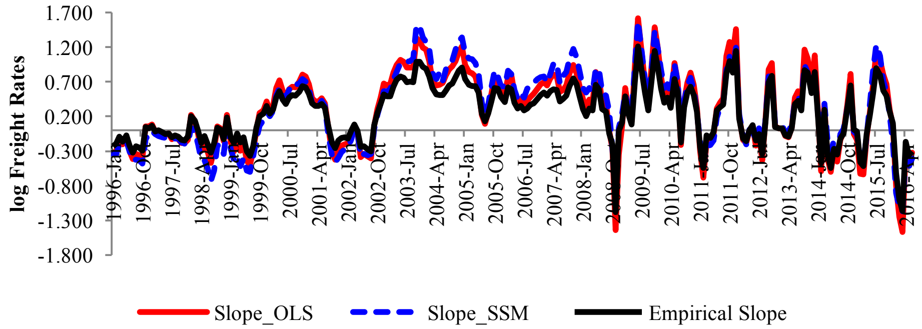
	Mean	Standard Deviation	Min	Max	$\hat{\rho}(1)$	$\hat{\rho}(12)$	$\hat{\rho}(36)$	RMSE	MAE
Panel A: Dynamic NS model - Full Sample – Model 1									
1 (spot)	0.004	0.010	-0.022	0.101	0.384	-0.027	0.086	0.011	0.000
6 (PTC6m)	-0.017	0.044	-0.438	0.096	0.384	-0.027	0.086	0.048	0.002
12 (PTC12m)	0.019	0.049	-0.107	0.488	0.384	-0.027	0.086	0.053	0.003
36 (PTC36m)	-0.006	0.015	-0.151	0.033	0.384	-0.027	0.086	0.016	0.000

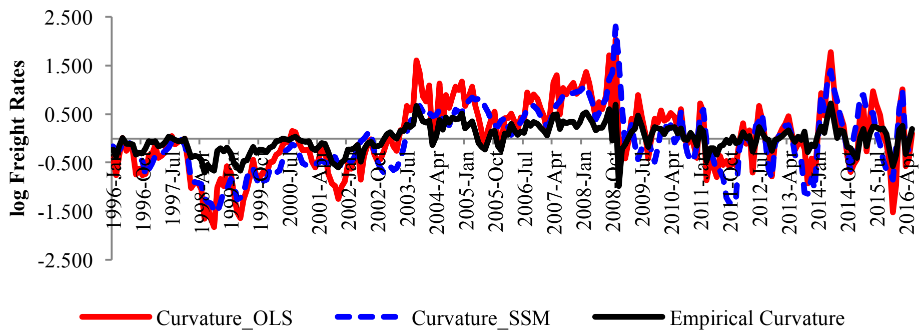
Notes: Table 3.9 presents the descriptive statistics of the freight rates curve residuals. The last two columns show the Mean Absolute Error - MAE and the Root Mean Squared Error - RMSE. The sample autocorrelations at displacements 1 ($\hat{\rho}(1)$), 12 ($\hat{\rho}(12)$), and 36 ($\hat{\rho}(36)$) months are also presented.

The correlation between the empirical and the estimated slope is negative since, according to Diebold and Li (2006), $\hat{\beta}_{2t}$ measured as the difference between long and spot rates. A negative slope means that the rates tend to decrease as the maturity lengthens. This can also be seen in Table 3.5 where the freight rate mean values are decreasing as the maturities increasing. For instance, the mean value of the spot rates is 10.011 while the ones of the 6-, 12- and 36-month period time charter rates are 9.887, 9.862 and 9.769 respectively.

Figure 3.1: Estimated Factors (i.e. Level, Slope and Curvature) versus data based Level, Slope and Curvature







The solid black line in Figure 3.1 represents the empirical latent factors, the solid red line plots the estimated latent factors based on the two-step OLS approach while the blue dotted line plots the estimated level, slope and curvature of the SSM approach. The level factor in the model is positive and shows a very high persistence with a mean value of 9.737. In contrast, the slope and curvature are less persistent and both have positive and negative values. All of the available combinations[3] of level, slope and curvature were examined due to the fact that there is no standard reference for their modelling in the freight market. Therefore, the level, slope and curvature for the best model are defined as follows: the level is the 36 month freight rates, the slope is measured as the difference between the 36-month and the spot rates and the curvature is defined as twice the P6m rates minus the sum of the spot and the 36-month rates.

Table 3.10 presents the descriptive statistics of the estimated factors for each model. These factors were estimated using a three-factor Nelson-Siegel model with a λ_t value fixed at 0.226. Regarding the autocorrelations of the three factors, the level factor appears to be more persistent compared to the other two. Additionally, the augmented Dickey-Fuller test suggests that only $\hat{\beta}_{1t}$ has unit roots. Additionally, no significant

[3] See Appendix 3.B for the list with all of the available combinations of level, slope and curvature in the dry bulk freight market.

difference was observed in the estimated factors when using the two-step OLS or the SSM approach (see Figure 3.1).

Table 3.10: Descriptive Statistics, estimated Latent Factors – Model 1

	Mean	Standard Deviation	Min	Max	$\hat{\rho}(1)$	$\hat{\rho}(12)$	$\hat{\rho}(36)$	ADF
Panel A: Dynamic NS model Full Sample – Model 1								
Level	9.737	0.542	8.355	11.469	0.970	0.512	0.281	-0.387
Slope	0.301	0.537	-1.472	1.613	0.805	0.252	0.152	-4.348
Curvature	0.009	0.698	-1.823	2.042	0.767	0.425	0.193	-5.685

Notes: Table 3.10 presents the descriptive statistics for the three estimated factors $\hat{\beta}_{1t}$, $\hat{\beta}_{2t}$, and $\hat{\beta}_{3t}$ from January 1996 to June 2016. The last column contains the augmented Dickey-Fuller (ADF) unit root test statistics, and the three columns on the left contain the sample autocorrelations at displacements 1, 12, and 36 months. The critical values for rejecting the hypothesis of a unit root are -2.575 at a 1% level, -1.942 at a 5% level and -1.616 at a 10% level.

Although the latent factor model explains a significant proportion of the variation of the freight rates term structure (i.e. R^2 = 92.73%), the next section examines whether including macroeconomic variables could help explain a larger portion of variance compared to the current model. The dynamic interactions between the term structures of freight rates and a series of macroeconomic variable are also examined.

3.3.3.2 Estimating the FAVAR Freight Rate Model – Benchmark Model

This part investigates whether the demand and supply factors extracted from the principal component analysis panel of macroeconomic variables can predict information regarding freight rates of higher maturity. More specifically, multiple regression models are performed to assess the robustness of the FAVAR model and more specifically whether the macroeconomic factors used in the FAVAR model of the freight rate curve can explain the cross-sectional variation of freight rates.

The demand and supply factors are included in the $FAVAR$ model proposed by Bernanke et al (2005). More specifically, the $FAVAR$ – benchmark model is estimated following the two-step approach proposed by Bernanke et al (2005). The approach uses initially principal component techniques to estimate the common factors F and then the parameters governing the dynamics of the state equation are obtained via conventional methods of $VARs$. Applying the Bayesian Information Criterion with a maximum of 16 months indicates an optimal number of 14 lags for the joint VAR of factors and the short rate.

The first step consists in estimating the parameters and the corresponding standard errors of the FAVAR model using standard OLS procedures. More specifically, unrestricted regressions of freight rates are used to examine whether the extracted macroeconomic factors are accurate explanatory variables in a term structure model. The regression equation based on dynamic factors, which represent state variables in the No-arbitrage FAVAR model, is defined as follows:

$$FR_t = a + \beta FR_{t-1} + (1-\beta)(\phi_F' F_t) \tag{3.14}$$

Where FR_t is the logarithmic differences of the spot, P6m, P12m and P36m freight rates at time t, FR_{t-1} is the logarithmic difference of freight rates at $t-1$ and F_t represents the extracted Demand and Supply factors. Table 3.11 reports the results from the regression analysis based on the Demand and Supply dynamic factors. The R^2 (coefficient of determination) values of 29.5%, 28.5%, 25.6% and 27.4% indicate a fairly good fit between the factor policy rule and the data of Demand dataset. Similarly, the R^2 values for the Supply dataset are 57.9%, 63.2%, 85.6% and 65.5% indicate a good fit between the supply factors and the freight rate series.

When the freight rates are regressed into the demand factors, the R^2 values increase along with the freight rate maturity, which suggests that the demand factors require longer freight rate maturities in order to have the effect on the market. This means for example that the variations in the demand variables Aluminium, Steel and Industrial Production do not directly affect the freight rates values. On the other hand, the supply factors are the ones that mainly affect the freight rates levels. More specifically, these factors can explain a large proportion (above 50%) of the variability of the spot, 6-, 12- and 36- months rates. Therefore, the supply factors such as ship prices variations, changes in the orderbook and fleet size seem to have a significant effect on the values of the freight rates.

As can be seen from Table 3.11, the coefficients of the steel production and seaborne trade are positive and significant when regressed against freight rates which suggests that an increase in any of these factors will result in an increase of the freight series. The seaborne trade factor when regressed against the 12- and 36-month rates remains positive although becomes insignificant. On the other hand, the results show that the relationship between the freight rates and the aluminium production is negative and significant. Although this is an unexpected empirical finding, there are various reasons that may explain this behaviour. One reason could be the fact that the dry bulk market in the sample being analysed has suffered from severe overcapacity and slow economy growth that have sustained low freight rates and charter rates during the period (UNCTAD, 2015). Additionally, aluminium is a US-dollar based commodity listed on the London Metal Exchange (LME) and therefore, changes in the price of aluminium might be linked to facts that are unrelated with the industry fundamentals (Nappi, 2013).

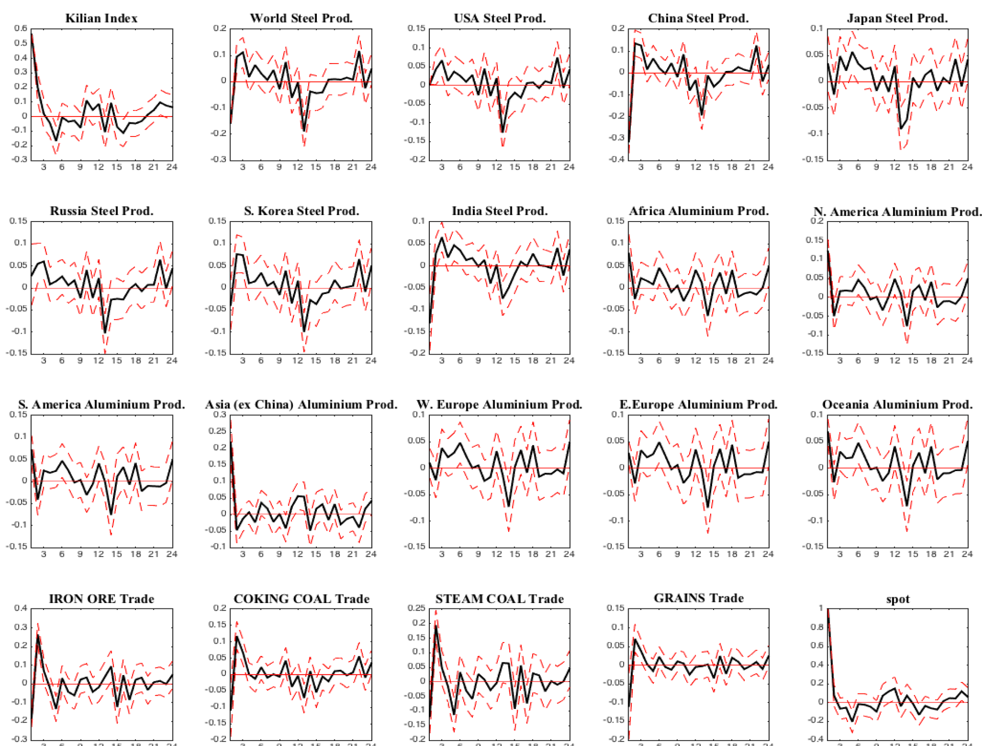
The Danish Ship Finance estimated that in 2015 China accounted for 38% of global dry bulk demand, from which 73% was iron ore, 21% was coal, 24% grain and 23% minor/other bulk demand (BIMCO, May 2016). China continues to invest heavily in its housing, construction, and infrastructure sectors meaning that it requires a significant amount of resources and materials which subsequently will affect the demand however this study does not include prices of aluminium production from China (responsible for 50% of the aluminium production). In essence this means that a significant portion of the world demand for aluminium has not been included in the analysis hence why the results might be unexpected.

Regarding the supply factors in Table 3.11, these are mostly negatively associated with the freight series exception from the asset prices factor, which show positive and significant coefficients. Changes in the order book and the demolition factor are also mostly negative but non-significant. As can be seen from the empirical findings, when the freight rates increase the asset prices follow the same trend while the factor fleet changes decrease. This might be due to the fact that the fleet dynamics change significantly when the market is strong as ship-owners tend to buy second hand vessels or even order new vessels in order to cover the demand and take advantage of the increasing market.

Negative associations between the freight series and the supply factors are expected since the supply factors usually require time in order to affect the freight rates mainly due to the construction lag of a newbuild vessel. Additionally, the empirical findings are affected by the financial crisis period (see Table D.3.22 – Appendix 3.D). For instance, when the crisis period is eliminated (i.e. August 2007 to January 2009), most of the coefficient signs remain the same except from the ones between the freight series and the orderbook and the fleet changes factor. This was expected since by eliminating the noisy period from 2007 to 2009 responsible for abnormal behavior, the dynamics of the orderbook and the fleet size are positively affected by an increase in the freight series.

An advantage of the $FAVAR$ approach is that impulse response functions can be formulated for any variable in the informational dataset, that is, for any element of Z_t (see Eq. 3.8) and not only for the fundamental factors. The purpose of the impulse responses is to illustrate how the freight rates react to a macroeconomic variables shock. The responses have been measured for the dependent variable with respect to the error term, that is one positive standard deviation shock. More specifically, the x-axis presents the time period (1, 2, …, 24 months) while the y-axis measures the magnitude of the system's error term response to shock. In other words, the y-axis measures the effect caused on the freight rate series by one standard deviation shock in the macroeconomic variable series.

Figure 3.2: Impulse Responses of Demand Variables to Spot Freight Rates



The impulse responses of the demand macroeconomic variables to each freight rates series at 90 percent confidence interval are presented in Figures 3.2 to 3.5 and refer to a two-year period. For instance, Figure 3.2 shows the impact of a macroeconomic shock on the spot freight series. One standard deviation shock to the Kilian's index causes significant decrease in the spot rates for approximately 6 months before increasing again around month 9. The same pattern is followed for the impulse response of spot rates to the spot rates meaning that the Kilian's index is positively related to the dry bulk freight market.

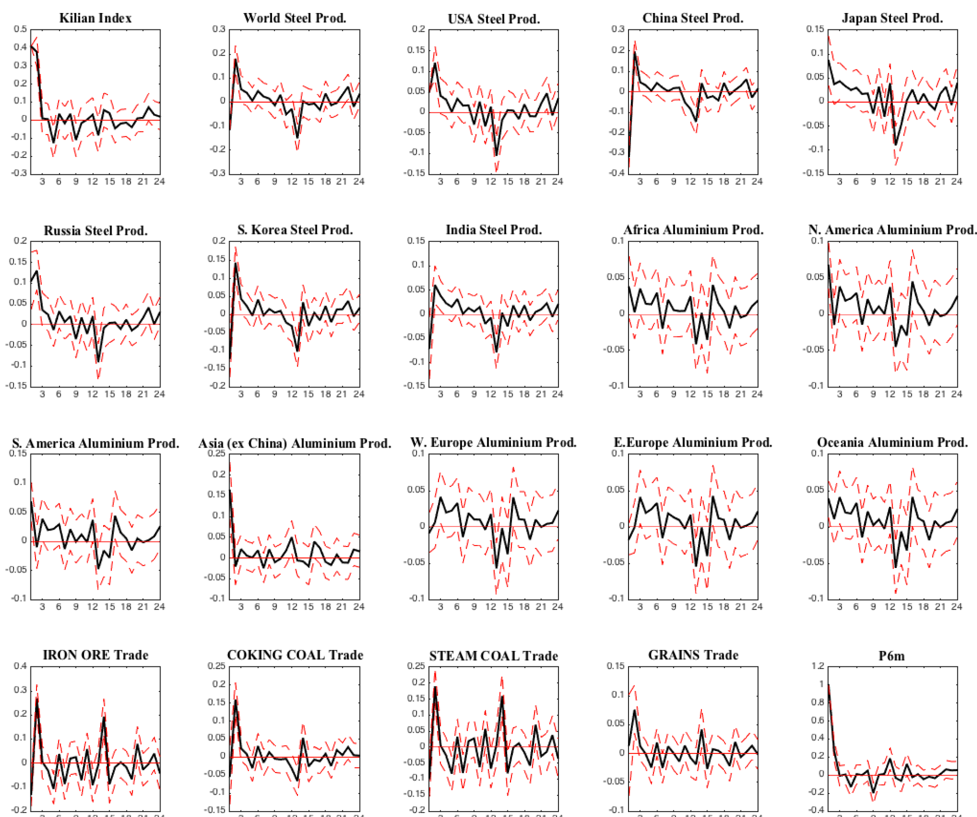
Table 3.11: Regressions based on the Demand & Supply Factors

	Demand					Supply			
Logarithmic Differences	**Spot**	**P6m**	**P12m**	**P36m**	**Logarithmic Differences**	**Spot**	**P6m**	**P12m**	**P36m**
Constant	-0.002	-0.002	-0.001	-0.001	**Constant**	-0.003	-0.001	-0.001	-0.005
SE	0.016	0.012	0.009	0.008	SE	0.015	0.009	0.005	0.005
pvalue	0.921	0.868	0.895	0.863	pvalue	0.845	0.892	0.777	0.465
F1 – Aluminium Production	-0.066	-0.059	-0.044	-0.038	**F1 – Asset Prices**	0.136	0.131	0.117	0.091
SE	0.015	0.017	0.013	0.012	SE	0.024	0.017	0.010	0.007
pvalue	0.000	0.000	0.000	0.000	pvalue	0.000	0.000	0.000	0.000
F2 – Steel Production	0.144	0.104	0.062	0.046	**F2 – Orderbook**	-0.021	-0.012	-0.002	0.004
SE	0.032	0.034	0.024	0.026	SE	0.015	0.011	0.005	0.006
pvalue	0.000	0.000	0.000	0.000	pvalue	0.133	0.202	0.729	0.558
F3 – Seaborne Trade	0.073	0.031	0.008	0.011	**F3 – Freight Market Changes**	-0.147	-0.063	-0.038	-0.026
SE	0.033	0.020	0.013	0.012	SE	0.024	0.011	0.008	0.006
pvalue	0.000	0.018	0.425	0.224	pvalue	0.000	0.000	0.000	0.000
					F4 – Demolition Market	-0.008	0.003	-0.004	-0.009
					SE	0.015	0.007	0.004	0.006
					pvalue	0.578	0.753	0.348	0.134
					F5 – Fleet Changes	-0.070	-0.046	-0.032	-0.021
					SE	0.017	0.009	0.005	0.007
					pvalue	0.000	0.000	0.000	0.002
					F6 – Supply Indicators	-0.146	-0.112	-0.094	-0.052
					SE	0.025	0.011	0.005	0.007
					pvalue	0.000	0.000	0.000	0.000
Logarithmic Differences (t-1)	0.014	0.033	0.141	0.203	**Logarithmic Differences (t-1)**	-0.116	-0.009	0.006	0.076
SE	0.079	0.080	0.060	0.115	SE	0.048	0.050	0.033	0.072
pvalue	0.805	0.579	0.027	0.003	pvalue	0.020	0.848	0.838	0.135
LL	-22.817	51.026	120.45	142.48	**LL**	34.991	122.854	300.26	210.06
R^2	0.295	0.285	0.256	0.274	**R^2**	0.579	0.632	0.856	0.655
RMSE	0.269	0.198	0.147	0.124	**RMSE**	0.212	0.144	0.066	0.087
MSE	0.072	0.039	0.022	0.015	**MSE**	0.045	0.021	0.004	0.008
Residual Diagnostics					**Residual Diagnostics**				
Jarque – Bera test	143.24	160.52	1078.53	738.22	**Jarque – Bera test**	58.00	706.55	16.269	1587.18
pvalue	0.001	0.001	0.001	0.001	pvalue	0.001	0.001	0.002	0.001
Q test	48.059	36.716	32.944	28.656	**Q test**	43.422	27.192	32.931	29.747
pvalue	0.000	0.013	0.034	0.095	pvalue	0.002	0.130	0.034	0.074
ARCH test	16.357	4.504	0.281	5.285	**ARCH test**	17.454	65.109	6.531	58.447
pvalue	0.000	0.034	0.596	0.022	pvalue	0.000	0.000	0.011	0.000

Notes: Table 3.11 – reports the estimates based on the extracted factors (see Equation 3.14), i.e. $FR_t = a + \beta FR_{t-1} + (1-\beta)(\phi_{F1}F1_t + \phi_{F2}F2_t + \cdots + \phi_{F6}F6_t)$, where FR denotes the spot, P6m, P12m and P36m freight rate, $F1_t$ to $F3_t$ indicate the three macroeconomic factors extracted from the Demand dataset and $F1_t$ to $F6_t$ represent the six macroeconomic factors extracted from the Supply datasets between 1996:01 to 2016:06. The table also reports the coefficient of each variable – B, the standard errors and their p-values. The Jarque-Bera, Ljung-Box Q test and the ARCH tests are used to examine the heteroscedasticity and normality of the residuals series. The loglikelihood test (LL), the coefficient of determination R^2, the RMSE and MSE assess the model's adequacy and significance. Newey and West (1987) method is used to estimate the standard errors of the regression coefficients, corrected for heteroscedasticity and serial correlation.

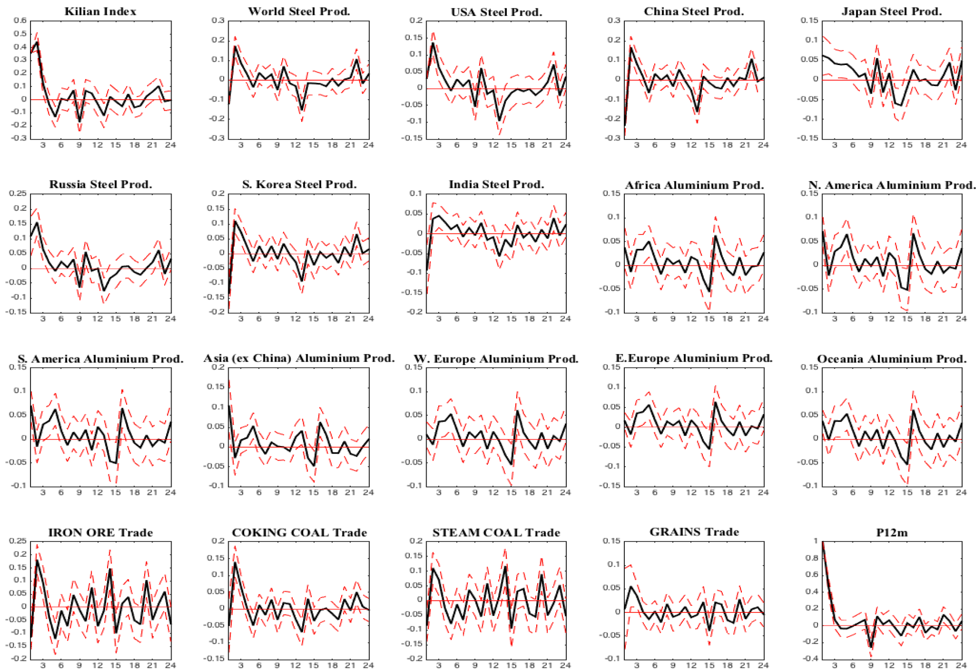
As can be seen from Figures 3.2 to 3.5, one standard deviation shock to Kilian's index causes significant and greater decrease in spot rates compared to the P6m, P12m and P36m rates, indicating that the period rates will move above the spot rates in the next three months. Both Table 3.11 and the impulse responses in Figures 3.2 to 3.5 show that the Aluminium Production is negatively associated with the freight rates series. For instance, as can be seen in Figures 3.2 to 3.5 a standard deviation shock to the aluminium production variables causes significant decrease to the spot, P6m, P12m and P36m rates. Additionally, one standard deviation shock to China Steel Production causes significant increase in spot rates for 4 months after which the effect dissipates.

Figure 3.3: Impulse Responses of Demand Variables to P6m Freight Rates



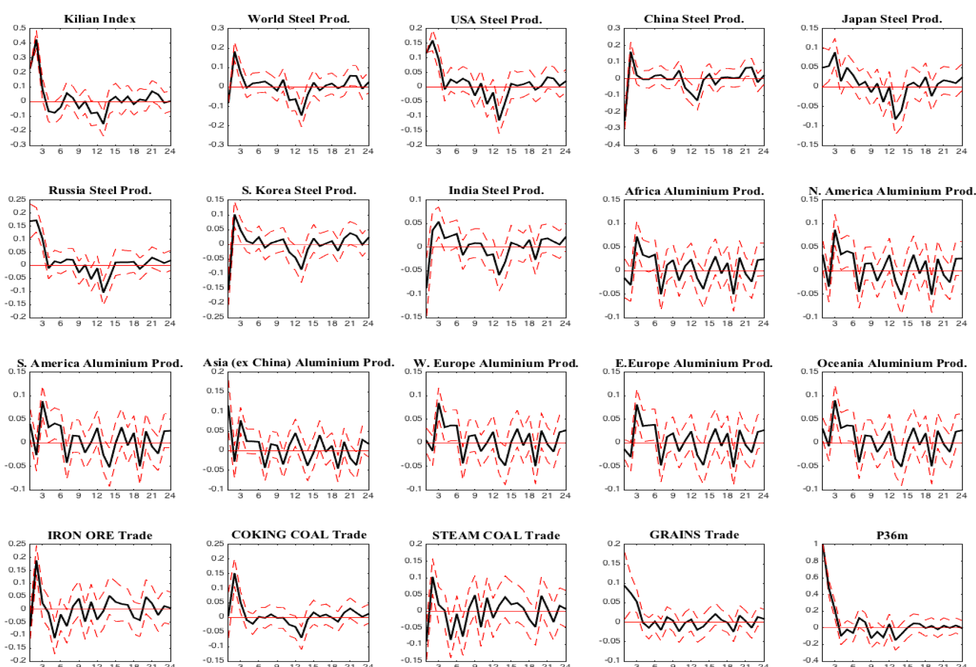
As expected, the impulse responses are very volatile since the dry bulk freight market is characterised with abnormal levels of risk. Additionally, the macroeconomic demand shocks on the freight rates series appear to be significant but only temporarily, since their impact on almost all demand variables fades out quickly by the first to second month except from the Kilian's index impact that lasts approximately 6 months.

Figure 3.4: Impulse Responses of Demand Variables to P12m Freight Rates



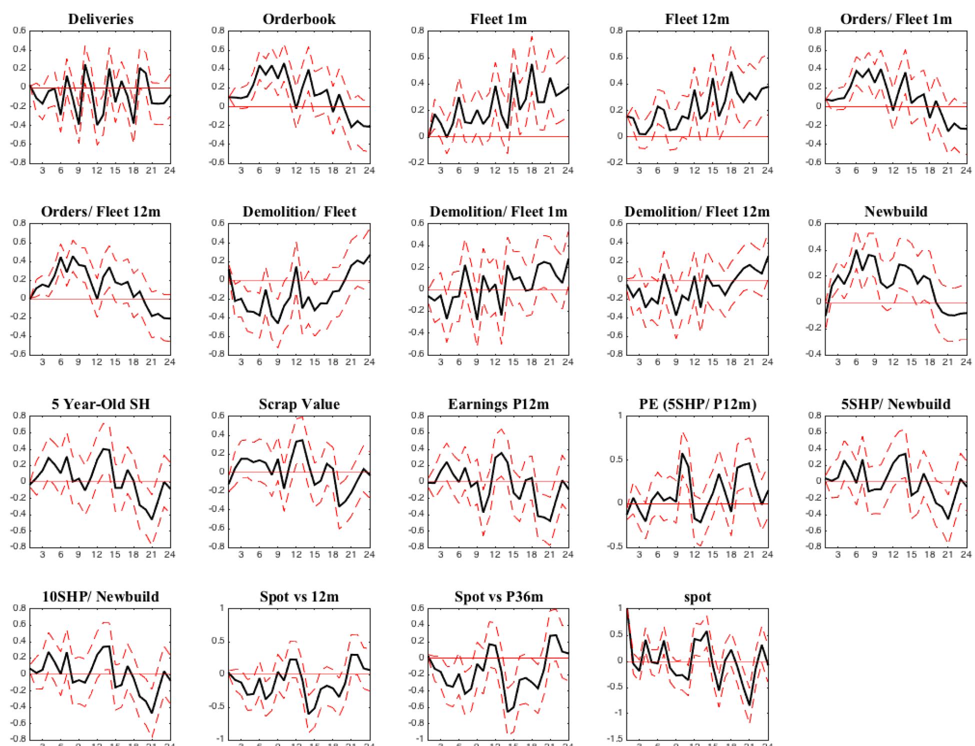
The impulse responses of the macroeconomic variables to the freight rates series for the period excluding the financial crisis period are presented in Appendix 3.C and are similar to ones observed for the entire planning horizon.

Figure 3.5: Impulse Responses of Demand Variables to P36m Freight Rates



Figures 3.6 to 3.10 present the impulse responses of the macroeconomic supply variables on the freight rates series at a 90 percent confidence interval. The impulse response of the supply variables also show that the dry bulk freight market is highly volatile and that most impacts do not last long and cease by the third month like in the case of deliveries, PE ratio and the ship price ratio. The orderbook, orders scaled by the fleet, demolition scaled by the fleet and the scrap value prices seem to be the exceptions as the results show that their impact last from 6 to 9 months. It is worth noting that one standard deviation shock to Fleet 1m, Fleet 12m and newbuilding prices causes an increase in the spot series for 3 months before decreasing and then increase again. These fluctuations are moving above zero and reach their peak in period 15 months. Furthermore, a decrease in the spot rates during the first three months results in an expected decrease in the impulse response of the demolition, the 12-month fleet and the number of orders.

Figure 3.6: Impulse Responses of Supply Variables to Spot Freight Rates



The impulse response function shows a link between the supply variables. For instance, apart from the individual impacts of the various shocks on the supply variables, Figures 3.6 to 3.9 also indicate dynamic interaction between variables themselves. For instance, when the number of vessels demolished decreases, most of the other variables increase (i.e. the prices 5- and 10-year old ship, number of orders placed, etc.) indicating that the market is strong and that shipowners keep their vessels to be able to meet the current demand.

Figure 3.7: Impulse Responses of Supply Variables to P6m Freight Rates

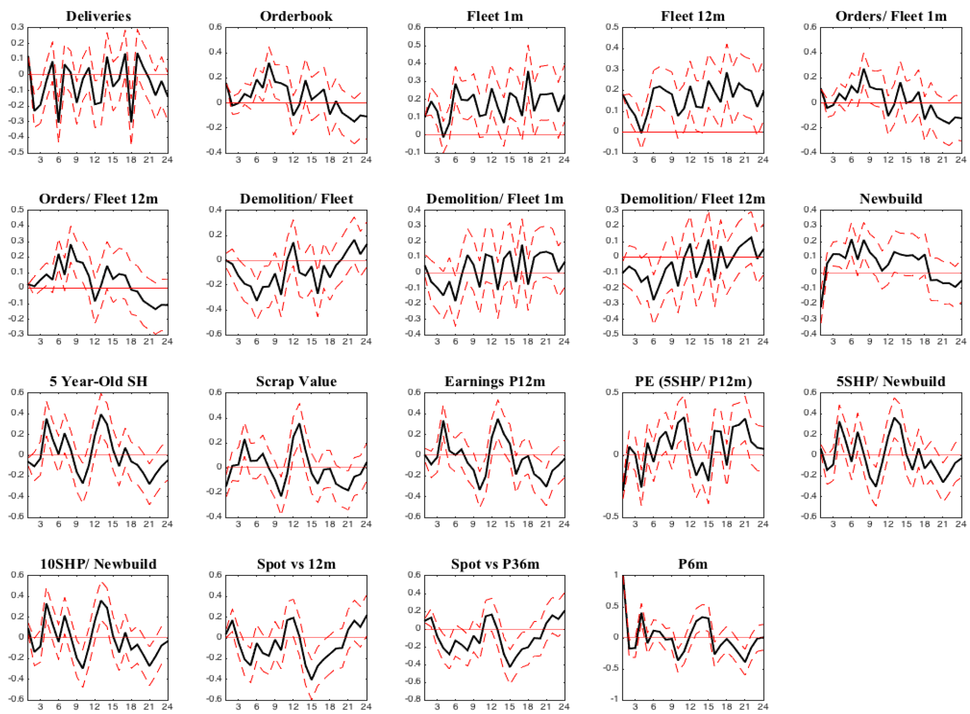


Figure 3.8: Impulse Responses of Supply Variables to P12m Freight Rates

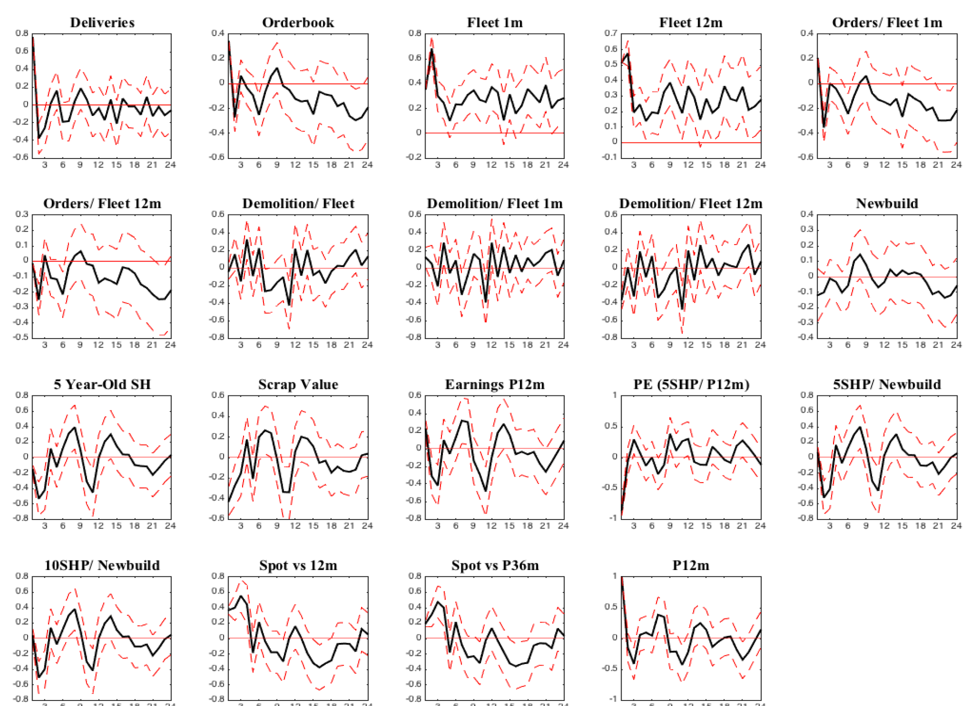
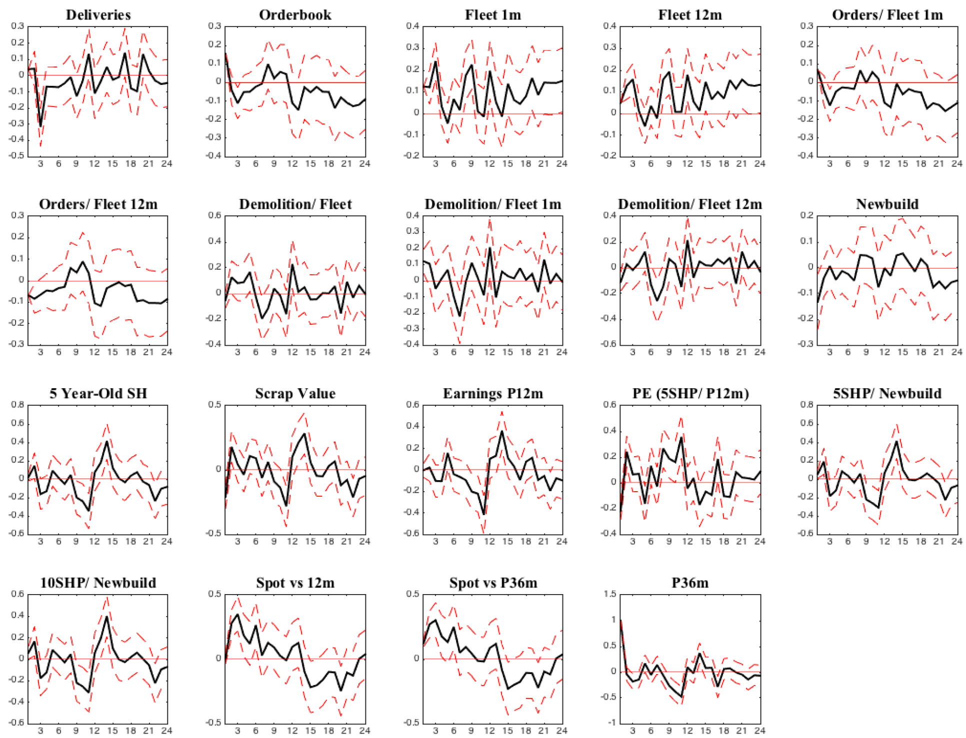


Figure 3.9: Impulse Responses of Supply Variables to P36m Freight Rates



Almost all impulse responses presented above reach a steady state approximately after 21 months. Appendix 3.C presents the impulse response of the supply variable to the freight rate series after eliminating the financial crisis period.

3.4 Robustness Tests

This sub-section presents a series of additional tests performed to enhance the robustness of the VAR framework models. At this point it is important to mention that the standard errors of the regression coefficients are calculated using the procedure proposed by Newey-West (1987) who suggested a more general variance-covariance matrix estimator that is consistent in the presence of both heteroskedasticity and autocorrelation of the residuals.

3.4.1 Robustness Tests for the Latent Freight Rate Model

This empirical analysis attempts to fit the dynamic latent freight rate model to the two additional datasets in order to assess the model's fit under different circumstances that can affect the robustness of the empirical findings. More specifically, the dynamic latent freight rate model is applied to:

a. The sample after having eliminated the financial crisis period, between August 2007 and January 2009 – *"Model 2"*
b. An extended version of the original dataset that spans a greater range of maturities – *"Model 3"*.

Model 1 refers to the latent freight rate model applied to the full sample from January 1996 to June 2016. The empirical findings of Model 1 are presented is section 3.3.3.1. The findings and the estimated R^2 values indicate that the latent factor freight rate model is robust across all scenarios and can adequately explain the level of freight rate variability. Additionally, the R^2 value increases slightly when the financial crisis is eliminated but decrease when additional maturities are added to the original sample, which could be due to the additional variability caused from the extra maturities. For instance, the R^2 is 92.73% for Model 1, 93.12% for Model 2, and 68.72% for Model 3.

Table 3.12: Descriptive Statistics: Freight Rate Curves Residual

	Mean	Standard Deviation	Min	Max	$\hat{\rho}(1)$	$\hat{\rho}(12)$	$\hat{\rho}(36)$	RMSE	MAE
Panel A: Dynamic NS model without the Financial Crisis period - Model 2									
1 (spot)	0.003	0.008	-0.022	0.037	0.571	-0.025	0.017	0.009	0.000
6 (PTC6m)	-0.015	0.035	-0.160	0.096	0.571	-0.025	0.017	0.038	0.001
12 (PTC12m)	0.017	0.039	-0.107	0.178	0.571	-0.025	0.017	0.042	0.002
36 (PTC36m)	-0.005	0.012	-0.055	0.033	0.571	-0.025	0.017	0.013	0.000
Panel B: Model with additional maturities - Model 3									
1 (spot)	0.000	0.033	-0.084	0.306	0.453	0.177	0.037	0.033	0.001
2	0.007	0.013	-0.028	0.119	0.435	-0.030	0.118	0.015	0.000
3	0.007	0.018	-0.069	0.073	0.556	0.278	0.023	0.019	0.000
4	0.004	0.025	-0.216	0.083	0.475	0.218	-0.012	0.025	0.001
5	-0.002	0.027	-0.294	0.065	0.418	0.121	0.010	0.027	0.001
6 (PTC6m)	-0.007	0.027	-0.296	0.048	0.397	0.029	0.056	0.028	0.001
7	-0.012	0.025	-0.239	0.046	0.411	-0.038	0.095	0.028	0.001
8	-0.014	0.024	-0.151	0.062	0.448	-0.033	0.084	0.028	0.001
9	-0.015	0.025	-0.087	0.073	0.485	0.043	0.026	0.029	0.001
10	-0.014	0.027	-0.108	0.096	0.509	0.126	-0.028	0.030	0.001
11	-0.010	0.029	-0.115	0.141	0.520	0.172	-0.049	0.030	0.001
12 (PTC12m)	-0.005	0.031	-0.107	0.223	0.519	0.172	-0.036	0.031	0.001
16	0.024	0.051	-0.101	0.451	0.428	-0.021	0.096	0.056	0.003
18	0.040	0.072	-0.184	0.515	0.423	-0.040	0.086	0.082	0.007
24	0.068	0.146	-0.764	0.540	0.455	-0.012	0.030	0.160	0.026
30	0.047	0.102	-0.596	0.306	0.515	0.030	0.029	0.112	0.013
36 (PTC36m)	-0.118	0.234	-1.283	1.003	0.444	-0.031	0.060	0.262	0.069

Notes: Table 3.12 presents the descriptive statistics of the freight rates curves residuals. The last two columns show the Mean Absolute Error - MAE and the Root Mean Squared Error - RMSE. The sample autocorrelations at displacements 1 ($\hat{\rho}(1)$), 12 ($\hat{\rho}(12)$), and 36 ($\hat{\rho}(36)$) months are also presented.

Table 3.12 presents the descriptive statistics of the residuals that analyse the fit after having applied the OLS approach to the monthly freight rates for each of the aforementioned models. More specifically, Table 3.12 shows that the estimated means of the residuals of all models present a good fit since most of them are close to zero while also the autocorrelations indicate that the residuals are persistent. In addition, the Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE) are close to zero and similar for each model which suggests that the latent freight rate model satisfactorily explains the freight rate variability.

Figure 3.10 plots the estimated level ($\hat{\beta}_{1t}$), slope ($\hat{\beta}_{2t}$) and curvature ($\hat{\beta}_{3t}$) along with the empirical level $(level_t)$, slope $(slope_t)$ and curvature $(curvature_t)$ for comparative assessment of each model. More specifically, the solid black lines show the empirical level, slope and curvature, the solid red line indicates the estimated factors using the two-step OLS approach (see Eq. 3.1) while the blue dotted line designates the estimated factors using the State-Space Model (SSM) approach (see Eq. 3.5).

Figure 3.10: Estimated Factors (i.e. Level, Slope and Curvature) versus data based Level, Slope and Curvature – Model 2

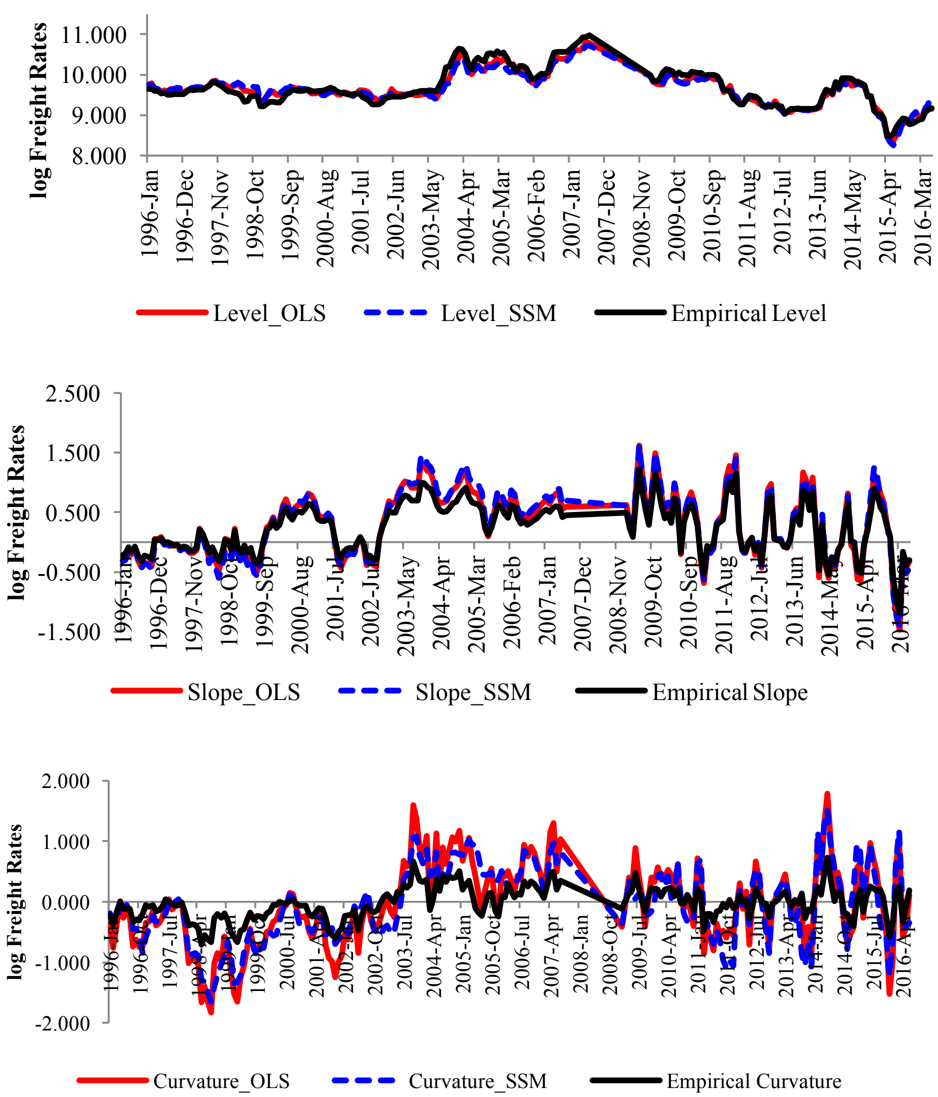


Table 3.13 – Panel A indicates that the mean estimated factors (i.e. level, slope and curvature) are very similar across both estimation approaches (i.e. the two-step OLS and the SSM approach) except from the slope factor in Model 3 and the curvature factors that appear to be different for each Model. Panel B in Table 3.13 indicates the freight rates used to capture the level, slope and curvature for all models. More specifically, these are the factors with the highest correlation amongst all available combinations.

Table 3.13: Comparing the estimated Factor Means

	Approach	**Level**	**Slope**	**Curvature**
Panel A: Mean values of the estimated factors				
	OLS	9.737	0.301	0.009
Model 1	SSM	9.661	0.258	-0.131
	OLS	9.652	0.300	-0.057
Model 2	SSM	9.598	0.273	-0.107
	OLS	9.910	0.150	-0.336
Model 3	SSM	10.461	-0.113	-0.992
Panel B: The estimated latent factors				
	OLS	P36m	P36m-Spot	P6m-(Spot+P36m)
Model 1	SSM	P36m	P36m-Spot	P12m-(Spot+P36m)
	OLS	P36m	P36m-Spot	P6m-(Spot+P36m)
Model 2	SSM	P36m	P36m-Spot	P12m-(Spot+P36m)
	OLS	P30m	P30m-Spot	P9m-(P5m+P30m)
Model 3	SSM	P30m	P12m-P10m	P7m-(P2m+P18m)

Notes: Panel A presents the estimated mean factors for all estimation approaches used and models. Panel B indicates the exact freight rates used to produce the latent factors. OLS refers to the two-step Ordinary Least Square estimation process of the Diebold and Li (2006) model and SSM is the State-Space Model approach by Diebold et al (2006).

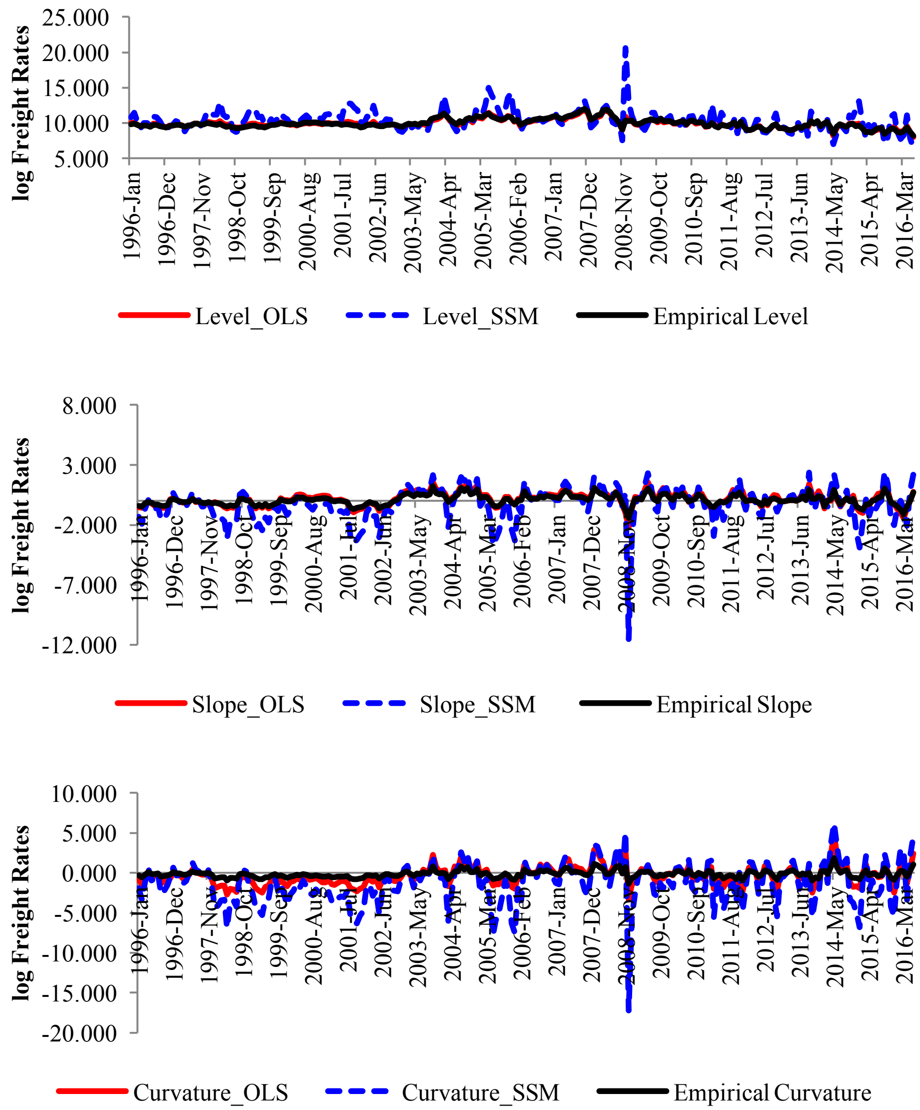
For instance, when using the OLS approach in Model 1, the level, slope and curvature of the best model defined as follows: the level is the 36 month freight rates, the slope is measured as the difference between the 36-month and the spot rates and the curvature is defined as twice the P6m rates minus the sum of the spot and the 36-month rates. At this point, it is important to mention that all combinations[4] of level, slope and curvature were examined since there is no standard reference for their modelling in the freight market. Figure 3.11 illustrates the highly correlated estimated and the empirical latent factors of each model.

Table 3.14 presents the descriptive statistics of the estimated factors for each model using the OLS two-step approach. The three-factor Nelson-Siegel model with a λ_t value fixed at 0.226 was used to estimate these factors. As indicated in Table 3.13, there is no significant difference in the estimated latent factors when using the two-step

[4] See Appendix 3.B for the list of all of the available combinations of level, slope and curvature in the dry bulk freight market.

OLS or the SSM approach, therefore arbitrarily the two-step OLS approach empirical findings will be the ones reported in detail.

Figure 3.11: Estimated Factors (i.e. Level, Slope and Curvature) versus data based Level, Slope and Curvature – Model 3



Considering the autocorrelations of the three factors, the level factor appears to be more persistent compared to the slope and curvature. Additionally, the augmented Dickey-Fuller test suggests that $\hat{\beta}_{1t}$ has unit roots unlike $\hat{\beta}_{2t}$ and $\hat{\beta}_{3t}$. No significant difference was observed between the estimated factors of the three models, which means that neither the increase in the number of maturities nor the elimination of the financial crisis affected or significantly improved the model fit.

Table 3.14: Descriptive Statistics, estimated Factors for the Alternative Models

	Mean	Standard Deviation	Min	Max	$\hat{\rho}(1)$	$\hat{\rho}(12)$	$\hat{\rho}(36)$	ADF
Panel A: Dynamic NS - Model 1								
Level	9.737	0.542	8.355	11.469	0.970	0.512	0.281	-0.387
Slope	0.301	0.537	-1.472	1.613	0.805	0.252	0.152	-4.348
Curvature	0.009	0.698	-1.823	2.042	0.767	0.425	0.193	-5.685
Panel B: Dynamic NS without the financial crisis period - Model 2								
Level	9.652	0.424	8.355	10.799	0.962	0.449	0.198	-0.428
Slope	0.300	0.535	-1.472	1.613	0.817	0.332	0.217	-4.036
Curvature	-0.057	0.662	-1.823	1.782	0.784	0.378	0.125	-5.222
Panel C: Dynamic NS Model with additional maturities - Model 3								
Level	9.910	0.621	7.978	11.831	0.797	0.411	0.237	-0.603
Slope	0.150	0.563	-2.174	1.574	0.760	0.139	0.100	-5.450
Curvature	-0.336	1.153	-3.345	4.887	0.587	0.146	0.003	-7.330

Notes: Table 3.14 presents the descriptive statistics of the three estimated factors $\hat{\beta}_{1t}$, $\hat{\beta}_{2t}$, and $\hat{\beta}_{3t}$. The last column shows the augmented Dickey-Fuller (ADF) unit root test statistics and the three columns on the left contain the sample autocorrelations at displacements 1, 12, and 36 months. The critical values for rejecting the hypothesis of a unit root are -2.575 at a 1% level, -1.942 at a 5% level and -1.616 at a 10% level.

3.4.2 Robustness Tests for the FAVAR Model

Multiple regression models are performed to assess the robustness of the FAVAR model and more specifically whether the latent variables (i.e. level, slope and curvature) of the freight rate curve can explain the cross-sectional variation of freight rates.

The FAVAR model seems to accurately explain freight rates throughout the sample period whilst the impulse response highlights the dynamic interactions between the term structure of freight rates and the demand and supply factors. The next step is to relate the macroeconomic factors used in the model to the level, slope, and curvature components of the freight rate curve. This is achieved through regressions of estimates of the latent freight rates factors onto the macroeconomic factors and the freight rate series.

The level factor loads significantly into the supply factors with an adjusted R^2 of about 60%. More specifically, the level factor is positively associated with the asset prices (0.035), the orderbook (0.433), the fleet (0.172) and the miscellaneous supply indicators (0.070) factors whilst a negative association is observed with the freight market changes (-0.104) and the demolition market (-0.073) factors. This suggests that the level factor captures a strong effect by the orderbook changes since the coefficient value is the largest (0.433) compared to the other factors (see Table 3.16).

As can be seen from Table 3.16, when regressed onto the supply factors, the slope factor results in a high R^2 of approximately 85% with both negative and positive loadings into the supply factors. Considering the significance and the coefficient of each supply factor, it appears that the majority of the traditional slope factor is related to the freight market changes factor (0.360). On the other hand, the curvature factor is poorly accounted by the supply factors (R^2 about 3%) possibly because the curvature factor is non-significantly associated with the supply factors (except from the demolition factor).

The demand factors on Table 3.15 present lower R^2 values compared to the supply ones with most of them being non-significant when regressed with the latent factors. Therefore, it can be concluded that the level, slope and curvature factors are poorly accounted by the demand factors during the January 1996 to June 2016.

The same regressions are also performed for the period from January 1996 to June 2016 after excluding the financial crisis period (August 2007 to January 2009) and the demand factors appear to still be poorly associated with the latent factors (see Appendix 3.D). The negative R^2 values indicate a worse data fit compared to a horizontal line. On the other hand, the supply factors, for the period without the financial crisis period present a good fit when regressed with the latent factors.

More specifically, the R^2 values of the level and slope factors are approximately 50% and 87%, whilst the R^2 value of the curvature factors increased significantly to 30%. The curvature factor is positively associated with the asset prices (0.078) and the orderbook changes (0.104) and presents a negative association with fleet changes (-0.025), freight market changes (-0.048), demolition market (-0.021) and supply indicator (-0.055) factors. The curvature factor captures a strong effect of the fleet changes since the coefficient value is the largest one compared to the other factors.

The empirical findings of the latent factors that were regressed against the demand and supply factors from January 1996 to June 2016, after eliminating the financial crisis period, are presented in Appendix 3.D. To sum up, Tables 3.15 and 3.16 show that the traditional level, slope and curvature factors are clearly associated with macroeconomic supply factors but the demand factors are not associated with the latent factors. In other words, it appears that freight rates are mainly affected by variations in the supply level rather than by changes in the demand level.

Table 3.15: Regression of Latent Factors in the model Demand Factors

	Spot Levels			P6m Levels			P12m Levels			P36m Levels		
	Level	**Slope**	**Curvature**	**Level**	**Slope**	**Curvature**	**Level**	**Slope**	**Curvature**	**Level**	**Slope**	**Curvature**
Constant	9.768	-0.245	0.079	9.772	-0.246	0.079	9.770	-0.247	0.080	9.795	-0.260	0.081
SE	0.084	0.042	0.086	0.085	0.046	0.085	0.084	0.046	0.085	0.083	0.045	0.093
pvalue	0.000	0.000	0.349	0.000	0.000	0.348	0.000	0.000	0.351	0.000	0.000	0.377
F1 – Aluminium Production	0.004	-0.018	-0.060	0.001	-0.008	-0.055	0.010	-0.011	-0.065	0.025	-0.009	-0.080
SE	0.022	0.019	0.047	0.021	0.017	0.056	0.023	0.016	0.066	0.027	0.019	0.083
pvalue	0.929	0.491	0.493	0.989	0.774	0.530	0.811	0.665	0.467	0.561	0.755	0.410
F2 – Steel Production	0.032	-0.002	-0.059	0.017	-0.024	-0.061	0.011	-0.024	-0.033	0.013	-0.044	-0.013
SE	0.042	0.041	0.103	0.040	0.041	0.065	0.040	0.038	0.044	0.047	0.047	0.034
pvalue	0.474	0.932	0.542	0.701	0.397	0.523	0.806	0.397	0.724	0.768	0.135	0.898
F3 – Seaborne trade	0.021	-0.024	-0.023	0.015	-0.045	-0.013	0.019	-0.051	0.002	0.013	-0.054	-0.001
SE	0.022	0.021	0.037	0.021	0.022	0.020	0.022	0.020	0.018	0.026	0.024	0.020
pvalue	0.601	0.344	0.791	0.707	0.083	0.877	0.631	0.043	0.985	0.758	0.048	0.988
lnLevels	-0.030	-0.481	0.434	0.100	-0.443	0.634	0.231	-0.682	0.545	0.545	-0.611	0.381
SE	0.144	0.097	0.559	0.170	0.131	0.416	0.309	0.187	0.327	0.430	0.227	0.242
pvalue	0.842	0.000	0.175	0.622	0.001	0.143	0.394	0.000	0.351	0.108	0.005	0.611
Residual Diagnostics Tests												
J - B test	43.616	4.710	467934.4	41.021	15.036	486425.3	43.068	21.558	492188.0	44.803	46.990	494027.0
pvalue	0.001	0.076	0.001	0.001	0.005	0.001	0.001	0.002	0.001	0.001	0.001	0.001
Q test	1961.8	482.45	3.883	1996.9	424.56	2.862	1942.5	417.74	2.509	1826.6	367.31	1.915
pvalue	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000	1.000
ARCH	217.21	91.733	0.004	223.39	44.261	0.004	223.14	54.273	0.005	223.29	32.248	0.005
pvalue	0.000	0.000	0.947	0.000	0.000	0.947	0.000	0.000	0.946	0.000	0.000	0.944
LL	-223.52	-108.50	-409.05	-224.29	-116.20	-408.89	-221.93	-113.20	-407.14	-208.93	-108.88	-388.03
R^2	-0.013	0.135	-0.004	-0.013	0.082	-0.003	-0.010	0.099	-0.008	0.000	0.078	-0.012
RMSE	0.613	0.382	1.316	0.615	0.394	1.315	0.614	0.391	1.324	0.619	0.397	1.373
MSE	0.376	0.146	1.733	0.379	0.156	1.730	0.377	0.153	1.754	0.384	0.158	1.885

Notes: Table 3.15 summarises the results of a regression of level, slope, and curvature freight rate factors onto the Demand factors of the FAVAR model. The coefficients of each variable are presented along with the standard errors and the p-values. Jarque-Bera, the Ljung-Box Q and the ARCH tests were used to examine the heteroscedasticity and normality of the residuals series. The loglikelihood test (LL), the coefficient of determination R^2, the RMSE and MSE assess the model's adequacy and significance. Newey and West (1987) method is used to estimate the standard errors of the regression coefficients, corrected for heteroscedasticity and serial correlation. The in-sample period is 1996:01 - 2016:06.

3.5 Conclusion

This chapter reviews the term structure models that can be applied to the shipping freight rate market and attempts to fit the term structure of freight rates to a dynamic latent freight rate (Diebold and Li, 2006) and the FAVAR (Bernanke et al 2005) model. The models' convenient state-space representation facilitates the estimation and testing of hypotheses regarding dynamic interactions between the macroeconomy and the freight rates curves. The empirical analysis indicated that both models explain a large portion of the freight rate variability and identified dynamic interactions between the macroeconomy and the term structure of freight rates.

The dynamic interactions between the term structure of freight rates and the macroeconomy can be assessed based on the macroeconomic demand and supply datasets that were constructed. More specifically, this chapter is the only one in the shipping literature that builds a large demand and supply macroeconomic dataset using explicitly macroeconomic variables that affect the dry bulk shipping market. Additionally, the rationale behind the use of these models (i.e. the latent freight rate and the FAVAR model) is that there is limited research on the dynamics between the freight rates and various macroeconomic variables in the literature and therefore understanding these interactions can be useful tool to assist the decision making process of shipping investments whilst also be used as forecasting tools.

The dynamic latent freight rate model explains a significant proportion (up to 90%) of the freight rate variability. A series of robustness tests also reveal that the dynamic latent model is not affected by the elimination of the turbulent financial crisis period ($R^2 = 93.12\%$) nor by the number of maturities added to the sample size ($R^2 = 68.72\%$).

Incorporating the additional maturities into equation (3.1) does not increase the level of variability that can be explained and thus the original series with four maturities are used for the remainder of the empirical analysis. Furthermore, when the latent factors are regressed with the demand and supply factors, the empirical findings indicate that only the latter explain a significant proportion of the level, slope and curvature factors, while the latent factors do not seem to be significantly explained by the demand factors.

Table 3.16: Regression of Latent Factors in the model Supply Factors

	Spot Levels			P6m Levels			P12m Levels			P36m Levels		
	Level	**Slope**	**Curvature**	**Level**	**Slope**	**Curvature**	**Level**	**Slope**	**Curvature**	**Level**	**Slope**	**Curvature**
Constant	9.779	-0.262	0.090	9.778	-0.263	0.092	9.779	-0.263	0.096	9.801	-0.268	0.091
SE	0.061	0.015	0.088	0.058	0.015	0.089	0.060	0.015	0.091	0.063	0.017	0.094
pvalue	0.000	0.000	0.308	0.000	0.000	0.296	0.000	0.000	0.277	0.000	0.000	0.342
F1 – Asset Prices	0.035	-0.067	-0.059	-0.016	-0.072	-0.141	-0.109	-0.081	-0.373	-0.014	-0.093	-0.072
SE	0.040	0.012	0.103	0.046	0.015	0.103	0.074	0.025	0.256	0.054	0.015	0.076
pvalue	0.248	0.000	0.565	0.642	0.000	0.236	0.038	0.000	0.041	0.725	0.000	0.605
F2 - Orderbook	0.433	-0.079	0.041	0.437	-0.080	0.038	0.430	-0.081	0.027	0.419	-0.078	0.017
SE	0.059	0.011	0.070	0.056	0.011	0.081	0.058	0.011	0.087	0.060	0.012	0.096
pvalue	0.000	0.000	0.643	0.000	0.000	0.666	0.000	0.000	0.762	0.000	0.000	0.855
F3 – Freight Market Changes	-0.104	0.360	0.023	-0.092	0.358	0.003	-0.071	0.359	0.055	-0.087	0.357	-0.055
SE	0.039	0.036	0.061	0.038	0.037	0.047	0.042	0.039	0.040	0.033	0.037	0.072
pvalue	0.001	0.000	0.827	0.001	0.000	0.978	0.015	0.000	0.587	0.002	0.000	0.583
F4 – Demolition Market	-0.073	0.057	0.180	-0.074	0.055	0.184	-0.067	0.057	0.196	-0.068	0.056	0.199
SE	0.021	0.012	0.200	0.021	0.012	0.200	0.021	0.012	0.207	0.021	0.012	0.215
pvalue	0.005	0.000	0.042	0.004	0.000	0.039	0.009	0.000	0.028	0.010	0.000	0.035
F5 – Fleet Changes	0.172	-0.057	0.086	0.186	-0.058	0.102	0.204	-0.055	0.148	0.200	-0.064	0.043
SE	0.034	0.013	0.029	0.034	0.013	0.024	0.037	0.015	0.043	0.043	0.015	0.049
pvalue	0.000	0.000	0.349	0.000	0.000	0.268	0.000	0.000	0.136	0.000	0.000	0.683
F6 – Supply Idicators	0.070	0.045	0.154	0.106	0.047	0.189	0.178	0.052	0.373	0.073	0.055	0.111
SE	0.031	0.017	0.183	0.027	0.013	0.143	0.050	0.019	0.269	0.029	0.013	0.114
pvalue	0.028	0.001	0.152	0.001	0.001	0.091	0.000	0.006	0.017	0.020	0.000	0.323
LogDiff	0.157	0.058	0.770	0.536	0.090	1.368	1.384	0.171	3.516	0.731	0.336	1.188
SE	0.115	0.059	0.848	0.167	0.058	0.822	0.507	0.202	2.241	0.326	0.127	0.893
pvalue	0.201	0.241	0.067	0.003	0.223	0.028	0.000	0.293	0.010	0.020	0.009	0.291
Residual Diagnostics Tests												
J - B test	19.942	1154.2	423586.1	19.007	1221.5	447434.8	19.505	1226.0	439468.8	19.106	1011.7	448254.2
pvalue	0.002	0.001	0.001	0.003	0.001	0.001	0.002	0.001	0.001	0.003	0.001	0.001
Q test	795.41	232.78	4.623	802.60	239.52	2.658	774.98	241.08	3.603	675.71	239.26	2.347
pvalue	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000	1.000
ARCH	32.721	1.119	0.005	41.693	0.467	0.005	42.314	0.999	0.004	42.664	0.414	0.005
pvalue	0.000	0.290	0.942	0.000	0.494	0.944	0.000	0.317	0.949	0.000	0.520	0.944
LL	-107.26	102.68	-392.57	-103.48	102.61	-391.58	-101.07	100.78	-388.39	-98.152	93.865	-372.70
R^2	0.602	0.851	0.008	0.617	0.852	0.017	0.622	0.851	0.023	0.617	0.851	-0.002
RMSE	0.391	0.158	1.337	0.385	0.158	1.332	0.382	0.159	1.333	0.389	0.159	1.396
MSE	0.153	0.025	1.789	0.148	0.025	1.773	0.146	0.025	1.777	0.152	0.025	1.948

Notes: Table 3.16 summarises the results of a regression of level, slope, and curvature freight rate factors onto the Supply factors of the FAVAR model. The coefficients of each variable are presented along with the standard errors and the p-values. Jarque-Bera, the Ljung-Box Q and the ARCH tests were used to examine the heteroscedasticity and normality of the residuals series. The loglikelihood test (LL), the coefficient of determination R^2, the RMSE and MSE assess the model's adequacy and significance. Newey and West (1987) method is used to estimate the standard errors of the regression coefficients, corrected for heteroscedasticity and serial correlation. The in-sample period is 1996:01 - 2016:06.

More specifically, the level factor loads significantly on orderbook changes whilst the slope factor loads considerably on freight market changes for both examined periods (with and without financial crisis). On the other hand, the curvature factor loads significantly on fleet changes but only on the period that excluded the financial crisis.

Additionally, the empirical analysis of the FAVAR model shows that the macroeconomic factors explain a high proportion (up to 70%) of the movements in the freight rate curve and the effects of the demand and supply shocks are stronger at the long end of the freight rate curve. Additionally, the impulse response functions allow us to measure the effect on the freight rates series caused by one standard deviation shock to the macroeconomic variables. The robustness of the FAVAR model is confirmed through a series of regression models (i.e. regressions with the supply and demand factors and latent factor regressions). More specifically, when the freight series are regressed with the demand factors, the empirical findings indicate that the steel production and the seaborne trade have a positive and significant impact on the freight rate series whilst the aluminium production is negatively associated with the freight series. Except from the asset prices, which are positively associated with the freight series, most supply factors are significant and negatively associated with the freight rates series.

To sum up, the analysis show that the supply factors can explain a significant portion of the freight rate variability. Since, the proposed models explain a large proportion of the freight rate variability this study can form a good starting point for extending the VAR framework by including additional VAR models to assess and compare the forecasting performance of the framework for the freight rate market.

Appendices

Appendix 3.A – List of Macroeconomic Variables

Table A.3.17 lists the 34 demand macroeconomic variables. In the transformation column, we report the transformations for the variables where 1 denotes no transformation, 2 denotes using changes and 3 denotes taking first differences. In addition, Table A.3.18 refers in the supply variables and their transformations.

Table A.3.17: Demand Dataset

		Unit of measurement	Transformations
A. World Economic Activity			
	GDP	% Yr/Yr	2
	Baltic Dry Index	Index	2
	Kilian's Index	Index	2
Inflation	Inflation OECD	% Yr/Yr	2
	Inflation OECD EU (excluding Turkey)	% Yr/Yr	2
	Inflation USA	% Yr/Yr	2
	Inflation Japan	% Yr/Yr	2
	Industrial Production OECD	% Yr/Yr	2
	Global Oil Production	M bpd	2
Steel Production	World Steel Production	,000 tonnes	2
	USA Steel Production	,000 tonnes	2
	China Steel Production	,000 tonnes	2
	Japan Steel Production	,000 tonnes	2
	Russia Steel Production	,000 tonnes	2
	S. Korea Steel Production	,000 tonnes	2
	India Steel Production	,000 tonnes	2
Aluminium Production	Africa Aluminium Production	,000 tonnes	2
	N. America Aluminium Production	,000 tonnes	2
	S. America Aluminium Production	,000 tonnes	2
	Asia (ex China) Aluminium Production	,000 tonnes	2
	W. Europe Aluminium Production	,000 tonnes	2
	E.Europe Aluminium Production	,000 tonnes	2
	Oceania Aluminium Production	,000 tonnes	2
B. International Seaborne Trade			
	Seaborne Trade Iron Ore	million tonnes	2
	Seaborne Trade Coking Coal	million tonnes	2
	Seaborne Trade Steam Coal	million tonnes	2
	Seaborne Trade Grains	million tonnes	2
C. Random Shocks			
Interest Rates	LIBOR Interest Rates	%	2
Exchange Rates	Exchange Rates Japan	¥/$	2
	Exchange Rates Euro	$/€	2
Commodity Prices	US Gulf Wheat Price	$/Tonne	2
	Thermal Coal Price	$/Tonne	2
	US Gulf Corn Price	$/Tonne	2
	Brent Crude Oil Price	$/bbl	2

Notes: Table A.3.17 presents all demand variables included in the demand dataset and their unit of measurement. Price changes of all series were taken so that all of the series are stationary. All variables cover the period from January 1996 to June 2016.

Table A.3.18: Supply Dataset

A. Stock of fleet available for trading			Transformations
	Capesize Bulkcarrier Deliveries	DWT	2
Fleet $[(\boldsymbol{t}-(\boldsymbol{t}-\boldsymbol{h})]$	Fleet $h=1m$	Million DWT	2
	Fleet $h=12m$	Million DWT	3
	Fleet $h=36m$	Million DWT	3
B. Shipbuilding Production			
	Orderbook	Million DWT	2
Orders/ Fleet $[(\boldsymbol{t}-(\boldsymbol{t}-\boldsymbol{h})]$	Orders/Fleet $h=1m$	Million DWT	2
	Orders/Fleet $h=12m$	Million DWT	3
	Orders/Fleet $h=36m$	Million DWT	3
C. Scrapping Rate and Losses			
Demolition/ Fleet $[(\boldsymbol{t}-(\boldsymbol{t}-\boldsymbol{h})]$	Demolition/ Fleet	DWT	2
	Demolition/ Fleet $h=1m$	DWT	2
	Demolition/ Fleet $h=12m$	DWT	2
	Demolition/ Fleet $h=24m$	DWT	2
	Scrap Prices	$ Million	2
D. Level of Freight Rates in the market			
Earnings	P12m	$ Million	2
Price Earning Ratio (PE)	PE (Newbuild/ P12m)	ratio	2
	PE (Newbuild/ P36m)	ratio	2
	PE (5SHP/ P12m)	ratio	2
	PE (5SHP/ P36m)	ratio	2
Premium or Discount	Spot and P12m rates Changes	$ per day	2
	Spot and P36m rates Changes	$ per day	2
E. Asset Prices			
Capesize Ship Prices	176-180K DWT Newbuilding	$ Million	2
	180K 5 Year Old Secondhand	$ Million	2
	170K 10 Year Old Secondhand	$ Million	2
Ship Price Ratio	5SHP/ Newbuild	ratio	2
	10SHP/ Newbuild	ratio	2

Notes: Table A.3.18 presents all supply variables included in the supply dataset and their unit of measurement. The transformation code differs depending on the holding period horizon (h) selected. All variables cover the period from January 1996 to June 2016.

Appendix 3.B – List of Slopes and Curvatures

Table B.3.19 presents the list of slopes and curvatures examined for Model 1 and 2. Table B.3.20 and B.3.21 report all the possible combinations of the slopes and curvatures examined for Model 3.

Table B.3.19: List of Slopes and Curvatures – Model 1 and 2

	Slopes	Curvatures
1	P36m – P12m	2*P12m – (Spot + P36m)
2	P36m – P6m	2*P12m – (P6m + P36m)
3	P36m – Spot	2*P6m – (Spot + P36m)
4	P12m – P6m	2*P6m – (Spot + P12m)
5	P12m – Spot	
6	P6m – Spot	

Table B.3.20: List of all Slopes – Model 3

SLOPES combinations			
P36m_Spot	P24m_P4m	P16m_P11m	P9m_P3m
P36m_P2m	P24m_P5m	P16m_P12m	P9m_P4m
P36m_P3m	P24m_P6m	P12m_Spot	P9m_P5m
P36m_P4m	P24m_P7m	P12m_P2m	P9m_P6m
P36m_P5m	P24m_P8m	P12m_P3m	P9m_P7m
P36m_P6m	P24m_P9m	P12m_P4m	P9m_P8m
P36m_P7m	P24m_P10m	P12m_P5m	P8m_Spot
P36m_P8m	P24m_P11m	P12m_P6m	P8m_P2m
P36m_P9m	P24m_P12m	P12m_P7m	P8m_P3m
P36m_P10m	P24m_P16m	P12m_P8m	P8m_P4m
P36m_P11m	P24m_P18m	P12m_P9m	P8m_P5m
P36m_P12m	P18m_Spot	P12m_P10m	P8m_P6m
P36m_P16m	P18m_P2m	P12m_P11m	P8m_P7m
P36m_P18m	P18m_P3m	P11m_Spot	P7m_Spot
P36m_P24m	P18m_P4m	P11m_P2m	P7m_P2m
P36m_P30m	P18m_P5m	P11m_P3m	P7m_P3m
P30m_Spot	P18m_P6m	P11m_P4m	P7m_P4m
P30m_P2m	P18m_P7m	P11m_P5m	P7m_P5m
P30m_P3m	P18m_P8m	P11m_P6m	P7m_P6m
P30m_P4m	P18m_P9m	P11m_P7m	P6m_Spot
P30m_P5m	P18m_P10m	P11m_P8m	P6m_P2m
P30m_P6m	P18m_P11m	P11m_P9m	P6m_P3m
P30m_P7m	P18m_P12m	P11m_P10m	P6m_P4m
P30m_P8m	P18m_P16m	P10m_Spot	P6m_P5m
P30m_P9m	P16m_Spot	P10m_P2m	P5m_Spot
P30m_P10m	P16m_P2m	P10m_P3m	P5m_P2m
P30m_P11m	P16m_P3m	P10m_P4m	P5m_P3m
P30m_P12m	P16m_P4m	P10m_P5m	P5m_P4m
P30m_P16m	P16m_P5m	P10m_P6m	P4m_Spot
P30m_P18m	P16m_P6m	P10m_P7m	P4m_P2m
P30m_P24m	P16m_P7m	P10m_P8m	P4m_P3m
P24m_Spot	P16m_P8m	P10m_P9m	P3m_Spot
P24m_P2m	P16m_P9m	P9m_Spot	P3m_P2m
P24m_P3m	P16m_P10m	P9m_P2m	P2m_Spot

Table B.3.21: List of all Curvatures – Model 3

CURVATURES combinations			
P7m_S_P18m	P8m_P5m_P30m	P10m_P4m_P18m	P12m_P2m_P30m
P7m_S_P24m	P8m_P5m_P36m	P10m_P4m_P24m	P12m_P2m_P36m
P7m_S_P30m	P8m_P6m_P18m	P10m_P4m_P30m	P12m_P3m_P18m
P7m_S_P36m	P8m_P6m_P24m	P10m_P4m_P36m	P12m_P3m_P24m
P7m_P2m_P18m	P8m_P6m_P30m	P10m_P5m_P18m	P12m_P3m_P30m
P7m_P2m_P24m	P8m_P6m_P36m	P10m_P5m_P24m	P12m_P3m_P36m
P7m_P2m_P30m	P9m_S_P18m	P10m_P5m_P30m	P12m_P4m_P18m
P7m_P2m_P36m	P9m_S_P24m	P10m_P5m_P36m	P12m_P4m_P24m
P7m_P3m_P18m	P9m_S_P30m	P10m_P6m_P18m	P12m_P4m_P30m
P7m_P3m_P24m	P9m_S_P36m	P10m_P6m_P24m	P12m_P4m_P36m
P7m_P3m_P30m	P9m_P2m_P18m	P10m_P6m_P30m	P12m_P5m_P18m
P7m_P3m_P36m	P9m_P2m_P24m	P10m_P6m_P36m	P12m_P5m_P24m
P7m_P4m_P18m	P9m_P2m_P30m	P11m_S_P18m	P12m_P5m_P30m
P7m_P4m_P24m	P9m_P2m_P36m	P11m_S_P24m	P12m_P5m_P36m
P7m_P4m_P30m	P9m_P3m_P18m	P11m_S_P30m	P12m_P6m_P18m
P7m_P4m_P36m	P9m_P3m_P24m	P11m_S_P36m	P12m_P6m_P24m
P7m_P5m_P18m	P9m_P3m_P30m	P11m_P2m_P18m	P12m_P6m_P30m
P7m_P5m_P24m	P9m_P3m_P36m	P11m_P2m_P24m	P12m_P6m_P36m
P7m_P5m_P30m	P9m_P4m_P18m	P11m_P2m_P30m	P16m_S_P18m
P7m_P5m_P36m	P9m_P4m_P24m	P11m_P2m_P36m	P16m_S_P24m
P7m_P6m_P18m	P9m_P4m_P30m	P11m_P3m_P18m	P16m_S_P30m
P7m_P6m_P24m	P9m_P4m_P36m	P11m_P3m_P24m	P16m_S_P36m
P7m_P6m_P30m	P9m_P5m_P18m	P11m_P3m_P30m	P16m_P2m_P18m
P7m_P6m_P36m	P9m_P5m_P24m	P11m_P3m_P36m	P16m_P2m_P24m
P8m_S_P18m	P9m_P5m_P30m	P11m_P4m_P18m	P16m_P2m_P30m
P8m_S_P24m	P9m_P5m_P36m	P11m_P4m_P24m	P16m_P2m_P36m
P8m_S_P30m	P9m_P6m_P18m	P11m_P4m_P30m	P16m_P3m_P18m
P8m_S_P36m	P9m_P6m_P24m	P11m_P4m_P36m	P16m_P3m_P24m
P8m_P2m_P18m	P9m_P6m_P30m	P11m_P5m_P18m	P16m_P3m_P30m
P8m_P2m_P24m	P9m_P6m_P36m	P11m_P5m_P24m	P16m_P3m_P36m
P8m_P2m_P30m	P10m_S_P18m	P11m_P5m_P30m	P16m_P4m_P18m
P8m_P2m_P36m	P10m_S_P24m	P11m_P5m_P36m	P16m_P4m_P24m
P8m_P3m_P18m	P10m_S_P30m	P11m_P6m_P18m	P16m_P4m_P30m
P8m_P3m_P24m	P10m_S_P36m	P11m_P6m_P24m	P16m_P4m_P36m
P8m_P3m_P30m	P10m_P2m_P18m	P11m_P6m_P30m	P16m_P5m_P18m
P8m_P3m_P36m	P10m_P2m_P24m	P11m_P6m_P36m	P16m_P5m_P24m
P8m_P4m_P18m	P10m_P2m_P30m	P12m_S_P18m	P16m_P5m_P30m
P8m_P4m_P24m	P10m_P2m_P36m	P12m_S_P24m	P16m_P5m_P36m
P8m_P4m_P30m	P10m_P3m_P18m	P12m_S_P30m	P16m_P6m_P18m
P8m_P4m_P36m	P10m_P3m_P24m	P12m_S_P36m	P16m_P6m_P24m
P8m_P5m_P18m	P10m_P3m_P30m	P12m_P2m_P18m	P16m_P6m_P30m
P8m_P5m_P24m	P10m_P3m_P36m	P12m_P2m_P24m	P16m_P6m_P36m

Appendix 3.C – Additional Impulse Response Functions

The Figures C.3.12 to C.3.15 present the impulse response functions of the demand macroeconomic variables to the spot, 6-, 12- and 36-month freight rates after eliminating the financial crisis period from August 2007 to January 2009.

Figure C.3.12: Impulse Responses of Demand Variables to Spot Rates – No Crisis Period

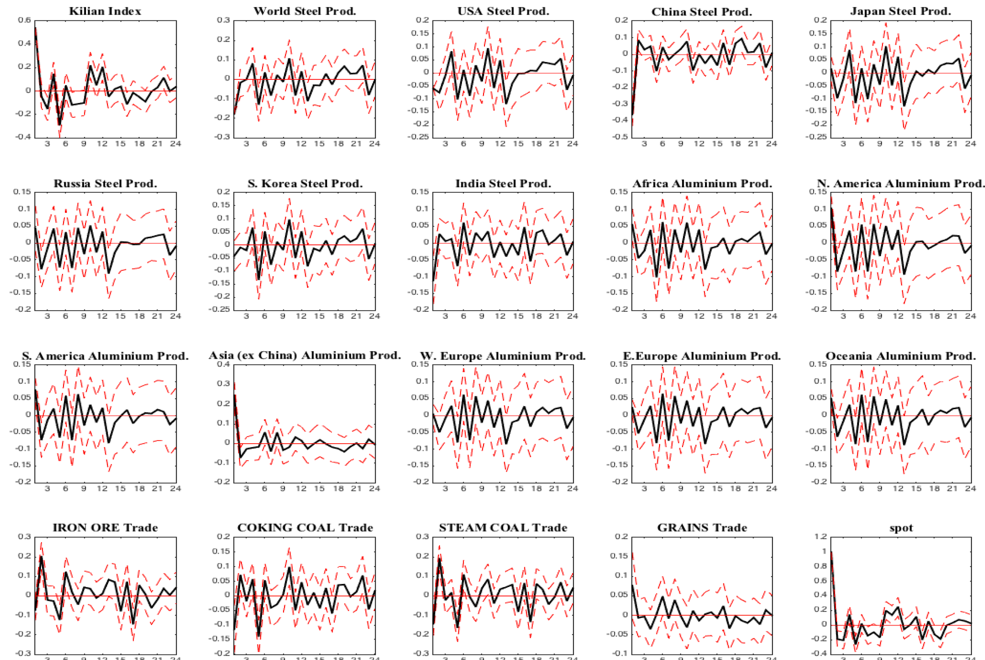


Figure C.3.13: Impulse Responses of Demand Variables to P6m Rates – No Crisis Period

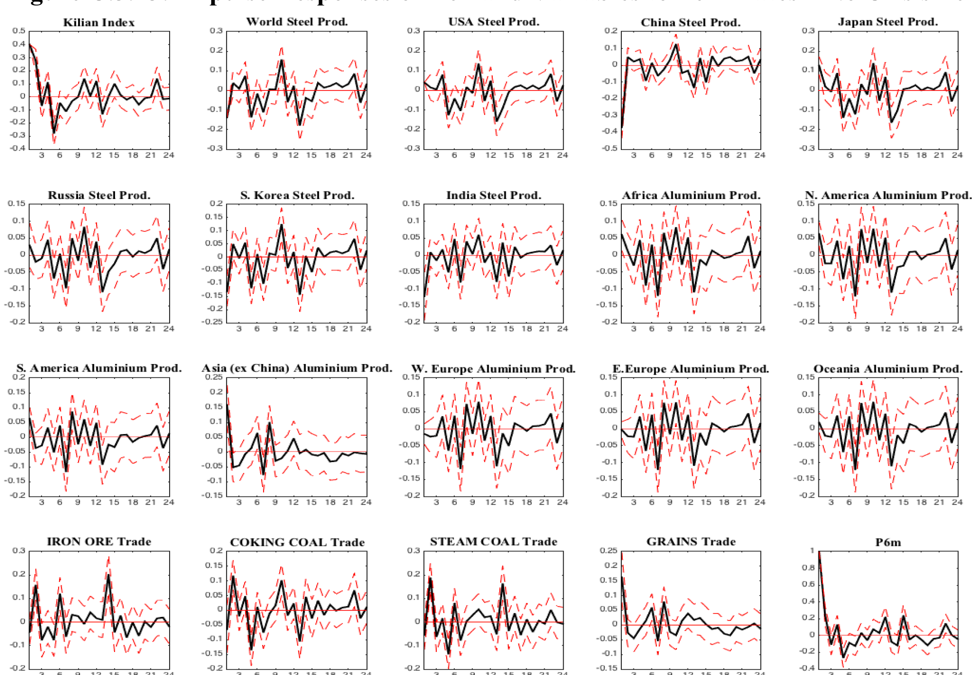


Figure C.3.14: Impulse Responses of Demand Variables to P12m Rates – No Crisis Period

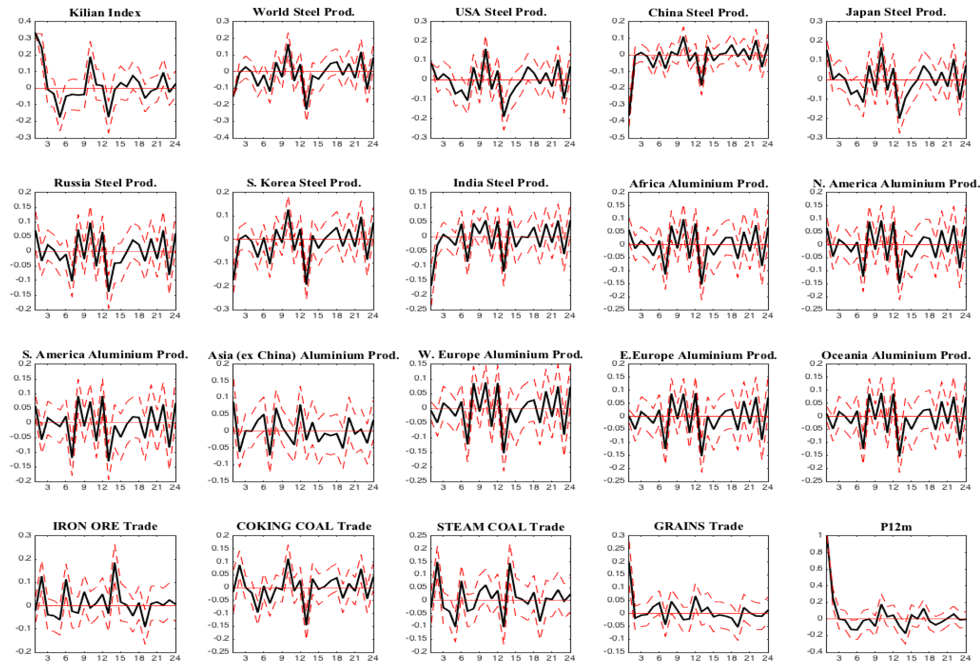
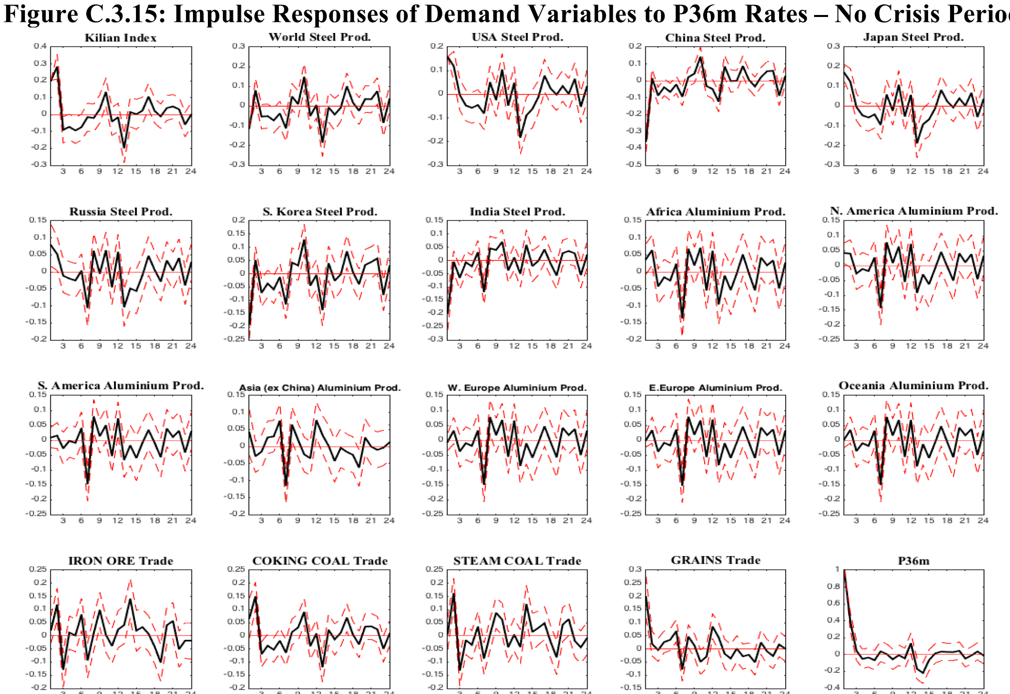


Figure C.3.15: Impulse Responses of Demand Variables to P36m Rates – No Crisis Period



The Figures C.3.16 to C.3.19 present the impulse response functions of the supply macroeconomic variables to spot, 6-, 12- and 36-month freight rates after eliminating the financial crisis period from August 2007 to January 2009.

Figure C.3.16: Impulse Responses of Supply Variables to Spot Rates – No Crisis Period

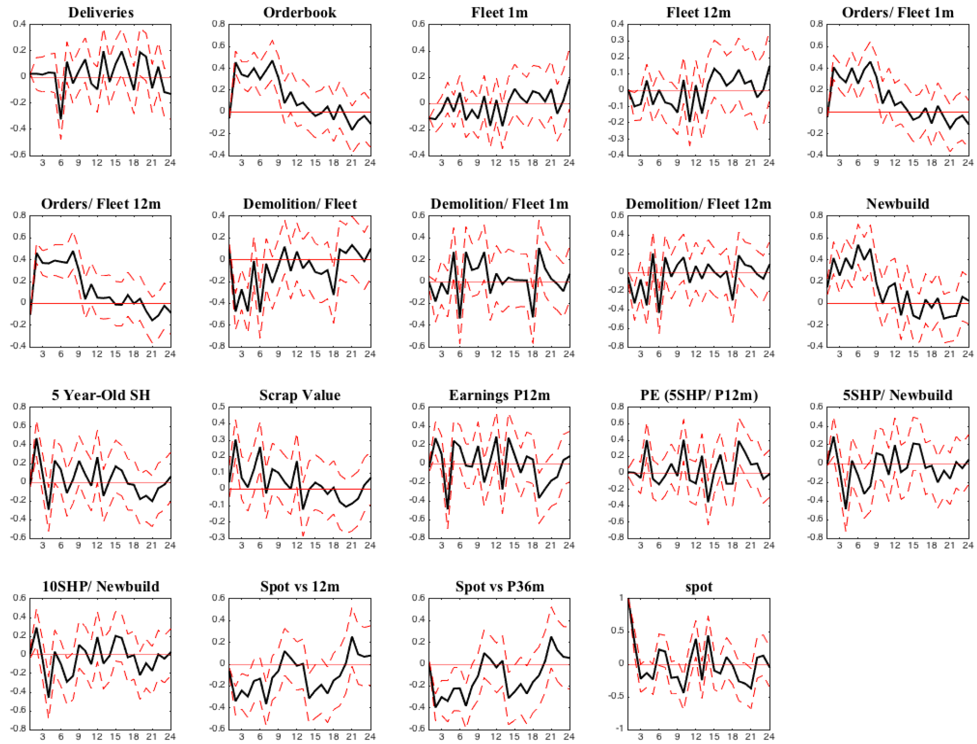


Figure C.3.17: Impulse Responses of Supply Variables to P6m Rates – No Crisis Period

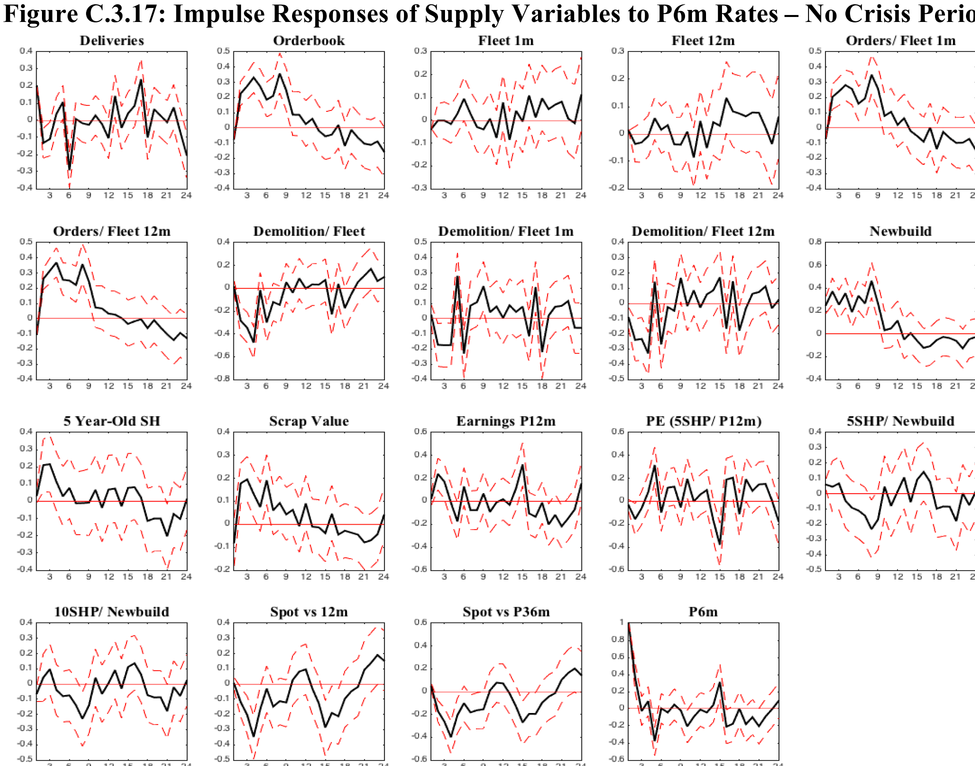


Figure C.3.18: Impulse Responses of Supply Variables to P12m Rates – No Crisis Period

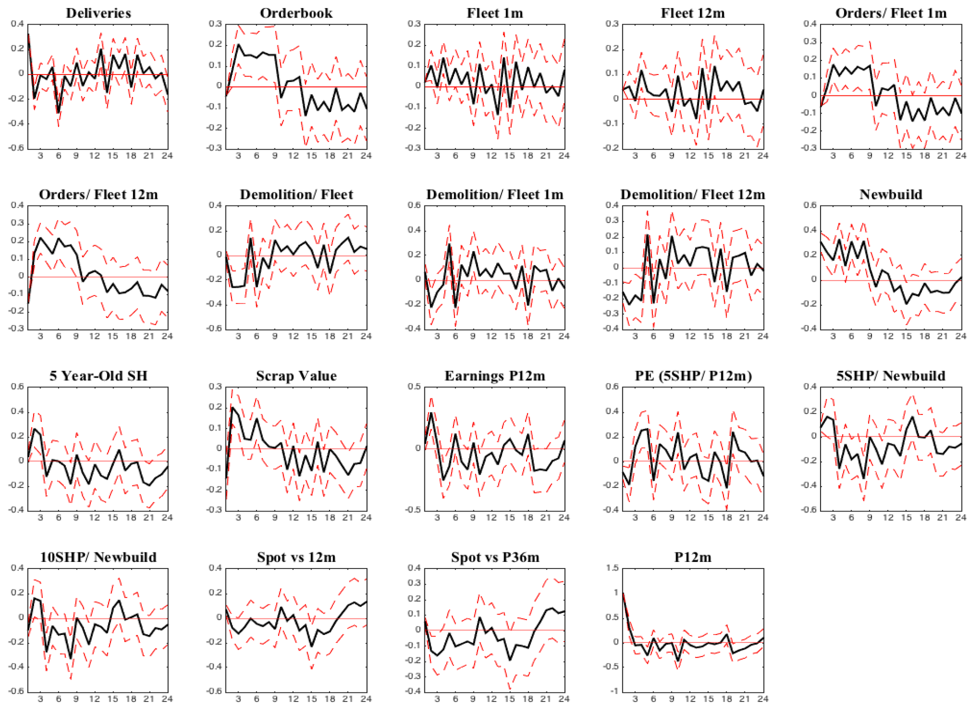
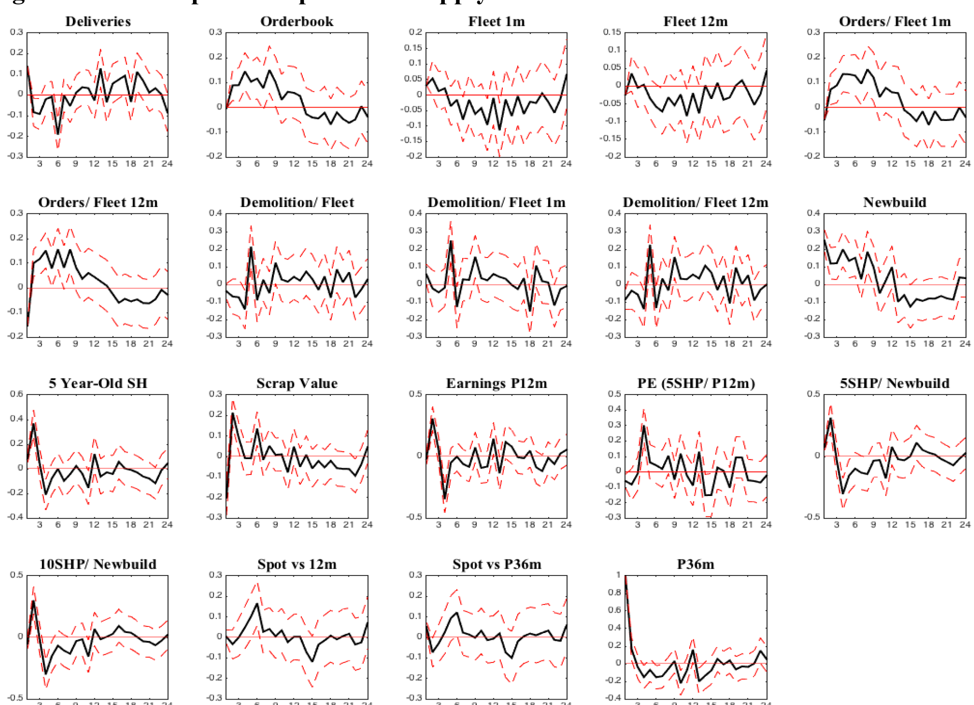


Figure C.3.19: Impulse Responses of Supply Variables to P36m Rates – No Crisis Period



Appendix 3.D – No Crisis Period Empirical Findings

Table D.3.22 presents the four and six demand and supply factors for the no financial crisis period. Table D.3.22 reports the estimated coefficients based on the demand and supply factors extracted from January 1996 to June 2016 after eliminating the financial crisis period from August 2007 to January 2009.

Table D.3.22: Demand and Supply Factors – No Crisis Period

Demand Factors		Supply Factors	
Factor 1 – Aluminium Prod. *(39.38% of total variance)*	R^2	**Factor 1 – Fleet** *(17.36% of total variance)*	R^2
N. America Aluminium Prod.	77.60%	Fleet 1m	76.81%
Oceania Aluminium Prod.	74.07%	Fleet 12m	62.38%
E.Europe Aluminium Prod.	73.61%	Orders/ Fleet 1m	61.52%
W. Europe Aluminium Prod.	72.33%	Orderbook	50.04%
		Orders/ Fleet 12m	30.54%
		Deliveries	15.64%
Factor 2 – Steel Production *(14.88% of total variance)*	R^2	**Factor 2 – Asset Prices** *(16.42% of total variance)*	R^2
China Steel Production	77.77%	5SHP/ Newbuild	89.72%
India Steel Production	45.05%	180K 5 Year Old Prices	79.14%
World Steel Production	43.58%	10SHP/ Newbuild	77.23%
South Korea Steel Production	21.07%	P12m	27.67%
		Scrap Value	14.36%
		Orderbook	0.98%
Factor 3 – Seaborne Trade *(10.50% of total variance)*	R^2	**Factor 3 – Freight Market Changes** *(12.41% of total variance)*	R^2
Seaborne Trade IRON ORE	68.41%	Spot vs P36m	89.48%
Seaborne Trade STEAM COAL	47.11%	Spot vs 12m	87.12%
Asia (ex China) Aluminium Prod.	12.50%	Demolition/ Fleet	18.41%
Seaborne Trade GRAINS	8.06%	Deliveries	7.40%
		Orders/ Fleet 12m	4.85%
		Fleet 12m	3.58%
Factor 4 – Economic Indicators *(9.00% of total variance)*	R^2	**Factor 4 – Demolition** *(11.27% of total variance)*	R^2
Kilian's Index	60.45%	Demolition/ Fleet 12m	68.50%
United States Steel Production	16.27%	Demolition/ Fleet 1m	66.77%
Japan Steel Production	15.97%	Demolition/ Fleet	55.88%
Seaborne Trade COKING COAL	15.61%	Deliveries	2.17%
		Orders/ Fleet 12m	1.37%
		Spot vs P36m	0.86%
		Factor 5 – Orderbook *(9.53% of total variance)*	R^2
		176-180K DWT Newbuilding Prices	58.76%
		Orders/ Fleet 12m	24.68%
		Orderbook	20.85%
		Orders/ Fleet 1m	18.65%
		Scrap Value	12.64%
		Deliveries	9.86%
		Factor 6 – Supply Indicators *(8.04% of total variance)*	R^2
		PE (5SHP/ P12m)	79.65%
		P12m	45.10%
		Deliveries	8.69%
		Demolition/ Fleet 1m	3.17%
		Fleet 12m	1.48%
		Orderbook	0.28%
Total Variance explained	**73.76%**	**Total Variance** explained	**75.00%**

Notes: Table D.3.22 presents the four and six factors of the *Demand* and *Supply* datasets, which explain in total approximately 73% and 75% of the total variation of the time series in each panel. The factors are extracted for the sample period from January 1996 to June 2016 after eliminating the financial crisis period from August 2007 to January 2009. The R^2 is obtained through univariate regressions of the factors extracted from the panel of macroeconomic variables on all individual variables. The table lists the four (six) most highly correlated variables with each factor. Note that prior to extracting the factors, the series have been transformed in order to be stationary, i.e. for most variables, the regressions correspond to regressions on percentage changes.

Table D.3.23: Regressions based on the Demand and Supply Factors – No Crisis Period

Demand					Supply				
Logarithmic Differences	**Spot**	**P6m**	**P12m**	**P36m**	**Logarithmic Differences**	**Spot**	**P6m**	**P12m**	**P36m**
Constant	-0.001	-0.001	-0.001	-0.002	**Constant**	-0.003	-0.001	-0.002	-0.004
SE	0.014	0.011	0.009	0.007	SE	0.015	0.011	0.008	0.006
pvalue	0.929	0.927	0.902	0.741	pvalue	0.848	0.923	0.784	0.638
F1 – Aluminium Production	0.026	0.023	0.020	0.016	**F1 – Fleet**	0.014	0.009	0.008	0.006
SE	0.020	0.010	0.010	0.011	SE	0.013	0.007	0.005	0.007
pvalue	0.096	0.034	0.016	0.020	pvalue	0.345	0.388	0.321	0.464
F2 – Steel Production	-0.044	-0.030	-0.023	-0.022	**F2 – Asset Prices**	0.041	0.045	0.037	0.026
SE	0.026	0.014	0.009	0.007	SE	0.024	0.020	0.017	0.015
pvalue	0.004	0.008	0.005	0.002	pvalue	0.008	0.000	0.000	0.001
F3 – Seaborne Trade	0.023	0.001	-0.017	-0.005	**F3 – Freight Market Changes**	-0.081	-0.025	-0.012	-0.002
SE	0.024	0.014	0.009	0.009	SE	0.018	0.009	0.006	0.008
pvalue	0.128	0.931	0.041	0.440	pvalue	0.000	0.014	0.110	0.793
F4 – Economic Indicators	0.181	0.122	0.093	0.061	**F4 – Demolition Market**	-0.006	0.000	-0.007	-0.011
SE	0.028	0.014	0.015	0.016	SE	0.018	0.007	0.004	0.007
pvalue	0.000	0.000	0.000	0.000	pvalue	0.685	0.971	0.367	0.136
					F5 – Orderbook	0.016	0.025	0.033	0.029
					SE	0.021	0.021	0.021	0.017
					pvalue	0.292	0.012	0.000	0.000
					F6 – Supply Indicators	-0.185	-0.140	-0.110	-0.052
					SE	0.028	0.013	0.008	0.009
					pvalue	0.000	0.000	0.000	0.000
Logarithmic Differences (t-1)	-0.062	-0.013	0.054	0.150	**Logarithmic Differences (t-1)**	-0.053	-0.016	-0.008	0.082
SE	0.065	0.051	0.060	0.067	SE	0.051	0.034	0.033	0.045
pvalue	0.255	0.809	0.323	0.012	pvalue	0.329	0.759	0.879	0.219
LL	17.022	90.458	149.34	177.47	**LL**	25.107	111.287	172.23	163.24
R^2	0.401	0.374	0.398	0.359	**R^2**	0.460	0.513	0.555	0.318
RMSE	0.227	0.163	0.124	0.098	**RMSE**	0.219	0.146	0.109	0.102
MSE	0.052	0.027	0.015	0.010	**MSE**	0.048	0.021	0.012	0.010
Residual Diagnostics					**Residual Diagnostics**				
Jarque – Bera test	12.274	5.880	34.626	360.03	**Jarque – Bera test**	571.84	20999.1	173569.3	46656.2
pvalue	0.009	0.047	0.001	0.001	pvalue	0.001	0.001	0.001	0.001
Q test	37.654	37.357	14.641	42.413	**Q test**	58.310	36.073	9.678	16.401
pvalue	0.010	0.011	0.797	0.002	pvalue	0.000	0.015	0.974	0.691
ARCH test	8.348	4.090	2.178	0.218	**ARCH test**	1.245	0.000	0.001	0.003
pvalue	0.004	0.043	0.140	0.640	pvalue	0.264	0.993	0.974	0.959

Notes: Table D.3.23 – reports the estimated coefficients based on the extracted factors (see Equation 3.14), i.e. $FR_t = a + \beta FR_{t-1} + (1-\beta)(\phi_{F1}F1_t + \phi_{F2}F2_t + \cdots + \phi_{F6}F6_t)$, where FR denotes the spot, P6m, P12m and P36m freight rate, $F1_t$ to $F4_t$ indicate the four macroeconomic factors extracted from the Demand dataset and $F1_t$ to $F6_t$ represent the six macroeconomic factors extracted from the Supply datasets between 1996:01 to 2016:06 after eliminating the financial crisis period from 2007:08 to 2009:01. The table also reports the coefficient of each variable – B, the standard errors and their p-values. The Jarque-Bera, Ljung-Box Q test and the ARCH tests are used to examine the heteroscedasticity and normality of the residuals series. The loglikelihood test (LL), the coefficient of determination R^2, the RMSE and MSE assess the model's adequacy and significance. Newey and West (1987) method is used to estimate the standard errors of the regression coefficients, corrected for heteroscedasticity and serial correlation.

Tables D.3.24 and D.3.25 present the performance for the regressions of the latent freight rates factors onto the macroeconomic factors and the freight rate series from January 1996 to June 2016 after eliminating the financial crisis period from August 2007 to January 2009.

Table D.3.24: Regressions of Latent Factors in the model Demand Factors – No Crisis Period

	Spot Levels			P6m Levels			P12m Levels			P36m Levels		
	Level	Slope	Curvature	Level	Slope	Curvature	Level	Slope	Curvature	Level	Slope	Curvature
Constant	9.674	-0.244	-0.024	9.679	-0.246	-0.023	9.676	-0.245	-0.023	9.697	-0.258	-0.030
SE	0.067	0.045	0.030	0.067	0.042	0.029	0.065	0.042	0.028	0.065	0.043	0.029
pvalue	0.000	0.000	0.166	0.000	0.000	0.170	0.000	0.000	0.181	0.000	0.000	0.104
F1 – Aluminium Production	0.003	-0.001	-0.011	-0.010	0.000	-0.025	-0.011	0.001	-0.025	-0.008	-0.008	-0.017
SE	0.021	0.025	0.011	0.019	0.028	0.010	0.021	0.030	0.012	0.024	0.029	0.014
pvalue	0.930	0.970	0.549	0.765	0.993	0.137	0.746	0.970	0.139	0.803	0.789	0.346
F2 – Steel Production	0.016	0.025	0.020	0.016	0.034	0.031	0.021	0.035	0.032	0.042	0.040	0.036
SE	0.031	0.034	0.012	0.032	0.039	0.011	0.033	0.041	0.011	0.039	0.045	0.010
pvalue	0.618	0.351	0.264	0.639	0.204	0.075	0.531	0.193	0.061	0.229	0.161	0.057
F3 – Seaborne Trade	0.015	-0.031	0.004	0.013	-0.038	0.003	0.024	-0.046	0.016	0.020	-0.044	0.007
SE	0.022	0.019	0.012	0.023	0.022	0.013	0.025	0.022	0.014	0.027	0.023	0.016
pvalue	0.653	0.239	0.814	0.690	0.147	0.865	0.459	0.088	0.341	0.559	0.117	0.687
F4 – Economic Indicators	0.019	-0.016	0.030	0.021	-0.056	-0.014	-0.004	-0.056	-0.022	-0.007	-0.081	0.002
SE	0.038	0.045	0.014	0.038	0.048	0.017	0.046	0.049	0.019	0.055	0.045	0.021
pvalue	0.646	0.635	0.177	0.610	0.090	0.508	0.912	0.093	0.290	0.869	0.015	0.922
Logarithmic Differences	0.029	-0.404	0.024	0.069	-0.273	0.424	0.323	-0.359	0.615	0.668	-0.134	0.611
SE	0.112	0.099	0.071	0.189	0.160	0.092	0.299	0.280	0.135	0.474	0.361	0.196
pvalue	0.843	0.001	0.764	0.735	0.100	0.000	0.225	0.100	0.000	0.062	0.648	0.002
Residual Diagnostics Tests												
J - B test	5.058	1.891	0.299	4.891	2.672	0.836	4.618	6.112	1.080	4.784	10.893	1.786
pvalue	0.065	0.340	0.500	0.070	0.215	0.500	0.079	0.043	0.500	0.073	0.012	0.360
Q test	1696.2	533.13	658.55	1754.1	480.76	795.43	1683.3	469.38	738.13	1544.6	450.28	670.69
pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ARCH	178.34	75.506	63.846	187.03	34.767	74.464	183.03	27.695	59.167	170.288	23.377	41.117
pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LL	-153.89	-103.66	-14.646	-155.50	-108.69	-7.443	-152.19	-107.62	-5.199	-141.93	-101.58	-13.121
R^2	-0.018	0.096	0.002	-0.017	0.058	0.075	-0.011	0.060	0.088	0.003	0.049	0.056
RMSE	0.486	0.389	0.262	0.490	0.398	0.254	0.485	0.397	0.251	0.487	0.401	0.262
MSE	0.236	0.151	0.069	0.240	0.158	0.064	0.236	0.158	0.063	0.238	0.161	0.068

Notes: Table D.3.24 summarises the results of a regression of level, slope, and curvature freight rate factors onto the demand factors of the FAVAR model. The coefficients of each variable are presented along with the standard errors and the pvalues. Jarque-Bera, the Ljung-Box Q and the ARCH tests were used to examine the heteroscedasticity and normality of the residuals series. The loglikelihood test (LL), the coefficient of determination R^2, the RMSE and MSE assess the model's adequacy and significance. Newey and West (1987) method is used to estimate the standard errors of the regression coefficients, corrected for heteroscedasticity and serial correlation. The sample period is 1996:01 - 2016:06, after eliminating the financial crisis period from 2007:08 to 2009:01.

Table D.3.25: Regressions of Latent Factors in the model Supply Factors – No Crisis Period

	Spot Levels			P6m Levels			P12m Levels			P36m Levels		
	Level	**Slope**	**Curvature**	**Level**	**Slope**	**Curvature**	**Level**	**Slope**	**Curvature**	**Level**	**Slope**	**Curvature**
Constant	9.682	-0.263	-0.016	9.682	-0.263	-0.015	9.681	-0.264	-0.015	9.697	-0.268	-0.023
SE	0.048	0.017	0.029	0.047	0.017	0.029	0.048	0.017	0.029	0.045	0.018	0.029
pvalue	0.000	0.000	0.315	0.000	0.000	0.329	0.000	0.000	0.355	0.000	0.000	0.177
F1 – Fleet Changes	0.027	0.032	-0.025	0.027	0.032	-0.031	0.030	0.032	-0.028	0.012	0.037	-0.023
SE	0.035	0.012	0.020	0.035	0.012	0.020	0.035	0.013	0.021	0.038	0.015	0.022
pvalue	0.253	0.002	0.102	0.253	0.002	0.046	0.209	0.002	0.079	0.661	0.001	0.207
F2 – Asset Prices	0.119	-0.054	0.078	0.124	-0.056	0.062	0.125	-0.057	0.066	0.120	-0.056	0.070
SE	0.035	0.012	0.020	0.035	0.013	0.021	0.033	0.012	0.020	0.034	0.012	0.018
pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F3 – Freight Market Changes	-0.202	0.362	-0.048	-0.197	0.362	-0.036	-0.193	0.362	-0.036	-0.182	0.360	-0.046
SE	0.039	0.037	0.035	0.037	0.037	0.035	0.036	0.037	0.034	0.035	0.040	0.038
pvalue	0.000	0.000	0.004	0.000	0.000	0.024	0.000	0.000	0.023	0.000	0.000	0.007
F4 - Demolition	-0.070	0.051	-0.021	-0.067	0.051	-0.015	-0.070	0.051	-0.019	-0.073	0.049	-0.018
SE	0.024	0.011	0.011	0.024	0.011	0.009	0.024	0.011	0.011	0.025	0.011	0.011
pvalue	0.003	0.000	0.179	0.006	0.000	0.354	0.004	0.000	0.241	0.003	0.000	0.284
F5 – Orderbook	0.267	-0.065	0.104	0.273	-0.067	0.099	0.272	-0.067	0.095	0.274	-0.067	0.098
SE	0.043	0.014	0.020	0.042	0.014	0.021	0.045	0.015	0.021	0.046	0.015	0.022
pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F6 – Supply Indicators	0.023	0.060	-0.055	0.021	0.065	-0.006	0.020	0.064	-0.010	0.035	0.063	-0.034
SE	0.040	0.017	0.020	0.041	0.016	0.024	0.043	0.015	0.024	0.036	0.013	0.017
pvalue	0.454	0.000	0.008	0.517	0.000	0.788	0.554	0.000	0.647	0.212	0.000	0.072
Logarithmic Differences	-0.161	0.011	-0.125	-0.225	0.050	0.195	-0.297	0.051	0.194	-0.279	0.089	0.031
SE	0.132	0.046	0.061	0.190	0.061	0.094	0.234	0.089	0.140	0.357	0.121	0.110
pvalue	0.142	0.812	0.086	0.173	0.473	0.074	0.185	0.591	0.191	0.268	0.411	0.858
Residual Diagnostics Tests												
J - B test	0.814	803.45	11.860	1.063	789.47	8.339	1.736	789.15	11.577	5.387	895.745	17.332
pvalue	0.500	0.001	0.010	0.500	0.001	0.022	0.370	0.001	0.010	0.056	0.001	0.004
Q test	723.38	222.35	384.54	734.82	226.12	418.15	712.70	220.35	393.75	604.37	221.42	372.59
pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ARCH	43.461	8.851	51.171	39.505	9.167	55.002	36.688	9.268	42.103	28.822	8.426	36.435
pvalue	0.000	0.003	0.000	0.000	0.002	0.000	0.000	0.002	0.000	0.000	0.004	0.000
LL	-71.808	111.55	17.860	-72.245	111.595	17.530	-71.665	109.99	16.230	-67.529	98.903	9.020
R^2	0.510	0.870	0.261	0.515	0.871	0.268	0.510	0.870	0.255	0.513	0.866	0.247
RMSE	0.344	0.147	0.227	0.345	0.147	0.227	0.345	0.147	0.229	0.347	0.150	0.236
MSE	0.119	0.022	0.052	0.119	0.022	0.052	0.119	0.022	0.052	0.121	0.022	0.056

Notes: Table D.3.25 summarises the results of a regression of level, slope, and curvature freight rate factors onto the Supply factors of the FAVAR model. The coefficients of each variable are presented along with the standard errors and the pvalues. Jarque-Bera, the Ljung-Box Q and the ARCH tests were used to examine the heteroscedasticity and normality of the residuals series. The loglikelihood test (LL), the coefficient of determination R^2, the RMSE and MSE assess the model's adequacy and significance. Newey and West (1987) method is used to estimate the standard errors of the regression coefficients, corrected for heteroscedasticity and serial correlation. The sample period is 1996:01-2016:06, after eliminating the financial crisis period.

Chapter 4
Prospect Theory and the Conditional Relationship Between Risk and Return in the Dry Bulk Shipping Market

This chapter focuses on the nature of the *relationship* between *risk* and *return* in the dry bulk freight market in order to understand firms' competitive behaviour. The purpose is to determine the nature of the risk and return relationship and to investigate how this relationship behaves under different scenarios (i.e. risk measures, return measures, subsamples, market conditions and controlling variables associated with the freight rate cycle). More specifically, the risk measures used are the Simple Variance Approach (SVA), the Exponentially Weighted Moving Average Variance (EWMAV), GARCH, eGARCH, gjrGARCH and Value at Risk (VaR) approach. Additionally, the returns are measured using the logarithmic differences of four different types of freight rates (i.e. the spot, the 6-, 12- and 36-month period charter rates). The returns are also estimated for three holding periods (i.e. $h = 1-, 12-\ and\ 24-months$) in order to examine whether the risk-return trade-off is robust over time. The empirical analysis shows that the relationship is sensitive in most of the aforementioned scenarios.

4.1 Introduction

One crucial problem that portfolio managers face on daily basis is the ability to predict the market returns in future periods and explain the nature of return variations. They usually have to decide whether or not to proceed with an investment based on the risk and return trade off. Sharpe (1964) and Lintner (1965) developed the Capital Asset Pricing Model (CAPM), an equilibrium model that determines asset returns in the financial world and implies that there is a positive relationship between risk and return. This positive relationship mainly arises from a risk-averse reasoning, for instance, investors usually require more volatile investments to pay higher returns and vice versa.

Assuming that the risk and return values of an investment can be characterised as either low or high, Table 4.1 shows that there are four different trade-offs.

According to the CAPM, investments are usually priced based on the trade-offs A (i.e. low risk and return) and B (i.e. high risk and return). Although a negative risk and return trade off (trade-off C and D) is considered as a paradoxical finding based on the financial theory, there is evidence in the literature supporting the existence of a negative risk and return relationship.

Table 4.1: Risk and Return trade-offs

	Low Risk	**High Risk**
High Return	**C** Low Risk High Return	**B** High Risk High Return
Low Return	**A** Low Risk Low Return	**D** High Risk Low Return

Ship-owners are attracted to the high return and low risk investments opportunities offered by the volatility of the shipping cycles and its other characteristics, especially the liquid market for shipping assets. For instance, when ship-owners order a new vessel that will be built in the next 2 to 3 years, the demand for shipping services might be low by the time it gets delivered therefore this high risk decision could result in low returns. For instance, a Capesize vessel ordered in August 2008 for \$99 million is worth \$52 million at the time it was delivered in July 2011 resulting in a \$47 million loss. However, this strategy could sometimes bring high returns too. For instance, a Capesize bulk carrier ordered in December 2005 for \$59 million was resold on delivery in December 2007 for \$97 million which means a \$38 million return on the \$2 million deposit paid when the ship was ordered.

Additionally, investments that present low risk and high return can reflect the price of giving up the volatility. If a ship-owner charters his ship for 10 years he will only be able to get in return the set and agreed charter hire price for that period which means that he might demand a higher return to compensate for the loss of flexibility. The unusual shipping risk-return profile can be explained from the fact that shipping entrepreneurs have different risk preference compared to typical financial institutions so they price investments differently (Stopford, 2009).

The risk and return relationship has been widely tested with financial data from the stock market using the beta of CAPM as the risk measure and the results appeared to be contradictory. Most research studies prior to Fama and French (1992) showed a significant positive relationship as the CAPM theory suggests. A new research group known as *"the death of beta"* (Clare et al, 1998; Grundy and Malkiel, 1996 amongst others) identified positive, negative or no correlation between return and beta. For instance, French et al (1987); Baillie and DeGennaro (1990); Campbell and Hentschel (1992); Genotte and Marsh (1993); Fletcher (2000); Hodoshima et al (2000); Ghysels et al (2005); Connolly et al (2005); Fama and French (2012) found that despite being insignificant in most cases, the relationship between conditional variance and conditional expected returns is positive. Using different approaches such as a GARCH-M model, VaR approach, etc. to model the conditional variance, Turner et al (1989); Glosten et al (1993); Harvey (2001); Brandt and Kang (2004) and Bae et al (2007) found both a positive and negative relation depending on the method that was used. On the other hand, Campbell (1987) and Nelson (1991) found a significant negative relation.

Additionally, practical applications in the financial sector proved that biases are generally present in beta estimates when the Ordinary Least Squares approach for one-factor market models is used. Therefore, over the last decades, many modifications of the CAPM have been introduced as an attempt to estimate betas with a better fit for the models.

Pettengill et al (1995); Pedersen and Hwang (2007) and Galagedera (2009) focused on how to overcome the biases resulting from the beta estimates. More specifically, they observed that investors are not equally concerned about the upside and downside risk as they mainly tend to focus on disastrous effects on their portfolios caused by downside risk. The traditional CAPM assumes that the covariance between the asset returns volatility in respect to market returns volatility remains constant throughout the whole investment horizon. Wu and Chiou (2007); Choudhry and Wu (2008) and Huang and Hueng (2008) observed that time-varying betas appear to react to most up-to-date information, which is accounted in asset returns, and therefore produce more accurate returns estimations for the next period. Additionally, the empirical findings confirm the existence of a positive risk-return relationship in the up market (positive market excess returns) and a negative one in the down market (negative market excess returns). Further studies conducted by Kaplanski and Kroll (2001), Bali et al (2009) and Talebnia et al (2011) confirmed the asymmetrical effect of the downside risk and portfolio returns using value at risk and conditional value at risk measures.

Multiple studies in the shipping literature focus on how returns react to contemporaneous changes in risk factors, which can be further divided into firm-specific, microeconomic and macroeconomic factors. For example, Grammenos and Marcoulis (1996) found that the returns are positively correlated with the stock market index beta and the financial leverage whereas a negative relationship was found between the average age of the fleet and the dividend yield. Later on, Kavussanos and Marcoulis (2000a and 2000b) investigated the relationship between macro- and micro-factors and the cross-section of US transport industry returns. Their empirical findings indicate that rising levels of industrial production and changes in oil prices were associated with higher stock returns whereas consumption levels appeared to be negatively correlated with the returns. Similarly, Grammenos and Arkoulis (2002) analysed the relationship between the returns and a set of macroeconomic factors and found that the oil prices and laid up tonnage are negatively associated with shipping stocks, whereas the exchange rate variable displayed a positive relationship. On the other hand, inflation and industrial production appeared to have a non-significant relationship. Kavussanos et al (2003) compared the return structure of different sectors of the shipping industry and did not detect notable differences in the systematic (market) risk across sectors but found a stock market beta smaller than unity for most sectors. Gong et al (2006) examined the stability of the beta estimates in the shipping industry and their empirical findings indicate that the estimated betas vary considerably depending on the estimation technique over their sample period from 1984 to 1995.

Syriopoulos and Roumpis (2009) focused on the risk and return characteristics and used alternative asymmetric volatility models such as, GARCH, EGARCH and APGARCH, in order to identify the best fit that can adequately describe shipping volatility dynamics. The models were found to be statistically satisfactory representations of the shipping stock volatility, while they were also able to take into account asymmetries in unanticipated shocks. For instance, the presence of leverage effect was found to be negative and statistically significant for some shipping stocks indicating that a negative shock is expected to potentially cause the volatility to rise more than a positive shock of the same magnitude. Additionally the authors used the Value at Risk measure to obtain a better empirical insight on the risk profile of shipping stocks. The results supported the fact that the GARCH model provides a more accurate estimation of Value at Risk. Drobetz et al (2010) investigated multiple macroeconomic risk factors (such as world stock market index, currency fluctuations against the US$, changes in industrial production and in the oil prices) that drive the expected stock returns in the shipping industry in its three sectors: container, tanker and bulker shipping. Tezuka et al (2012) main focus was on whether the introduction of policies for promoting competition increases beta, and if an increase in market power due to cooperation and concentration among firms reduces beta. Therefore, it can be concluded that most of the research studies in the shipping literature support the existence of a positive risk and return relationship.

Apart from the financial stream where a negative relationship between risk and return was found, there are also empirical studies from an economic and organisation theory perspective that also identified a negative slope between risk and return (Bowman, 1980, 1982, 1984). More specifically, Bowman noted the existence of a *risk-return paradox* (also known as *Bowman's paradox*) in strategic management; namely that business risk and returns are negatively correlated across companies within most industries.

An extensive number of researchers studied the Bowman's paradox from a strategic management perspective. These studies can be grouped into two themes with one consisting of research studies that theoretically justify the paradox (Nickel and Rodriguez, 2002) and the other, which includes studies that address methodological mistakes presented in previous studies. More specifically, regarding the first theme, the paradox can be explained using one of the following two main points: the decision-maker's behaviour towards risk as defined by prospect and behavioural theory or the strategic position of the firm (i.e. diversification strategy, the market power or the negative effects of the historic risk of returns). As for the second theme, the focus is on methodological errors attributed to alternative 'measures' used in the studies as well as the statistical methodology. The term 'measures' refers to the nature of the industry, the time period studied (Fiegenbaum and Thomas, 1985, 1986), firm size, diversification strategies (Bettis and Hall, 1982; Bettis and Mahajan, 1985), risk measures and risk attitudes (Bowman, 1982). Nickel and Rodriguez (2002) stated that the weakness of most existing studies is around the correct measure of risk, the stability of the relationship or their cross sectional design There are multiple research studies that focus on different risk measures that can be used to overcome the problem of identification.

The problem of identification is due to the fact that the mean and variance are measured based on the same variable and that the variance is measured ex-post rather than be ex-ante. Therefore, using GARCH models that measure mean and variance through different equations should overcome the problem of identification. Three more methods, the simple variance approach, Value at Risk approach and the exponentially weighted moving average variance approach, are used to measure the risk in order to compare different risk estimation and test whether financial risk measures can explain the risk and return relationship.

Even though the aforementioned studies investigated factors that affect the risk and return relationship whilst focusing on ways to accurate estimate volatility, to the best of our knowledge there is a limited number of studies that investigate important aspects that might affect the nature of the risk and return relationship of operational strategies in the dry bulk freight market. Therefore, this study contributes to the literature on finance and management by investigating the nature of the relationship between risk and returns in the shipping industry through several dimensions such as time; multiple (i.e. bull and bear) market conditions and using multiple valuation models.

The risk and return relationship is analysed using multiple risk and return measures since various studies support the fact that the negative association between risk and return may be due to statistical errors (Denrell, 2004; Ruefli, 1990; Ruefli and Wiggins, 1994) or to the choice of risk and return measures used (Baucus, Golec and Cooper, 1993). This study then looks into the nature of the relationship under different time periods and market conditions in order to examine the potential influence time period and market conditions on the risk-return results. For instance, the asymmetric risk-return relationship in the up- and down-markets of shipping freight rates is analysed and the expected result is that the risks are positively correlated with the returns in a bull market and negatively associated in a bear market.

Additionally, this study attempts to examine whether or not there is evidence of a negative association between risk and returns in the past and what can explain this phenomenon. None of the existing studies investigates the attitudes toward risk and the risk-return paradox in the shipping industry by relying on behavioural decision theory and Prospect Theory. Therefore, the analysis will use behavioural decision theory and *Prospect Theory* (Kahneman and Tversky, 1979), which supports the fact that decision makers become risk seekers or risk averse depending on if the performance has been below or above a specific target level. This examination of past performance could potentially explain the relationship between risk and return in shipping investments.

There are only a few studies that investigate risk preferences or risk attitudes in the shipping industry. Norman (1971) attempted to estimate risk preferences from market data whilst Lorange and Norman (1971) examined risk preferences in the Scandinavian (Norwegian) tanker industry. They assumed that Norwegian shipowners acted in accordance with the von Neumann-Morgenstern (1953) axioms in terms of choice under uncertainty and took under consideration capital market imperfections. More specifically, they specified two different liquidity positions and tested how these affected the results. The outcome suggested that risk preferences fall into three distinct groups. According to the first profile, ship-owners are risk seekers under the assumption of good liquidity but are risk averse when faced with a weak liquidity position. Shipowners are risk neutral when the market liquidity is good and become risk averse under conditions of weak liquidity (second risk profile). Thirdly, Lorange and Norman (1971) linked risk preferences to the following series of business policy parameters: distribution of fleet across trades (tank, bulk, etc.), rate of expansion in various trades, age and size distribution of the fleet and chartering policy. Cullinane (1991) developed a concave utility function for risk-averse ship-owners and a convex utility function for risk-seeking ship-owner. The empirical findings show that factors such as nationality, industry and liquidity conditions have no influence over the risk averse and risk-seeking attitude.

Greenwood and Hanson (2015) study demonstrated that high current ship earnings are associated with higher ship prices and industry investment but suggest low future returns on capital. They also found that shipowners tend to over invest in new capacity during booms due to being overconfident and incorrectly believing that investments will continue to reap high returns. Greenwood and Hanson (2015) attribute this behaviour partly to *“competition neglect”* by shipowners, which is caused by the time lag in the shipbuilding process (Kahneman, 2011). They also found that shipping firms overinvest in boom periods because they over-extrapolate abnormally high future profits. The empirical findings support the fact that decision makers become risk seekers (a convex value function) or risk averse (a concave value function) depending on if the performance has been below or above a certain target level.

To sum up, the contribution of this chapter is that it investigates the nature of the risk and return relationship in shipping investments under multiple dimensions such as time and market conditions (i.e. bull and bear) using multiple valuation models and risk attitudes conceptualised by the prospect theory. It is expected for the risk-return relationship to be dependent on the particular time period studied and the risk measure used. Additionally, risk-seeking attitudes should be below return levels and risk-averse attitudes above return levels. This means that the utility function is an S-shape and the expectation is that there is a negative risk-return association below target levels and a positive risk-return association above target-levels. Finally, the findings should also provide useful insight for investment decisions in the sale and purchase, shipbuilding and demolition shipping markets.

The rest of the chapter defines the conceptual model that determines the behaviour of shipping investments (Section 4.2). Following that, section 4.3 presents and evaluates the data and empirical results whilst the final section concludes and discusses future research.

4.2 Methodology

The next sections present the measures used to investigate the nature of the risk and return relationship. The purpose is to test whether or not the use of different risk and return measures, time periods, market conditions, control variables and risk attitudes can affect the relation of the risk and return profile.

4.2.1 Benchmark Risk and Return Relationship

The benchmark model investigates the relationship between risk and return using the $eGARCH\ (p, q)$ model to measure risk whilst the returns R_{Tij} are estimated using the continually compounded logarithmic freight rate differences:

$$R_{tij} = a + b_{tij}\mathrm{E}_{t-1,i,j}\left(VAR_{tij}\right) + \varepsilon_{tij} \tag{4.1}$$

where R_{Tij} represents the monthly returns of a type i vessel (where $i\ =$ Capesize) and freight rate j (where $j\ =$ spot, 6-, 12- and 36-months period freight rates). The returns R_{Tij}, are estimated using the continually compounded logarithmic freight rate differences expressed as:

$$R_{tij} = lnFR_{tij} - lnFR_{(t-1)ij} \tag{4.2}$$

ε_{Tij} represents the residual term whilst the coefficients a and b_{Tij} should be zero and equal to the relative risk aversion coefficient respectively according to the CAPM theory. The conditional volatility $\mathrm{E}_{t-1,i,j}\left(VAR_{tij}\right)$ is measured using the $eGARCH\ (p, q)$ approach. An $eGARCH\ (p, q)$ model is an innovation process that addresses conditional heteroscedasticity while also measuring the variance of returns over time. The model suggests that the current conditional variance is the sum of past logged conditional variances and magnitudes of past-standardised innovations, also known as the leverage component. Additionally, the use of an $eGARCH$ model is appropriate when positive and negative shocks of equal magnitude do not equally contribute to the volatility (Tsay, 2010). The $eGARCH$ approach mathematically models the conditional variance process as follows:

$$\Delta lnFR_t = \mu + \varepsilon_t \qquad \varepsilon_t \sim N(0, logh_t^2)$$
$$\text{where } logh_t^2 = a_0 + \sum_{i=1}^{p} \gamma_i logh_{t-i}^2 + \sum_{j=1}^{q} a_j \left[\frac{|\varepsilon_{t-j}|}{h_{t-j}} - \mathrm{E}\left\{\frac{|\varepsilon_{t-j}|}{h_{t-j}}\right\}\right] + \sum_{j=1}^{q} \xi_j \left(\frac{\varepsilon_{t-j}}{h_{t-j}}\right) \tag{4.3}$$

where h_t^2 is the current conditional variance, a_0 is the conditional variance model constant, γ_i is the GARCH component coefficient, a_j is the ARCH component coefficient and ξ_j is the leverage component coefficient. Section 4.2.2 presents the additional risk and return measures used to assess the risk and return relationship.

4.2.2 Additional Risk and Return Methods

Many researchers support the fact that the negative association between risk and return may be attributed to statistical errors (Denrell, 2004; Ruefli, 1990; Ruefli and Wiggins, 1994), or to the choice of risk and return measures that were used (Baucus, Golec and Cooper, 1993). Therefore, this study examines 51 additional risk measures to assess historic volatility and three extra return approaches in order to enhance the robustness of the findings.

4.2.2.1 Return Measures

As mentioned before (see Eq. 4.2), the returns R_{tij}, are estimated using the continually compounded logarithmic freight rate differences expressed as:

$$R_{tij} = lnFR_{tij} - lnFR_{(t-1)ij}$$

Three holding period horizons are used (i.e. $h = 1-, 12- \; and \; 24- \; months$) to observe how the risk and return relationship is affected over time. Therefore, equation 4.2 can be expressed mathematically as follows:

$$R_{tij} = lnFR_{tij} - lnFR_{(t-h)ij} \tag{4.4}$$

Using three holding period horizon results in 12 return combinations (i.e. 4 freight rates series over 3 holding period periods each).

4.2.2.2 Risk Measures

Considering the specifications of the volatility process, there is a need to examine whether the use of additional risk measures will affect the sign of the risk and returns relationship. Therefore, in order to enhance the robustness of the empirical analysis, the returns' volatility was also assessed using the following risk measures: a *Simple Variance Approach* (SVA), the *Exponentially Weighted Moving Average Variance* approach ($EWMAV$), the $GARCH\ (p, q)$, $gjrGARCH\ (p, q)$ approach while also testing the systematic risk using Value-at-Risk (VaR) methodology.

4.2.2.2.1 Simple Variance Approach – SVA

The Simple Variance Approach (SVA) also known as a rolling window variance forecast model, which is one of the simplest ways to capture volatility clustering. The variance prediction function is a constant-weight sum of m past squared returns. A rolling window of 12 and 24 observations, $m = 12$, and 24 is used. It is clear that a high m will lead to an excessively smooth evolving σ_{t+1}^2 and a low m will generate an extremely volatile pattern of σ_{t+1}^2. Additionally, extreme returns (positive or negative) today will bump up by $1/m$ times the variance of the return squared for exactly m periods and immediately drop back afterwards. However, such extreme rotations do not reflect the economics of the underlying financial market, thus there is a need to use additional risk measures. The simple variance approach is the average of the squared returns and is defined as:

$$variance = \sigma_t^2 = \frac{1}{m-1}\sum_{i=t-m}^{t-1}(R_i - \mu)^2 \tag{4.5}$$

The parameter m specifies the number of months included in the moving average (i.e. the observation period), R_i is the return on day i, and μ is the mean of the return series. Following the recommendations of Figlewski (1994) and Hendricks (1996) μ is always assumed to be zero.

4.2.2.2.2 Exponentially Weighted Moving Average Variance Approach – EWMAV

Similarly to the SVA approach, the risk is estimated using the Exponentially Weighted Moving Average Variance method (EWMAV), which applies a nonuniform weighting to time series data and allows for more data to be used whilst weighting recent one more heavily. In other words, the EWMAV captures short-term movements in volatility. The EWMAV approach is estimated using the following equation:

$$\sigma_t^2 = \lambda\sigma_t^2 + (1-\lambda)(R_t - \mu)^2 \tag{4.6}$$

where λ is the weighted coefficient (decay factor) set at 0.94 which is the value that the RiskMeterics database uses to estimate the EWMA volatility. For small values of λ, recent observations affect the variance estimation quickly while for values of λ closer to 1, the estimates change slowly based on recent variations in the returns of the underlying variable. As in the SVA approach, μ is the mean of the return series and is assumed to be zero.

The purpose is to show that the risk-return trade-off is robust over time. As proved by Ghysels et al (2005), the use of the lagged realised variance as risk measure allows assessing the time-varying risk-return relationship (Kavussanos and Alizadeh, 2002b). Therefore, a 12- and 24-months rolling window is used to assess if the construction lag of a vessel has an impact on the risk and return relationship.

4.2.2.2.3 $GARCH$ (p, q) Approach

The variance of returns over time is also estimated using a $GARCH$ (p, q) approach, an autoregressive moving average model for conditional variances, with p $GARCH$ coefficients associated with lagged variances and q $ARCH$ coefficients associated with squared innovations. $GARCH$ models attempt to address volatility clustering in an innovation process. Additionally, the $GARCH$ approach is suitable when a series exhibits volatility clustering and serial correlation suggesting that past variances might be predictive of the current variance. Precisely, in the case of the $GARCH$ (p, q) model, the conditional variance is measured as follows:

$$\begin{gathered}\Delta lnFR_t = \mu + \varepsilon_t \qquad \varepsilon_t \sim N(0, h_t) \\ \text{where } h_t = a_0 + \textstyle\sum_{j=1}^{p} \gamma_j h_{t-j} + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2\end{gathered} \tag{4.7}$$

where μ is the specification of the conditional mean of $\Delta lnFR_t$, ε_t is a white noise error term with the usual classical properties (i.e. mean zero), but a time varying variance h_t. More specifically, h_t is the conditional variance process at time t. The following constraints are necessary to ensure the stationarity and positivity of the $GARCH$ model:

$$a_0 > 0, a_i \geq 0, \gamma_j \geq 0 \text{ and } \textstyle\sum_{i=1}^{Q} a_i + \sum_{j=1}^{P} \beta_j < 1$$

In order to determine the optimal values of p and q, the likelihood ratio test of multiple lags and the AIC and BIC values are compared.

4.2.2.2.4 $gjrGARCH$ (p, q) Approach

Additional, the variance is modelled using the Glosten, Jagannathan and Runkle (1993) GARCH $-gjrGARCH$ model. The $gjrGARCH$ can be applied when negative shocks contribute more significantly to the volatility compared to positive shocks (Tsay, 2010). The model posits that the current conditional variance is the sum of past conditional variances; past squared innovations and past squared negative residuals. The mathematical formulation for the $gjrGARCH$ is the following:

$$\Delta lnFR_t = \mu + \varepsilon_t \qquad \varepsilon_t \sim N(0, h_t^2)$$
$$\text{where } h_t^2 = a_0 + \sum_{i=1}^{p} \gamma_i h_{t-i}^2 + \sum_{j=1}^{q} a_j\, \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \xi_j\, I\left[\varepsilon_{t-j} < 0\right] \varepsilon_{t-j}^2 \tag{4.8}$$

where a_0 is the conditional variance model constant, γ_i is the GARCH component coefficient, a_j refers to the ARCH component coefficient and ξ_j is the leverage component coefficient.

4.2.2.2.5 Value-at-Risk – VaR Methodology

An additional measure of market risk used to determine the nature of the risk and return relationship is the Value-at-Risk (VaR) approach, which has become an essential tool in the financial markets.

The VaR is defined as the maximum expected loss in the value of an asset or a portfolio of assets over a time horizon subject to a specified confidence level. Mathematically the VaR can be expressed as follows:

$$\Pr(R_{t+1} \leq VaR_{t+1}^{a} | \Omega_t) = a \tag{4.9}$$

where R_{t+1} shows the returns between t and $t+1$, a is the confidence level, and Ω_t represents the information set at time t. The VaR can be measured using: (1) Historical Simulation, (2) Monte-Carlo Simulation or (3) Variance – Covariance Method which is the method that was selected in this chapter and is calculated as follows:

$$VaR_{tij} = R_{tij} + z_a \sigma_{tjj} \tag{4.10}$$

Where R_{tij} shows the expected returns at time t and σ_{tij} is the conditional standard deviation of the return series for a type i vessel (i = Capesize) with freight rate j (j = spot, 6-, 12- and 36-months period freight rates). The choice of the method that will be used to estimate the volatility (σ_{tjj}) and distribution of the underlining series (R_{tij}) is very important for the VaR estimations. As mentioned before, the models that estimate the volatility are the SVA, EWMAV, GARCH, eGARCH and gjrGARCH approach, while the expected returns are estimated using equation 4.2 and 4.4. z_a represents the left a-quantile of the underling distribution of the return series. The Normal, Student's t, Cauchy and Generalized Error Distribution are commonly used to assess their impact on the estimated volatility model.

The descriptive statistics (see Tables 4.2 and 4.3) show that the distribution of the freight rates return series is positively skewed and leptokurtic indicating that extreme outcomes happen much more frequently than it would have been predicted using the normal distribution. Additionally, the values of the Jarque and Bera (1987) test indicate that the freight rate series depart from normality at a 5% significance level. This suggests that estimating the VaR under the normality assumption may be an inaccurate way to capture the risk faced by operating in the dry bulk freight market. Therefore, the skewed *t*-Student's distribution of Hansen (1994) is used to account for the skewness and excess kurtosis in the freight series. z_a represents the left a-quantile of the skewed *t*-Student distribution (Hansen, 1994). a is the confidence level that can take values of 1%, 5% and 10%. For instance, under the normal distribution assumption if $a = 1\%$ then $z_{a=0.01} = 2.326$ and $z_{a=0.05} = 1.645$ and $z_{a=0.10} = 1.28$ when using 5% and 10% confidence levels. The z_a values of the skewed *t*-Student distribution are calculated using Matlab.

Additionally, following the approach used by Fan et al (2008), the VaR is separated and treated as upside and downside VaR using the following equations:

$$VaR_{tij}^{up} = R_{tij} - z_a \sigma_{tjj} \quad (4.11)$$

$$VaR_{tij}^{down} = -R_{tij} + z_a \sigma_{tjj} \quad (4.12)$$

where VaR_{tij}^{up} and VaR_{tij}^{down} measure the upside and downside VaR in the dry bulk freight market. Therefore, the total number of VaR risk measure combinations is 28 (see Appendix 4.A). VaR is measured as the quantile of underlying distribution, which is divided into downside $\left(VaR_{tij}^{down}\right)$ and upside risk (VaR_{tij}^{up}). The upside (downside) risk represents the right (left) quantile of the underlying distribution that is adopted to illustrate the changes in the risk measure after an increase (decrease) in the freight rate return.

4.2.3 Robustness Tests

Following the calculation of the return series and the variance series, regression 4.1 is performed to examine the nature of the relationship between risk and return in shipping investments. More specifically, equation 4.1 examines the relationship between the conditional mean and conditional volatility of market returns at a monthly level. Multiple robustness checks are performed to enhance the robustness of the empirical findings and establish that the risk-return relationship in this study remains intact. More specifically, the purpose is to prove that the risk and return relation is robust and is not affected by different risk and return measures, subsamples, market conditions and controlling variables associated with the business cycle.

4.2.3.1 The Use of Multiple Risk and Return Measures

The purpose of using multiple risk and return measures is first to ensure that the relationship is robust regardless of the risk and return method used whilst incorporating more information compared to traditional measures and finally present alternative robust methods to measure the risk in the dry bulk freight market.

At this point it is important to mention that the Newey-West (1987) adjusted *t*-statistic is used to indicate that the risk and return relationship is statistically significant whether positively or negatively. In other words, the standard errors of the regression coefficients are calculated using the procedure proposed by Newey-West (1987) who suggested a more general variance-covariance matrix estimator that is consistent in the presence of both heteroskedasticity and autocorrelation of the residuals.

4.2.3.2 Subsample periods

Additionally, although using large number of historical observations allow identifying an asymptotic relationship between risk and returns, a structural change may produce misleading estimators and create inaccurate statistical inference.

Therefore, this study assesses the risk-return relationship by examining the period from January 1990 to June 2016 excluding the financial crisis period from August 2007 to January 2009 while also breaking down the sample period into 4 subsamples to evaluate whether the risk-return relationship is stable over time or varies due to different time periods being analysed. The non-overlapping sub-periods are: January 1990 to December 1995 (subsample A), January 1996 to December 2001 (subsample B), January 2002 to December 2008 (subsample C) and January 2009 – June 2016 (subsample D).

The reason the aforementioned sub-samples were analysed was because they consist of both bullish and bearish periods. For instance, the period from 1996 to 2001 is a bearish period since the market collapsed due to the Asia and Dotcom Crisis. After that, from 2002 to 2008, the market entered a bullish period since it recovered from the Asia and Dotcom crisis. Between 2009 and 2011 the market once again entered a bearish period due to the Credit Crisis, while from January 2012 to June 2016 the market went through a recovery period from the financial crisis.

There are different ways that have been proposed in the literature when it comes to identifying bearish and bullish periods. Fabozzi and Francis (1977), Kim and Zumwalt (1979) and Chen (1982) examined definitions of bull markets simply based on returns exceeding a certain threshold value in any given month. Pagan and Sossounov (2003) filtered the monthly returns through sequence of censoring operations. More precisely, a bull (bear) market was considered as one with returns greater (less) than $(-)$ 20% or $(-)$ 25% meaning that the definition of a bear (bull) market is given either as a market return that is (not) exceeding specific threshold values (e.g., Fabozzi and Francis (1977) and Kim and Zumwalt (1979)) or based on market trends (Chauvet and Potter (2000)). When a bear (bull) market is defined based on a threshold value, the problem is that such a definition fails to take into account market trends and requires determining which threshold value (e.g., zero, average market return, or others) should be used.

The definition provided by Chauvet and Potter (2000) seems to be more appropriate when it comes to characterising the financial cycle in the freight rate market, which is why it will be the one used in this empirical study. Based on this definition, one may then identify bulls and bears parametrically or non-parametrically so this study uses the Bry-Boschan (1971) non-parametric approach, which has been widely applied when identifying bull and bear markets in recent years; see e.g., Pagan and Sossounov (2003), Gonzalez et al (2005), Candelon et al (2008) and Fernandez-Perez et al (2014).

The Bry-Boschan (1971) algorithm identifies bear and bull markets as follows: p_t represents the natural logarithm of market price at time t and then a trough (peak) occurs at time t when $p_t < (>)\ p_{t\pm i}, i = 1, \dots, w$, where w is a window size. As a result, the peak-to-trough (trough-to-peak) periods correspond to the bear (bull) markets with $D_t = 1$ $(D_t = 0)$. As for the value of w, this thesis follows the model proposed by Candelon et al (2008) so $w = 6$ (i.e., six months). As a robustness check, $w = 8$ is also assessed with the censoring rules suggested by Pagan and Sossounov (2003). The expectation is to find that the risk and return relationship differs between bear and bull markets. More specifically, a negative association between the risk measures and the return measures is more likely to be present during bearish periods compared to bullish periods.

4.2.3.3 Backtesting VaR Models

Since the VaR model is used as an additional risk measure, there is a need to backtest whether it can accurately estimate the real extreme risk. Backtesting is a process that compares actual profits and losses to projected VaR estimates. If the VaR estimates are not accurate then the models should be re-examined for incorrect assumptions, wrong parameters or inaccurate modelling.

Various methods have been proposed for backtesting purposes (i.e. Basel Committee 1996, 2005; Kupiec, 1995; Christoffersen, 1998, 2003; Haas, 2001). Kupiec's (1995) test examines the frequency of losses in excess of VaR. The failure rate ($f = N/T$) is defined as the ratio of days of failure (N) over the same size T that should also be in line with the selected confidence level. For instance, if monthly VaR estimates are calculated at 95% confidence for one year (12 trading months), it is expected that 1.2 VaR violations or exceptions will occur on average during this period. The likelihood test examines whether the number of observed exceptions is reasonable compared to the expected one.

The Kupiec test assesses if the observed failure rate is significantly different from the failure rate suggested by the confidence level (i.e. H_o: $f = a$). The loglikelihood statistic that is used to test the hypothesis is calculated as follows:

$$LR = 2ln[(1-f)^{T-N} f^N] - 2ln[(1-a)^{T-N} a^N] \tag{4.13}$$

The LR statistic follows a chi-square (χ^2) distribution, if the value of LR is larger than the corresponding critical value[1], then the null hypothesis should be rejected meaning that the VaR model is not an adequate risk measure for the shipping freight market.

4.2.3.4 Control Variables

Campbell (1987) and Scruggs (1998) suggest that the difficulties in measuring the risk-return relation may be due to misspecification of equation 4.1. More specifically, they support the fact that changes in the investment opportunity set are captured not only by the conditional variance itself but also by state variables and thus these variables should be included in equation 4.1.

State variables are a series of macroeconomic variables that proxy the freight rate fluctuations and are included in model 4.1 in order to increase the testing power and identify areas of misspecification.

[1] The critical values of its 95% and 99% confidence level are 3.84 and 6.64 respectively.

At this point it is important to mention that due to limited data availability (i.e. from 1996 onwards), the macroeconomic variables that were identified in Chapter 3 as significant and explain a large variation of the term structure variability (i.e. aluminium, steel production, orderbook freight market changes, etc.) cannot be incorporated in the analysis of this Chapter. Therefore, the macroeconomic variables that used to capture the fluctuations of the freight market are the Kilian's Index, Inflation Indicator OECD, Industrial Production OECD, newbuild and 5-year old ship prices.

4.2.4 The Risk-Return Relationship under the Prospect Theory

There is a need to examine whether or not the past relationship between risk and return in shipping investments is associated with risk attitudes governed by the Prospect Theory (Kahneman and Tversky, 1979). The theory supports that decision makers are risk seekers when performance has been below some target level and risk averse when performance has been above a certain point. In other words, the prospect theory argues that individuals use target or reference points when evaluating risky choices. Furthermore, individuals are not uniformly risk averse but adopt a mixture of risk-seeking characteristics when their outcomes are below the target level and become risk-averse when their outcomes are above that level. In order to determine the investors' risk attitudes, Tversky and Kahneman (1992) proposed estimating the utility (value) function of each outcome as follows:

$$\begin{aligned} u_t(x) &= {R_t}^a && if\ R_t \geq R_{median} \\ u_t(x) &= -\lambda(-R_t)^a && if\ R_t < R_{median} \end{aligned} \tag{4.14}$$

where u is the value function, with $R \geq R_{median}$ denoting returns above the target return, which in turn is the median of the returns under investigation. Parameter a of the value function measures the curvature of the value function and λ represents the loss aversion parameter. A value of $a < 1$ implies that individuals are risk averse over gains and risk seeking over losses, while $\lambda > 1$ implies that individuals are loss averse. Tversky and Kahneman (1992) estimated a to be equal to 0.88 and λ to be 2.25.

Instead of formulating a questionnaire that will assess real ship-owners regarding their risk preferences, the study will test whether the historical risk and return relation follows the risk averse and risk-seeking behaviour. Assuming that the return and risk measure used present a good proxy for shipping investments, the goal is to examine whether or not shipping investment obey risk attitudes conceptualised in the prospect theory's utility function.

Initially, the target level needs to be defined. There is no general rule that defines an appropriate target level for each situation although Tversky and Kahneman (1981) and Laughhunn et al (1980) drew a close analogy between a target return level and a reference point. Lev (1969) suggested that firms adjust their performance to the industry average. More specifically, Lev (1969) performed an empirical study on 900 major U.S. firms that confirmed the hypothesis that firms periodically adjust their financial ratios to their industry means. Frecka and Lee (1983) used a different dataset to study financial ratios and their results agree with Lev's hypothesis that firms dynamically adjust financial ratios to targets that appear to be industry-wide averages. Therefore, in this study, an average performance (returns) level may serve as an appropriate proxy to be used as a firm's target level.

The next step is to use the target level to distinguish the returns previously estimated between those moving above the target level and the ones that are below it. Running time-series regression allows examining if historical risk and returns obey the risk averse and risk-seeking behaviour. The regression is the same as before (Eq. (4.1)) with the only difference being that the dependent variable, R_{Tij} is now a dichotomous dummy variable, which will take a value of 1 for returns that exceed the target level and 0 for returns below the target level.

$$R_{Tij} = a + b_{Tij}\mathrm{E}_{t-1,i,j}\left(VAR_{Tij}\right) + \varepsilon_{Tij} \tag{4.15}$$

According to the prospect theory, the risk-return relationship has a nonlinear functional form. Therefore, using the above and below returns and risk measures, equation 4.15 is examined in order to identify if there is a negative (positive) association between the risk measures $\left(\mathrm{VAR_{Tij}}\right)$ and the return measures ($\mathrm{R_{Tij}}$) in investments below (above) their target returns.

Equation 4.15 is tested for a Capesize vessel and four freight markets (spot, P6m, P12m and P36m). Additionally, the utility functions are estimated in order to further support the existence of risk seeking and risk averse relationship for returns above and below the target level. More specifically, the present study examines if the investors utilities function is risk averse when the returns are above the target level and risk seeking if the returns are below it. All the empirical findings are presented in the next section.

4.3 Data Description and Empirical Analysis

The empirical analysis is conducted in the dry bulk market for a Capesize vessel, which can operate in four types of charter markets (i.e. the spot, the 6-, 12 or 36-

month period charter market). A description of the data is initially provided and then the empirical findings will be presented.

4.3.1 Data Description and Descriptive Statistics

The freight rates from Clarkson's Shipping Intelligent Network (SIN) are expressed in $ per day and recorded each month starting from January 1990 to June 2016 for a total of 318 monthly curves of four maturities each. The analysis is performed for a Capesize (more than 120,000 dwt) which is one of the most commonly used vessels in the dry bulk shipping market but the research can be extended to include other vessel types *Panamax*, *Handymax*/ *Supramax* or *Handysize*.

The data consist of monthly average spot earnings as well as six-month, one-year and three-year period charter rates. The *Time-Charter Equivalent* (TCE)[2] rates will be used to measure the performance of the spot charters. For a Capesize vessel, the average spot earnings are calculated based on coal and ore voyage earnings, while also the period charter rates (i.e. a performance measure for the long-term charters) are calculated for a 150,000 dwt Capesize,

Tables 4.2 and 4.3 present the descriptive statistics for the annualised freight rate returns (i.e. spot, 6-, 12- and 36-months) over three holding periods (i.e. $h = 1-, 12-$ and $24-$ months) and multiple samples. Traditional descriptive measures such as the mean, standard deviation, skewness, kurtosis, minimum and maximum are calculated for both the return and the risk measures. The Jarque-Bera (1987) test statistic along with the skewness and kurtosis are used to provide further insight on the distribution characteristics of the series.

Panel A in Table 4.2 presents the descriptive statistics of the annualised returns for period from January 1990 to June 2016 whilst Panel B presents the same statistics but excludes the financial crisis period. The returns of each sample presented in Table 4.2 appear to be negative for the period between January 1990 and June 2016 even after eliminating the financial crisis period (August 2007 to January 2009). The analysis also shows that the annualised standard deviations decrease as the maturity of the contracts increases whilst the no financial crisis period (Table 4.2 – Panel B) is as expected less volatile since the turbulent period between August 2007 and January 2009 that created uncertainty was eliminated.

[2] The TCE (or spot earnings) calculates the average daily revenues of a vessel in the spot market allowing the comparison with daily earnings generated by vessels on long-term charters.

Most of the annualised returns are negatively skewed and leptokyrtic indicating that the return series are not normally distributed. The Jarque-Bera test strongly rejects the distributional assumption of normality except from the returns of the 24-month holding period horizon in Panel A. The 12-month return series of the sample without financial crisis period (see Panel B) retained the normality hypothesis.

Three tests were performed in order to assess the stationarity of the series. The traditional ADF - Augmented Dickey-Fuller (1981) and PP - Phillips and Perron (1988) tests examined for a unit root in the time series.

Schwert (1989) mentioned that the ADF- and the PP- test lack power in rejecting the null hypothesis of a unit root when it is false and therefore the KPSS - Kwiatkowski, Phillips, Schmidt and Shin (1992) test was used in order to further support the null hypothesis of non-stationarity of all of the series. The ADF, PP and KPSS test indicate that the return series are stationary.

Additionally, the Engle's ARCH (1982) model tests for autoregressive conditional heteroscedasticity and the Ljung-Box test (1978) assesses the serial correlation. The results of the Engle's ARCH (1982) and the Ljung-Box (1978) test indicated that the residuals of the return series are autocorrelated and present ARCH effects. Due to the size of the tables, these empirical findings are not presented in Tables 4.2 and 4.3 due to the large size of the result tables but are available upon request.

The annualised returns and their descriptive statistics are calculated for the four subsamples see Table 4.3). The results suggest that the annualised 1-month holding period returns are negative across all subsamples. This can be due to the fact that the freight rates series are highly volatile and fluctuate significantly throughout each subsample. For instance, the average difference between the maximum and minimum freight rate series ranges from approximately 13,000 $/day in subsample A to 138,605 $/day in subsample C.

Additionally, the 12-month holding period returns in sub-sample B (i.e. from January 1996 to December 2001) are also negative because of the Dotcom Crisis that affected the period time rates significantly more compared to the spot rates. For instance, the period time charter rates in subsample B decreased by approximately 2,500 $/day compared to the period time charter rates in subsample A where the spot rates decreased by 1000$/day.

Table 4.2: Descriptive Statistics by holding period

	Freight Rate Series				Returns h = 1m				Returns h = 12m				Returns h = 24m			
	spot	**P6m**	**P12m**	**P36m**	**spot**	**P6m**	**P12m**	**P36m**	**spot**	**P6m**	**P12m**	**P36m**	**spot**	**P6m**	**P12m**	**P36m**
Panel A: Sample Period from January 1990 to June 2016																
Mean (Ann)	29323	25465	24135	20700	-0.043	-0.027	-0.034	-0.024	-0.396	-0.297	-0.313	-0.276	-0.724	-0.485	-0.481	-0.491
Standard Dev. (Ann)	30591	27002	24329	16544	0.977	0.720	0.524	0.423	2.450	2.258	1.975	1.704	2.917	2.781	2.479	2.073
Skewness	2.594	2.710	2.886	3.058	-0.619	-0.889	-2.609	-2.331	-0.543	-0.736	-0.728	-1.114	0.186	0.200	0.160	-0.006
Kurtosis	10.531	10.482	11.684	13.049	8.320	14.162	27.662	26.889	5.624	5.409	4.665	6.059	3.336	3.042	3.026	3.315
Minimum	2287	4250	4725	4775	-1.452	-1.501	-1.430	-1.102	-3.640	-3.135	-2.380	-2.238	-2.764	-2.477	-1.691	-1.631
Maximum	188643	147500	137200	107500	1.167	1.069	0.533	0.629	2.377	2.247	1.390	1.061	2.325	2.040	1.734	1.558
J - B test	1108.0	1131.0	1440.7	1833.8	395.289	1692.6	8419.6	7849.3	106.862	105.578	64.842	189.784	3.323	2.139	1.363	1.320
pvalue	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.158	0.307	0.469	0.484
ADF & PP	-2.146	-1.742	-1.631	-1.394	-15.000	-13.992	-13.005	-12.191	-4.618	-3.765	-3.252	-3.071	-4.172	-3.194	-2.461	-2.400
pvalue	0.031	0.077	0.097	0.152	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.003	0.001	0.002	0.014	0.016
KPSS	2.502	2.387	2.344	2.125	0.027	0.039	0.064	0.058	0.394	0.408	0.477	0.389	1.069	1.011	1.120	1.000
pvalue	0.010	0.010	0.010	0.010	0.100	0.100	0.100	0.100	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
Panel B: Sample Period from January 1990 to June 2016 after eliminating the Financial Crisis Period																
Mean (Ann)	24680	20961	19920	17760	-0.045	-0.029	-0.036	-0.026	-0.420	-0.315	-0.332	-0.292	-0.768	-0.514	-0.510	-0.520
Standard Dev. (Ann)	20004	16258	13889	8775	0.891	0.634	0.489	0.354	2.048	1.892	1.686	1.391	2.560	2.382	2.090	1.611
Skewness	1.819	2.069	2.077	1.902	-0.204	-0.852	-2.014	-2.956	0.069	-0.041	0.044	-0.235	0.401	0.467	0.405	0.197
Kurtosis	5.741	7.161	7.273	7.410	7.175	9.768	21.954	30.384	2.749	2.702	3.016	3.952	3.652	3.497	3.555	3.284
Minimum	2287	4250	4725	4775	-1.108	-1.181	-1.229	-0.969	-1.656	-1.600	-1.459	-1.402	-2.318	-1.726	-1.601	-1.137
Maximum	99859	95625	83125	58000	1.167	0.634	0.533	0.297	1.469	1.365	1.390	1.046	2.139	2.040	1.734	1.240
J - B test	259.331	430.560	443.910	423.999	220.009	608.841	4693.5	9810.6	1.028	1.191	0.101	14.086	13.357	14.017	12.034	2.943
pvalue	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.500	0.500	0.500	0.006	0.007	0.006	0.009	0.193
ADF & PP	-2.167	-1.997	-1.769	-1.290	-15.790	-14.797	-14.619	-13.555	-4.609	-3.705	-3.536	-3.038	-3.943	-3.049	-2.574	-2.355
pvalue	0.029	0.044	0.073	0.182	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.003	0.001	0.003	0.010	0.018
KPSS	2.624	2.495	2.524	2.299	0.027	0.039	0.056	0.054	0.491	0.467	0.496	0.391	1.209	1.098	1.172	1.109
pvalue	0.010	0.010	0.010	0.010	0.100	0.100	0.100	0.100	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010

Notes: Table 4.2 presents the descriptive statistics of the freight rates returns with different maturities for a Capesize vessel from January 1990 to June 2016 (Panel A) and for the same period after eliminating the financial crisis period from August 2007 to January 2009 (Panel B). *Skewness* and *kurtosis* are the centralised third and fourth moments of the data and assess the distribution of the time series. The *mean* is the annualised average of each return series and *Standard Dev.* is the annualised standard deviation. The *Jarque and Bera* (1987) *test* examines the normality of the series whilst the *ADF* (i.e. Augmented Dickey and Fuller (1981)), the PP (i.e. Phillips and Perron (1988)) and KPSS (i.e. Kwiatkowski, Phillips, Schmidt and Shin (1992)) test examine the unit root of the series. The critical values for the JB, ADF, PP and KPSS test are 5.71, -1.94, -194 and 0.146 respectively.

Additionally, the annualised returns of the 24-month holding period are positive for all subsamples with an exception being the returns in subsample D (January 2009 to June 2016), which are negative. This was expected since the sub-sample includes the recovery period of the Credit Crisis in 2008 during which the freight rates series decreased on average from 50,421 $/day in subsample C to 16,911 $/day in subsample D.

The volatilities illustrate the existence of a downward sloping volatility term structure which is attributed to the fact that contracts, such as *PTC6m*, *PTC12m* and *PTC36m* with a maturity of up to three years are less volatile than contracts with shorter maturity dates like for example *spot* contracts (Kavussanos, 1996a,b and Kavussanos and Alizadeh, 2002b). A downward sloping volatility of the term structure is observed in every sub-sample. Sub-sample C has the highest volatility compared to the other three subsamples whist the results suggest that subsample A is the most stable one.

The annualised return series of subsample D appear to be asymmetrically distributed with negative coefficients of skewness and mainly leptokurtic which can lead to erratic future movements of the freight rates and potentially to significant losses. The results of the Jarque-Bera test statistic indicate that all the series are non-normal at 5% significance level.

The annualised return series of the other subsamples present a mixture of negative and positive coefficients of skewness and are mainly leptokurtic although skeweness and kurtosis values are very close to a normal distribution. Therefore, the Jarque-Bera (1987) test confirms the null hypothesis of retained normality at a 5% significance level. Additionally, most of the annualised return series are non-stationary across all subsamples except from the 1-month holding period.

The Ljung-Box (i.e. Q-test) and the ARCH tests indicate that all return series and subsamples are autocorrelated and present ARCH effects at 5% significance level. This existence of ARCH effects (conditional heteroscedasticity) in the series is an indication of strong volatility clustering meaning that large (small) shocks to the series are followed by large (small) shocks. As mentioned previously, 68 different risk measures (see Appendix 4.A) are used to assess the risk and return relationship in the dry bulk freight market. The use of an extensive number of risk measures allows us to assess how these affect the relationship with the returns as well as compare which better capture the volatility of the dry bulk freight market.

Table 4.3: Descriptive Statistics of subsamples by holding period

SubSample A	Freight Rate Series				Returns h =1m				Returns h -12m				Returns h = 24m			
January 1990 – December 1995	**spot**	**P6m**	**P12m**	**P36m**	**spot**	**P6m**	**P12m**	**P36m**	**spot**	**P6m**	**P12m**	**P36m**	**spot**	**P6m**	**P12m**	**P36m**
Mean	16735	15138	15774	16947	-0.077	-0.023	-0.011	-0.002	0.273	0.715	0.609	0.491	-0.040	1.071	1.033	1.065
Standard Deviation	4443	3815	3218	2525	0.346	0.305	0.251	0.191	1.391	1.111	1.019	0.709	1.284	0.954	0.692	0.506
Skewness	-0.089	0.617	0.221	-0.774	0.535	0.236	0.374	0.322	-0.341	-0.060	-0.262	0.557	0.462	1.029	0.825	0.462
Kurtosis	2.013	2.857	2.217	3.164	2.816	3.603	4.427	7.735	2.644	2.333	2.926	4.952	2.600	3.614	3.781	2.370
Minimum	8178	8950	10003	10288	-0.197	-0.224	-0.167	-0.214	-0.869	-0.559	-0.676	-0.492	-0.639	-0.363	-0.327	-0.198
Maximum	25229	24725	22288	21200	0.244	0.252	0.254	0.208	0.754	0.682	0.754	0.708	0.885	0.772	0.609	0.427
J - B test	3.020	4.637	2.428	7.266	3.531	1.760	7.783	68.505	1.773	1.378	0.842	15.150	3.038	13.839	9.990	3.753
ADF & PP	-1.002	-0.564	-0.430	-0.229	-5.191	-5.422	-5.587	-5.716	-1.080	-1.568	-1.735	-1.954	-1.030	-1.350	-1.377	-1.451
SubSample B: January 1996 – December 2001																
Mean	15321	13089	13227	13914	-0.044	-0.073	-0.066	-0.065	0.307	-0.072	-0.045	-0.209	1.292	0.380	0.222	-0.321
Standard Deviation	5407	3726	2953	1788	0.486	0.393	0.270	0.189	1.627	1.506	1.200	0.689	1.580	1.500	1.211	0.626
Skewness	0.771	0.151	-0.001	-0.241	0.240	0.643	0.402	-1.114	-0.194	-0.185	-0.163	-0.095	0.318	0.296	0.430	-0.147
Kurtosis	2.696	2.135	2.114	2.976	3.366	6.024	5.661	8.848	3.299	2.897	2.453	2.648	2.547	2.433	2.494	2.977
Minimum	8173	7050	7800	10000	-0.347	-0.335	-0.236	-0.258	-1.097	-0.971	-0.793	-0.460	-0.798	-0.697	-0.567	-0.397
Maximum	29314	20750	19000	18200	0.346	0.438	0.264	0.132	1.014	0.920	0.652	0.400	1.083	0.913	0.776	0.434
J - B test	7.414	2.519	2.355	0.696	1.091	32.4	23.2	117.5	0.722	0.443	1.219	0.478	1.830	2.013	2.984	0.262
ADF & PP	-0.625	-0.695	-0.796	-0.986	-6.838	-5.930	-5.508	-6.336	-1.033	-0.754	-0.752	-1.152	-1.452	-1.113	-0.902	-1.110
SubSample C: January 2002 – December 2008																
Mean	61304	53835	49644	36903	-0.023	-0.084	0.048	-0.039	2.497	2.719	2.685	2.271	4.508	4.972	5.113	4.570
Standard Deviation	43030	39099	35700	25158	1.021	0.893	0.764	0.624	2.882	2.686	2.336	1.972	3.215	3.072	2.673	2.216
Skewness	1.008	0.939	1.067	1.213	-2.270	-2.638	-3.362	-3.185	-1.852	-1.810	-1.351	-1.728	-0.346	-0.278	-0.037	-0.245
Kurtosis	3.586	2.918	3.239	3.524	12.412	15.817	22.985	18.748	8.592	7.942	6.144	7.948	3.625	3.017	2.150	2.872
Minimum	4048	4875	9500	8000	-1.452	-1.501	-1.430	-1.102	-3.640	-3.135	-2.380	-2.238	-2.764	-2.477	-1.405	-1.631
Maximum	188643	147500	137200	107500	0.675	0.634	0.533	0.297	1.348	1.365	1.390	1.046	2.139	1.951	1.734	1.558
J - B test	15.428	12.372	16.132	21.550	382.214	672.400	1556.1	1010.0	157.439	131.352	60.141	127.482	3.046	1.084	2.547	0.896
ADF & PP	-0.979	-0.864	-0.847	-0.767	-5.585	-4.865	-6.090	-4.123	-0.715	0.645	-0.615	0.732	-1.130	-0.663	-1.170	-0.596
SubSample D: January 2009 – June 2016																
Mean	20746	17150	15741	14008	-0.115	-0.067	-0.121	-0.070	-2.552	-2.171	-2.022	-1.575	-4.656	-4.096	-3.673	-3.090
Standard Deviation	15521	10435	8138	5938	1.439	0.860	0.557	0.403	2.130	1.855	1.654	1.624	2.364	2.190	2.004	1.718
Skewness	1.404	1.142	0.740	0.323	0.022	0.039	0.096	-0.194	0.162	-0.211	-0.172	-0.426	-0.452	-0.199	-0.100	0.198
Kurtosis	4.995	4.062	2.563	1.722	3.282	3.373	2.958	6.036	3.446	3.112	3.045	3.303	3.163	2.480	2.419	2.182
Minimum	2287	4250	4725	4775	-1.108	-0.745	-0.423	-0.422	-1.656	-1.600	-1.459	-1.402	-2.318	-1.726	-1.601	-1.121
Maximum	78755	54325	37563	25300	1.167	0.624	0.403	0.383	1.469	0.988	0.942	0.761	1.229	0.892	0.890	0.756
J - B test	44.500	23.786	8.939	7.695	0.306	0.545	0.146	35.125	1.138	0.716	0.452	3.071	3.161	1.608	1.417	3.093
ADF & PP	-1.973	-1.323	-1.035	-0.811	-9.516	-8.879	-8.428	-8.253	-3.642	-2.368	-1.847	-1.392	-3.115	-1.842	-1.026	-0.915

Notes: Table 4.3 presents the descriptive statistics of the freight rates returns with different maturities for a Capesize vessel over four separate subsamples. For further definition refer to Table 4.2. The non-significant values of the *Jarque and Bera* (1987), Augmented Dickey and Fuller (1981) and Phillips and Perron (1988) tests are highlighted in blue at a 5% significance level. The critical values of the JB and ADF/PP test are 5.71 and -1.94 respectively.

Table 4.4 reports the results from an autoregressive model of order 1 (noted as $AR(1)$). The $AR(1)$ regression assesses whether the risk measures can proxy the expected volatility of the dry bulk freight market.

$$Risk\_Measure_{kijt} = a + bRisk\_Measure_{kijt-1} + e_{kijt-1} \quad (4.16)$$

where $Risk\_Measure_{kijt}$ represents the risk measure k of a type i vessel (where i = Capesize) and freight rate j (where j = spot, 6-, 12- and 36-months period freight rates). k is the list of all risk measures used in the analysis (see Appendix 4.A for details). The intercept a, $AR(1)$ coefficient b, their Newey-West (1987) standard errors, p values and the adjusted R^2 values are presented for each regression and risk measure in Appendix 4.B. As can be seen from Table 4.4 the coefficients are either positive or negative and significant at a 5% significance level. The high R^2 values support the use of these risk measures since it means they are good proxies of the expected volatility of the dry bulk freight market.

4.3.2 Estimating the Risk and Return Relationship

This section presents the empirical results of the relationship between the multiple risk and return measures. The residual diagnostic tests presented in Table's 4.2 and 4.3 show that the annualised freight return series are affected by heteroscedasticity, autocorrelation, whilst the series are also nonstationary. Random trending may result in invalid inferences and thus cannot provide a robust estimation of the risk and return relationship, which is why the series were transformed into logarithmic return series.

Having found that the return series are stationary and also present heteroscedasticity and autocorrelation, equation 4.1 is estimated using Ordinary Least Squares with standard errors corrected for heteroscedasticity and serial correlation using Newey and West (1987) method. More specifically, the Newey-West (1987) adjusted t-statistic indicates whether or not the risk and returns relationship is statistically significant either positively or negatively.

Tables 4.5 to 4.8 present the signs of the beta coefficient values calculated using equation 4.1 for all return and risk measures of a Capesize vessel in each sample. More specifically, the signs of the GARCH approach risk measures are presented in Table 4.5 whilst the ones of the SVA and EWMA risk measures are included in Table 4.6. The beta coefficient signs of the Value at Risk approach using the GARCH and the SVA/EWMA measures are presented in Tables 4.7 and 4.8

respectively. The actual values of the beta coefficients of each of the aforementioned tables can be found in Appendix 4.C.

For instance, using the Value at Risk approach for the 1-month holding period, the risk and return relationship is mainly positive and significant. On the other hand, when the 12- and 24- holding period returns are regressed into the multiple risk measures, the relationship becomes negative and significant indicating a lag in impact of the shipping freight industry. These empirical findings can help identify optimal chartering strategies. For instance, if a ship-owner was only focusing on the 1-month return when make a decision (i.e. sign a 12month period contract) whilst ignoring the next periods, then this decision could be a suboptimal since, as can be seen in the 12- and 24-month returns, this would result in a negative payoff.

In essence, this means that the freight rates might be positive and high at time t but after 12 or 24 months they can drop to a lower level resulting in a negative trade off between risk and return.

The return series to which the t-eGARCH models was fitted was suboptimal, driving the ARCH coefficient (or q parameter) to zero and resulting in the blank cells that can be found in Table 4.7. Since q becomes equal to zero, the observed data cannot affect its own volatility, which is why MATLAB returned an error. Despite attempting to use a different solver as well as setting the model to use values from previous eGARCH model iterations, the suboptimality could not be overcome for the freight rate series so the Value at Risk t-eGARCH risk measure could not be calculated for this series.

Following this, there is a need to consider the nature of the relationship in different time periods and market conditions in order to examine the possibility that these influence risk-return results. For instance, the expectation is that the risks are positively correlated with returns in a bull market and negatively associated in a bear market.

The full sample is divided into four subsamples each of which representing bear and bull markets. For instance, as stated previously, the period from January 1990 to December 1995 (subsample A) and January 1996 to December 2001 (subsample B) are characterised by weak freight market conditions whilst the period between January 2002 and December 2008 (subsample C) was stronger for the dry bulk freight market.

Table 4.4: AR(1) Regressions of the SVA and EWMA Risk Measures

	SVA12				SVA24				EWMA12				EWMA24			
	spot	**P6m**	**P12m**	**P36m**	**spot**	**P6m**	**P12m**	**P36m**	**spot**	**P6m**	**P12m**	**P36m**	**spot**	**P6m**	**P12m**	**P36m**
Risk Measures h = 1m																
Constant	0.004	0.005	0.005	0.003	0.001	0.002	0.003	0.001	0.003	0.002	0.003	0.001	0.002	0.002	0.002	0.001
se	0.004	0.005	0.004	0.003	0.001	0.002	0.002	0.001	0.002	0.002	0.002	0.000	0.001	0.001	0.002	0.001
pvalue	0.233	0.127	0.041	0.128	0.752	0.425	0.171	0.332	0.236	0.195	0.051	0.270	0.316	0.197	0.033	0.228
AR(1) Coefficient	0.978	0.970	0.954	0.970	0.992	0.988	0.978	0.986	0.958	0.946	0.884	0.940	0.971	0.958	0.902	0.952
se	0.024	0.040	0.043	0.044	0.011	0.020	0.023	0.023	0.040	0.063	0.105	0.069	0.021	0.043	0.093	0.057
pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.960	0.939	0.909	0.941	0.986	0.974	0.958	0.973	0.920	0.893	0.781	0.883	0.944	0.917	0.813	0.907
Risk Measures h = 12m																
Constant	0.014	0.014	0.011	0.006	0.007	0.005	0.004	0.002	0.018	0.012	0.007	0.004	0.010	0.006	0.003	0.001
se	0.011	0.009	0.007	0.004	0.010	0.009	0.007	0.004	0.014	0.010	0.004	0.003	0.009	0.006	0.005	0.003
pvalue	0.078	0.055	0.064	0.151	0.235	0.343	0.329	0.491	0.109	0.142	0.171	0.343	0.233	0.349	0.429	0.707
AR(1) Coefficient	0.969	0.968	0.970	0.974	0.988	0.989	0.990	0.991	0.943	0.950	0.961	0.964	0.978	0.983	0.988	0.989
se	0.029	0.029	0.030	0.027	0.020	0.022	0.021	0.019	0.069	0.070	0.044	0.045	0.029	0.027	0.031	0.028
pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.937	0.937	0.940	0.954	0.977	0.976	0.980	0.986	0.888	0.903	0.924	0.931	0.957	0.966	0.975	0.980
Risk Measures h = 24m																
Constant	0.013	0.013	0.010	0.007	0.003	0.002	0.001	0.001	0.015	0.011	0.006	0.005	0.011	0.006	0.002	0.001
se	0.010	0.008	0.005	0.004	0.008	0.008	0.005	0.004	0.011	0.010	0.005	0.004	0.009	0.009	0.005	0.003
pvalue	0.132	0.111	0.113	0.152	0.711	0.724	0.770	0.767	0.155	0.172	0.230	0.253	0.262	0.407	0.631	0.730
AR(1) Coefficient	0.969	0.966	0.967	0.972	0.993	0.993	0.993	0.993	0.953	0.956	0.964	0.963	0.976	0.983	0.988	0.989
se	0.030	0.027	0.021	0.022	0.015	0.016	0.014	0.014	0.056	0.061	0.040	0.057	0.022	0.026	0.026	0.028
pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.935	0.929	0.933	0.943	0.974	0.976	0.981	0.985	0.906	0.913	0.928	0.927	0.947	0.962	0.974	0.978

Notes: Table 4.4 presents the summary statistics of the *A(1)* regression that assesses whether the SVA and EWMA risk measures can proxy the expected volatility of the dry bulk freight market for the period between January 1990 to June 2016.

Finally, the period from January 2009 to June 2016 is also a weak period since the market was recovering from the Credit Crisis that took place in 2008. Table 4.5 presents the beta coefficients of the eGARCH, GARCH and gjrGARCH model for all sub-samples for a Capesize vessel.

As can be seen from Table 4.5, there is a positive and significant relationship between the risk and spot returns across all samples except from sub-sample C and D where the relationship was found to be negative and significant. The reason for a negative and significant risk and return relationship in sub-samples C and D is the fact that it covers the turbulent period after the Credit Crisis which affected the freight market in the shipping industry.

Additionally, the risk and return relationship for the 12-month holding period is also negative and significant for the period from January 1990 to June 2016 in subsamples C and D. Regarding the relationship between risk and returns for a 1-month holding period, this appears to be mainly positive and significant but the one for the 12- and 24-month periods is negative and significant. These findings indicate that the decisions in shipping industry affect the returns but the exact impact cannot be estimated hence why the majority of the risk and return relationship was negative or, in other words, ship owners did not make the best decisions.

As can be seen from Table 4.6, the risk and return relationship when using the SVA and the EWMA measures is mixed and follows the same pattern as when the GARCH method is used. More specifically, the relationship of the 1-month holding period is positive and significant except from subsample C. The returns for the 12 – and 24-month holding periods are negative and significant throughout the planning horizon, as well as during subsample C and D.

Table 4.7 and 4.8 present the risk and return relationship using the Value at Risk approach. The empirical findings show that the relationship is positive and significant across all risk measures and sub samples. On the other hand, when the same relationship is assessed using the downside Value at Risk approach, it becomes negative and significant in all samples (see Appendix 4.D). The study also analyses the relationship between the above (below) target returns and their risk measures for each sub-sample (see Appendix 4.D). The results show that the relationship between the risk and returns is negative for the below the target returns and positive for the above the target ones however the relationship appears to be mainly insignificant at the 5% significance level.

Table 4.5: Beta coefficients signs of risk and return relationship (GARCH approach)

		h = 1m				h = 12m				h = 24m			
		Spot	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**
FULL	eGARCH		-	-	-	-	-	-	-		+		
	pvalue		0.019	0.003	0.000	0.002	0.000	0.000	0.000		0.015		
	GARCH			-		-	-	-	-	+			
	pvalue			0.018		0.000	0.000	0.000	0.000	0.028			
	gjrGARCH			-	-	-	-	-	-				
	pvalue			0.011	0.011	0.000	0.000	0.000	0.000				
A	eGARCH		+	-			+		+	+	+	+	
	pvalue		0.001	0.002			0.026		0.000	0.000	0.000	0.000	
	GARCH								+	+	+	+	+
	pvalue								0.001	0.002	0.000	0.000	0.000
	gjrGARCH		+	-			+		+	+	+	+	+
	pvalue		0.012	0.022			0.008		0.000	0.003	0.000	0.000	0.000
B	eGARCH									+	+	+	-
	pvalue									0.000	0.002	0.001	0.000
	GARCH									+	+	+	
	pvalue									0.000	0.005	0.001	
	gjrGARCH									+	+	+	-
	pvalue									0.000	0.002	0.019	0.000
C	eGARCH	-	-	-	-	-	-	-	-				+
	pvalue	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000				0.016
	GARCH		-	-	-	-	-	-	-	+	+	+	+
	pvalue		0.002	0.027	0.000	0.000	0.000	0.029	0.007	0.009	0.000	0.000	0.000
	gjrGARCH	-	-	-	-	-	-	-	-	+	+	+	+
	pvalue	0.045	0.001	0.020	0.000	0.000	0.000	0.001	0.000	0.015	0.000	0.000	0.000
D	eGARCH					-	-	-	-	-	-	-	-
	pvalue					0.010	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	GARCH						-	-	-	-	-	-	-
	pvalue						0.000	0.000	0.000	0.000	0.000	0.000	0.000
	gjrGARCH					-	-	-	-	-	-	-	-
	pvalue					0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000
No Crisis	eGARCH								-	+	+	+	
	pvalue								0.017	0.015	0.000	0.006	
	GARCH								-	+	+	+	
	pvalue								0.002	0.000	0.000	0.002	
	gjrGARCH								-	+	+	+	
	pvalue								0.002	0.002	0.000	0.022	

Notes: Table 4.5 presents the signs of the risk and return relationship for all samples using the GARCH approaches. The blue values indicate a significant negative relationship, while the green ones indicate a significant positive relationship at a 5% significance level. All beta coefficients values (i.e. significant and non significant) are presented in Appendix 4.C – Tables C.4.13 and C.4.14.

Table 4.6: Beta coefficients signs of risk and return relationship (SVA and EWMA)

		h = 1m				h = 12m				h = 24m			
		Spot	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**
FULL	SVA12					-	-	-	-	-	-	-	-
	pvalue					0.000	0.000	0.000	0.000	0.000	0.001	0.017	0.002
	SVA24					-	-	-	-	-	-	-	-
	pvalue					0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	EWMA12			-		-	-	-	-	-	-	-	-
	pvalue			0.003		0.001	0.000	0.000	0.000	0.000	0.000	0.002	0.000
	EWMA24			-	-	-	-	-	-	-	-	-	-
	pvalue			0.001	0.040	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A	SVA12	+							+	+	+	+	-
	pvalue	0.001							0.048	0.000	0.000	0.000	0.000
	SVA24					-				+	+	+	
	pvalue					0.024				0.000	0.000	0.004	
	EWMA12	+			+				+	+	+	+	-
	pvalue	0.000			0.008				0.006	0.000	0.000	0.000	0.003
	EWMA24	+	+							+	+	+	
	pvalue	0.017	0.040							0.000	0.000	0.001	
B	SVA12							-					
	pvalue							0.046					
	SVA24	+	+	+	+			+	+			+	+
	pvalue	0.016	0.001	0.000	0.014			0.046	0.006			0.019	0.006
	EWMA12												
	pvalue												
	EWMA24	+	+	+					+			+	+
	pvalue	0.015	0.000	0.000					0.007			0.004	0.008
C	SVA12	-	-	-	-	-	-	-	-	-	-	-	-
	pvalue	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SVA24	-	-	-	-	-	-	-	-	-	-	-	
	pvalue	0.003	0.000	0.000	0.000	0.000	0.001	0.008	0.004	0.000	0.002	0.005	
	EWMA12	-	-	-	-	-	-	-	-	-	-	-	-
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000
	EWMA24	-	-	-	-	-	-	-	-	-	-		
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.008		
D	SVA12						-	-	-				
	pvalue						0.000	0.000	0.003				
	SVA24						-	-	-		-		
	pvalue						0.000	0.000	0.005		0.043		
	EWMA12						-	-	-	-	-	-	
	pvalue						0.000	0.000	0.000	0.000	0.001	0.005	
	EWMA24						-	-	-	-	-	-	-
	pvalue						0.000	0.000	0.001	0.026	0.004	0.007	0.029
No Crisis	SVA12			-	-	-	-	-	-				
	pvalue			0.047	0.045	0.009	0.000	0.000	0.000				
	SVA24				-		-	-	-		+	+	
	pvalue				0.049		0.002	0.000	0.000		0.013	0.031	
	EWMA12			-	-	-	-	-	-		+		
	pvalue			0.002	0.000	0.010	0.000	0.000	0.000		0.020		
	EWMA24		-	-	-		-	-	-	+	+	+	
	pvalue		0.016	0.000	0.000		0.001	0.000	0.000	0.004	0.001	0.012	

Notes: Table 4.6 presents the signs of the risk and return relationship for all samples using the Simple Variance (SVA) and the Exponentially Weighted Moving Average (EWMA) variance approaches. The values in blue indicate a significant negative relationship while the green values ones show a significant positive relationship at a 5% significance level. All beta coefficients values (i.e. significant and non significant) are presented in Appendix 4.C – Table C.4.15 and C.4.16.

These empirical findings support the existence of a paradoxical relationship that contradicts the CAPM theory. More specifically, the risk and return relationship remains almost always unaffected by the method that is selected to measure the risk and return, however the results confirm that the relationship (between the risk and returns) is affected by time periods and market conditions. These results need to be treated with caution due to the small number of observation per sub-sample.

Nevertheless, a negative association between risk and return seems logical for investments in a highly volatile shipping market where ship-owners need to commit to long-term contracts. For instance, by the time that a period time charter contract is completed (i.e. 6-, 12 or 36-months), the market condition dynamics might have changed significantly affecting the trade-off between risk and return.

The purpose of using a series of macroeconomic variables is to prove that the risk and return relationship remains unaffected. The R^2 of equation 4.1 appears to increase as control variables are included in the model, indicating that the innovations in macroeconomic variables generate a better proxy for state variables capturing shifts in the investment opportunity set. Tables E.4.21 to E.4.26 in Appendix 4.E show the empirical findings of equation 4.1 after controlling for macroeconomic variables. The empirical findings remain unaffected, enhancing the robustness of the findings of Tables 4.5 and 4.8.

The adequacy of the Value at Risk approach was assessed using the Kupiec (1995). More specifically, when the corresponding log likelihood ratio value is larger than the corresponding critical value, then the null hypothesis is rejected indicating the VaR is not adequate risk measure (see Equation 4.13). At a 99% confidence interval, the Value at Risk models based on the SVA, EWMA and the GARCH approaches are all able to efficiently estimate the risk over every period included in this study (see Appendix 4.F – Table F.4.35).

4.3.3 Estimating the Utility Functions

Using the above and the below the target returns the utility functions are also estimated using equation (4.14). A graphical illustration of the utility functions shows whether shipping investment obey risk attitudes conceptualised as per the prospect theory's utility function (i.e. concave for gains and convex for losses). The estimated return measures are distinguished into returns that move above the target level (gains) and the ones that are below it (losses). As mentioned before, the target level is defined as the average performance (returns) level of each return measure.

Figures 4.1 to 4.6 present the value (utility) functions of the freight rate return measures in different samples and for three holding period horizons. The value function is defined as deviations from the reference point, which as can be seen from Figures 4.1 to 4.6, is convex for gains (implying risk seeking) and concave for losses (risk aversion).

Table 4.7: Beta coefficients signs of risk and return relationship (VaR GARCH)

			h = 1m				h = 12m				h = 24m			
			Spot	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**
FULL	eGARCH		+	+	+	+	+	+	+		+		+	
		pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000		0.000	
	GARCH		+	+	+	+	+	+	+	+	+	+	+	+
		pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	gjrGARCH		+	+	+	+	+	+	+	+	+	+	+	+
		pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A	eGARCH		+	+	+	+	+	+	+	+	+		+	+
		pvalue	0.000	0.000	0.000	0.000	0.000	0.039	0.000	0.022	0.003		0.000	0.000
	GARCH		+	+	+	+	+	+	+		+	+	+	+
		pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000
	gjrGARCH		+	+	+	+	+	+	+	+	+	+	+	+
		pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
B	eGARCH		+	+	+	+	+	+	+	+	+			
		pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000			
	GARCH		+	+	+	+	+	+		+	+	+	+	+
		pvalue	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000
	gjrGARCH		+	+	+	+	+	+	+	+	+	+	+	+
		pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C	eGARCH		+	+	+				+		+	+		
		pvalue	0.000	0.000	0.000				0.000		0.001	0.000		
	GARCH		+	+	+	+	+	+	+	+	+	+	+	+
		pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	gjrGARCH		+	+	+	+	+	+	+	+	+	+	+	+
		pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.010	0.000	0.000	0.000	0.000	0.000
D	eGARCH		+	+	+	+	-	+	+	+	+			
		pvalue	0.000	0.000	0.000	0.000	0.005	0.000	0.000	0.000	0.000			
	GARCH		+	+	+	+		+	+	+	+	+	+	+
		pvalue	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000
	gjrGARCH		+	+	+	+	+	+	+	+	+	+	+	+
		pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
NoCrisis	eGARCH			+	+	+	+	+	+		+		+	
		pvalue		0.008	0.000	0.000	0.000	0.000	0.000		0.000		0.000	
	GARCH		+	+	+	+	+	+	+	+	+	+	+	+
		pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	gjrGARCH		+	+	+	+	+	+	+	+	+	+	+	+
		pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table 4.7 presents the signs of the risk and return relationship for all samples using the Value at Risk (VaR) GARCH approaches. The values in blue indicate a significant negative relationship and the green ones show a significant positive relationship at a 5% significance level. All beta coefficients values (i.e. significant and non significant) are presented in Appendix 4.C – Table C.4.17.

Table 4.8: Beta coefficients of risk and return relationship (VaR SVA and EWMA)

		h = 1m				h = 12m				h = 24m			
		Spot	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**
FULL	SVA12	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SVA24	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	EWMA12	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	EWMA24	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A	SVA12	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SVA24	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	EWMA12	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	EWMA24	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
B	SVA12	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SVA24	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	EWMA12	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	EWMA24	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C	SVA12	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SVA24	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	EWMA12	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	EWMA24	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D	SVA12	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SVA24	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	EWMA12	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	EWMA24	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
NoCrisis	SVA12	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SVA24	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	EWMA12	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	EWMA24	+	+	+	+	+	+	+	+	+	+	+	+
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

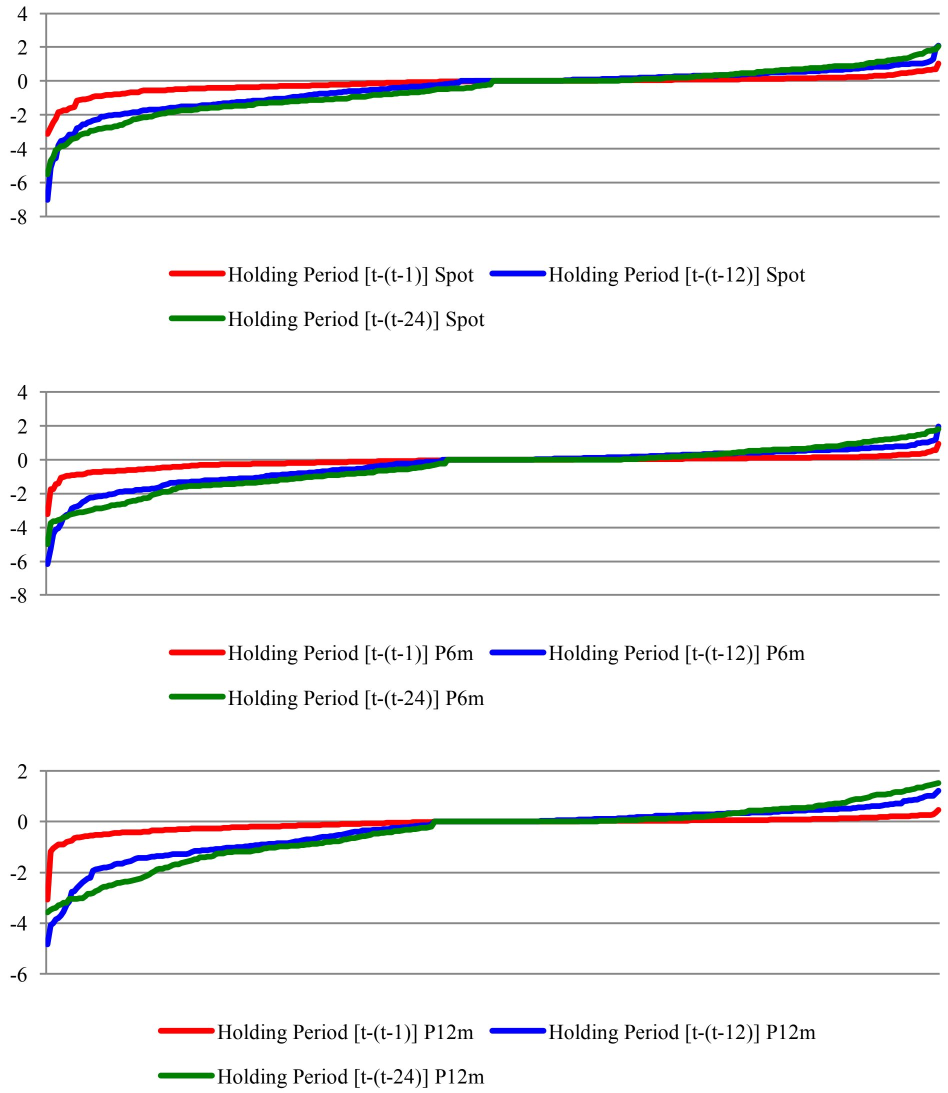
Notes: Table 4.8 presents the signs of the risk and return relationship for all samples using the Value at Risk (VaR) Simple Variance (SVA) and the Exponentially Weighted Moving Average (EWMA) Variance approaches. The values in blue indicate a significant negative relationship and the green ones show a significant positive relationship at a 5% significance level. All beta coefficients values (i.e. significant and non significant) are presented in Appendix 4.C – Table C.4.18 and C.4.19.

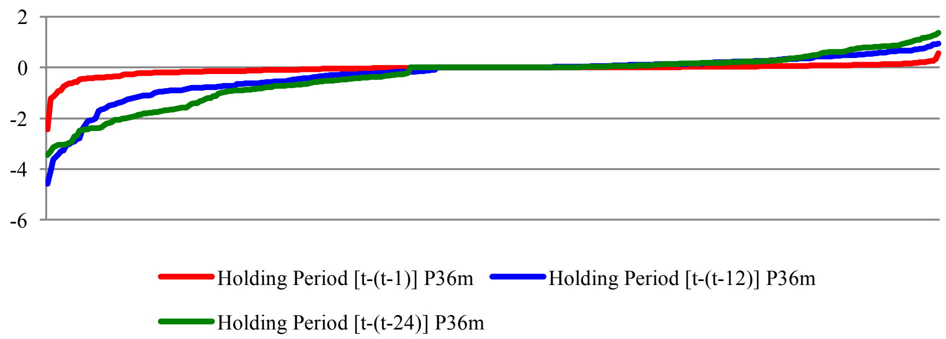
This is the opposite of what the prospect theory is implying meaning that shipowners tend to be risk-seeking when the returns are moving above the reference point and risk averse when the returns are moving below the reference point.

In other words, during good market conditions (i.e. when the returns are moving above the target level), ship-owners prefer spot contracts that bear more risk compared to the period ones but also result in higher returns. Oppositely, during weak market conditions (i.e. when the returns are moving below the target level) shipowners prefer period contracts that have less risk compared to the spot contracts. A long-term contract guarantees a fixed freight rate for a predetermined period (i.e. 6 months Period Time Charter – PTC6m, 12 months – PTC12m or 36 months – PTC36m) and minimises the risk of having vessels chartered in low freight rates

The red, blue and green lines indicate the utility functions of the freight rate returns series of 1-, 12- and 36-month holding period returns respectively.

Figure 4.1: Utility (Value) Functions – from January 1990 to June 2016 for a Capesize vessel





The shipping literature suggests that if the freight market is expected to be in an upward trend, ship-owners may charter their vessels under short-term (spot) charters in order to take advantage of the rising freight rates. Oppositely, if expecting a downward trend, a long-term contract guarantees a fixed freight rate for a determined period (i.e. 6 months Period Time Charter – PTC6m, 12 months – PTC12m or 36 months – PTC36m) and minimises the risk from having vessels chartered in low freight rates.

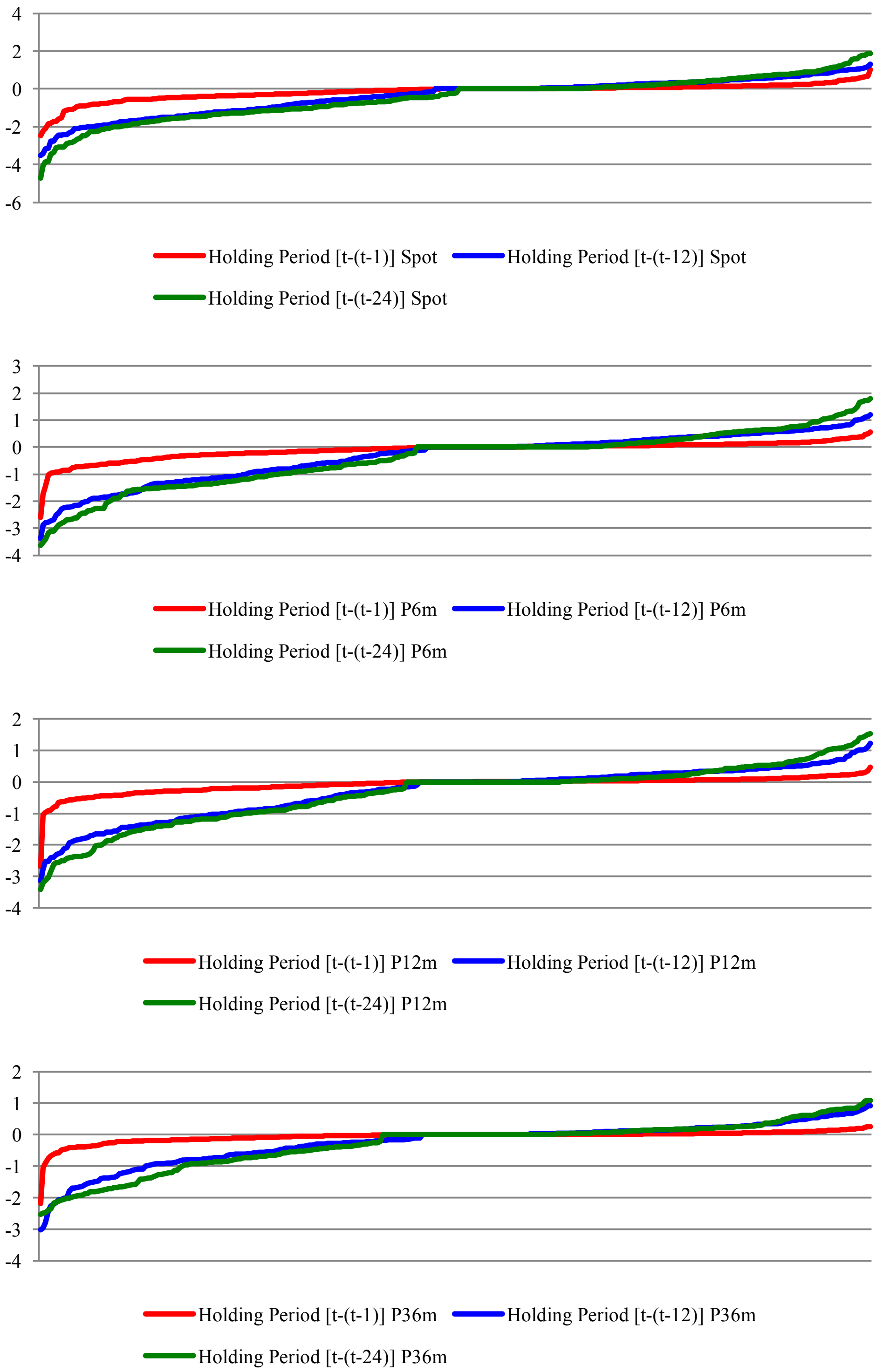
On the other hand, the Prospect Theory supports the fact that investors tend to be risk-seekers during weak market conditions and risk-averse during strong market periods. Applying the aforementioned fact to the shipping freight market would mean that during weak market conditions ship-owners should operate their vessels under spot contracts and prefer select period time charter contracts during strong market periods.

By measuring the utility functions of shipping investments in the dry bulk freight market, it is observed that shipping investments do not obey the risk attitudes conceptualised by the prospect theory's utility function, except from the utility functions of longer holding periods (i.e. 12- and 36- months).

This means that, if after the end of a 12-month period charter, the freight rates are lower than when the contract was signed (i.e. the 12-month return is negative), a shipowner would prefer a spot contract despite the added risk. This can be explained by the fact that shipowners might want to compensate for the lost returns during the period when the vessel was operating under a period contract.

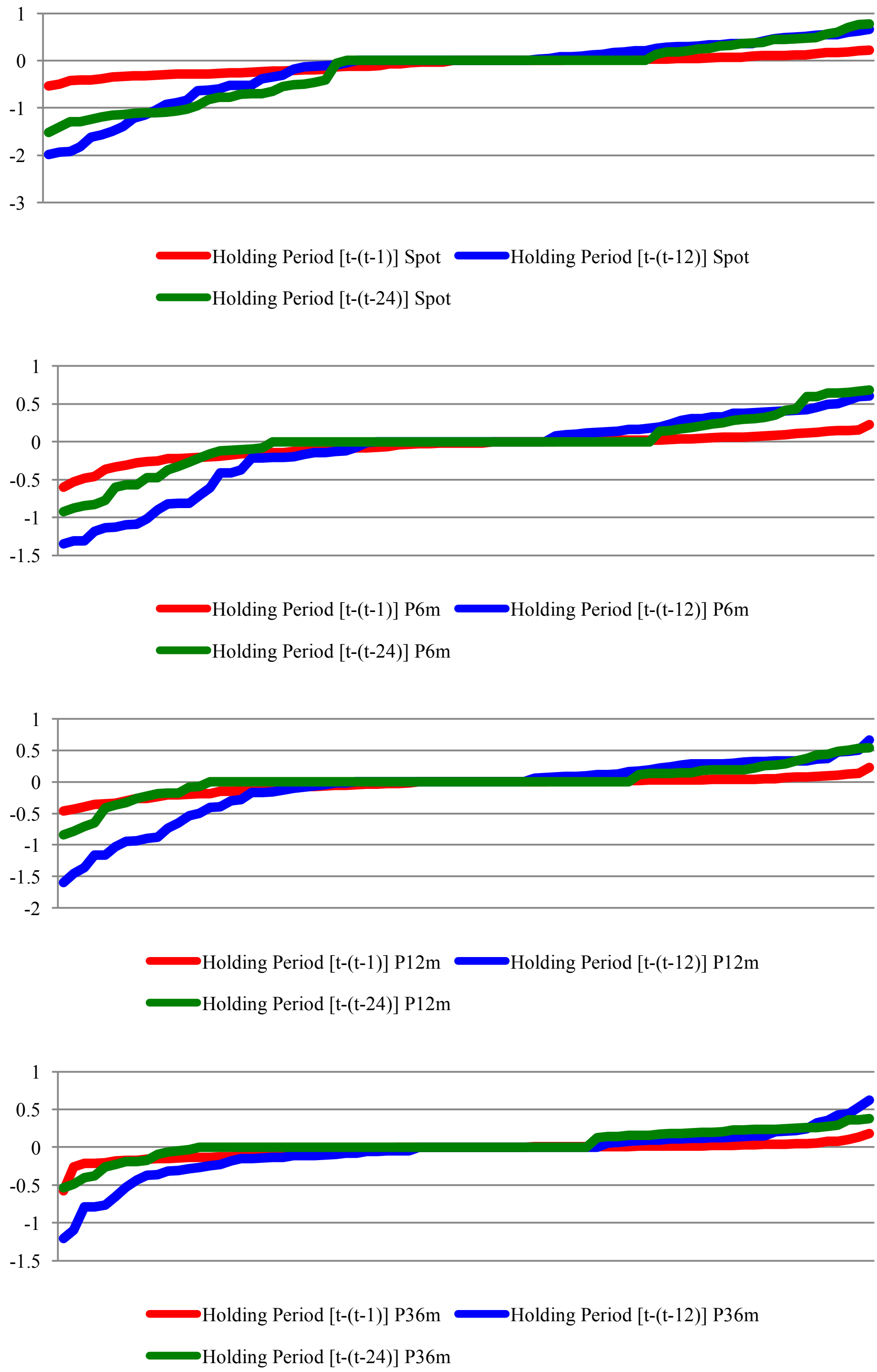
As this study uses historical return measures to estimate the utility functions, it is important to note that risk attitudes are usually assessed using large representative surveys and complementary experiments. Therefore, the utility function presented in the next figures need to be treated cautiously and should mainly be used to explain the paradoxical findings observed during the longer holding periods (i.e. 12 or 24 months).

Figure 4.2: Utility (Value) Functions – No Crisis period for a Capesize vessel



More specifically, the current findings can be considered as preliminary evidence that risk attitudes conceptualised as per the prospect theory's utility function are not applicable to the shipping freight market except from cases when longer period returns are used.

Figure 4.3: Utility (Value) Functions – Subsample period A for a Capesize vessel



For instance, as can be seen from Figure 4.5, the utility functions during subsample C are mainly convex for gains and concave for losses. On the other hand, during subsample B and more specifically for longer holding periods (see Figure 4.4), the utility functions are concave for gains and convex for losses (see blue and green lines). Considering the average return generated during these subperiods, it can be seen that the average the returns of subsample C were positive whereas the ones during subsample B were negative. This means that during weak market conditions, ship-owners become risk seekers when their investments are below the expected target level.

Figure 4.4: Utility (Value) Functions – Subsample period B for a Capesize vessel

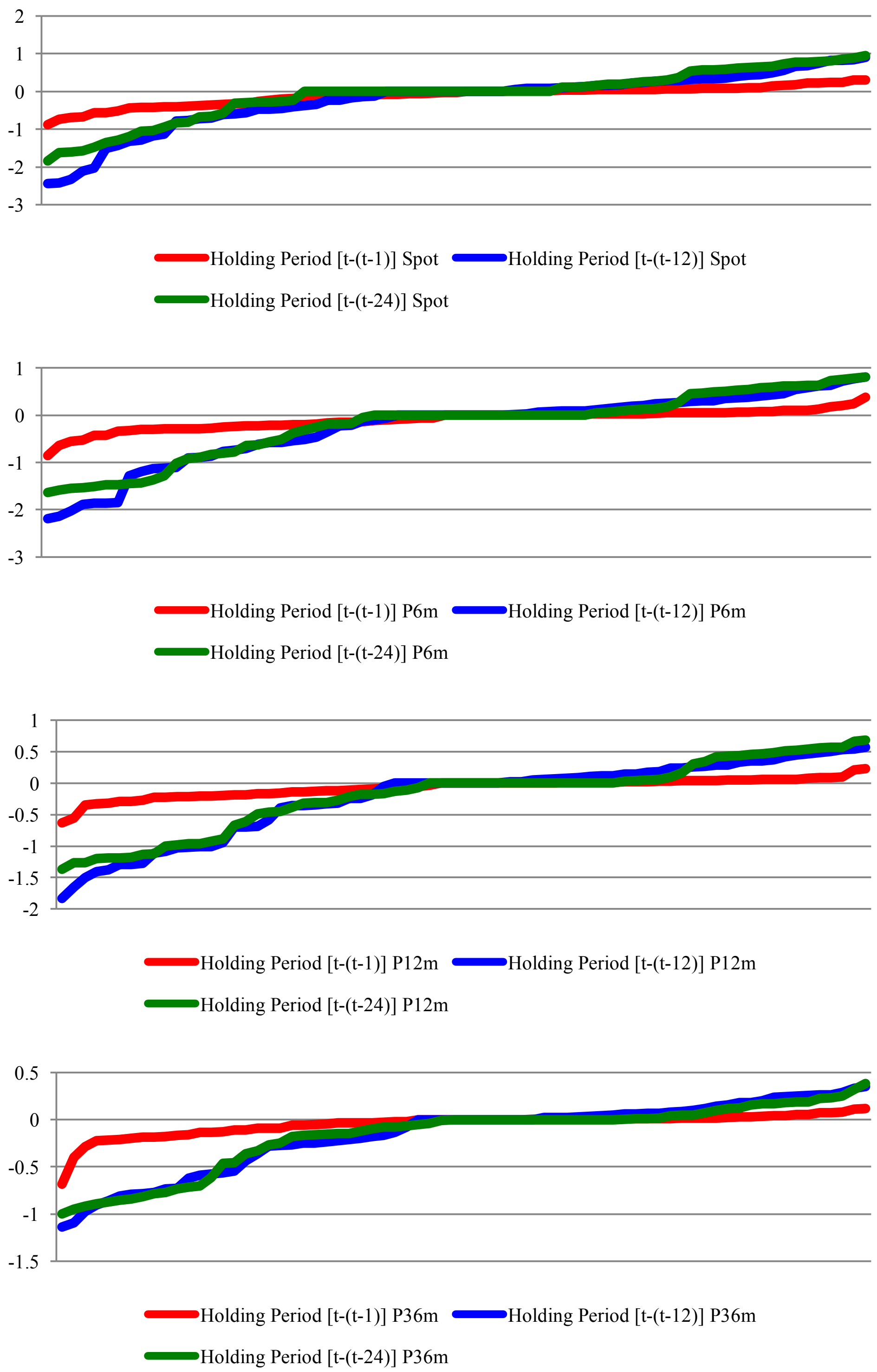
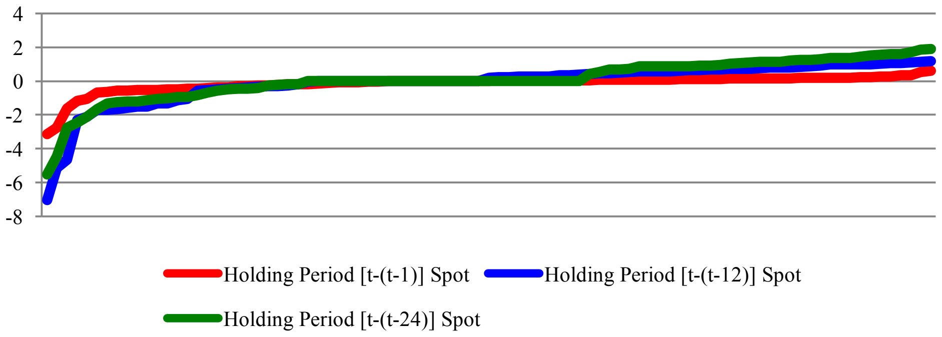
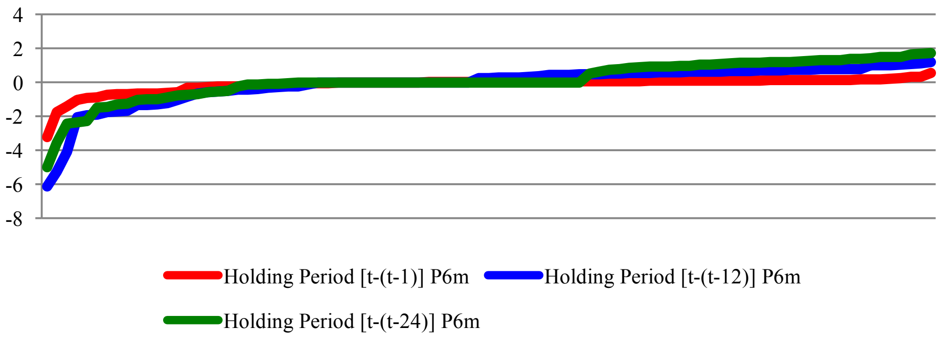
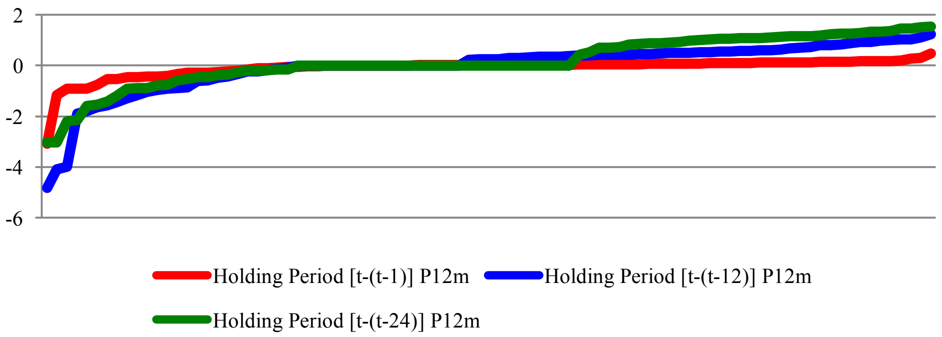


Figure 4.5: Utility (Value) Functions – Subsample period C for a Capesize vessel







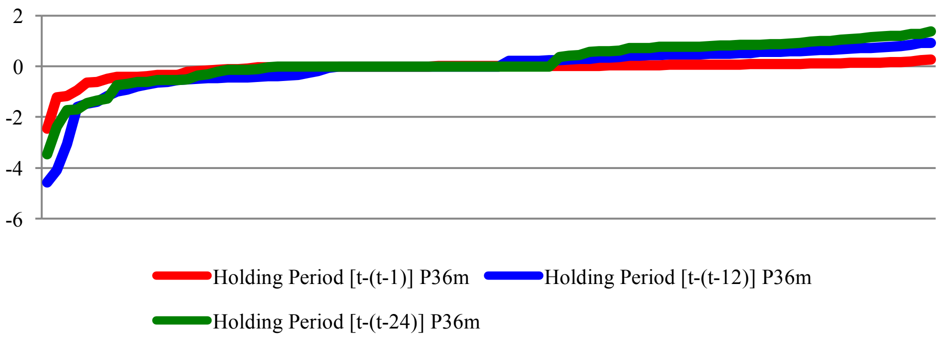
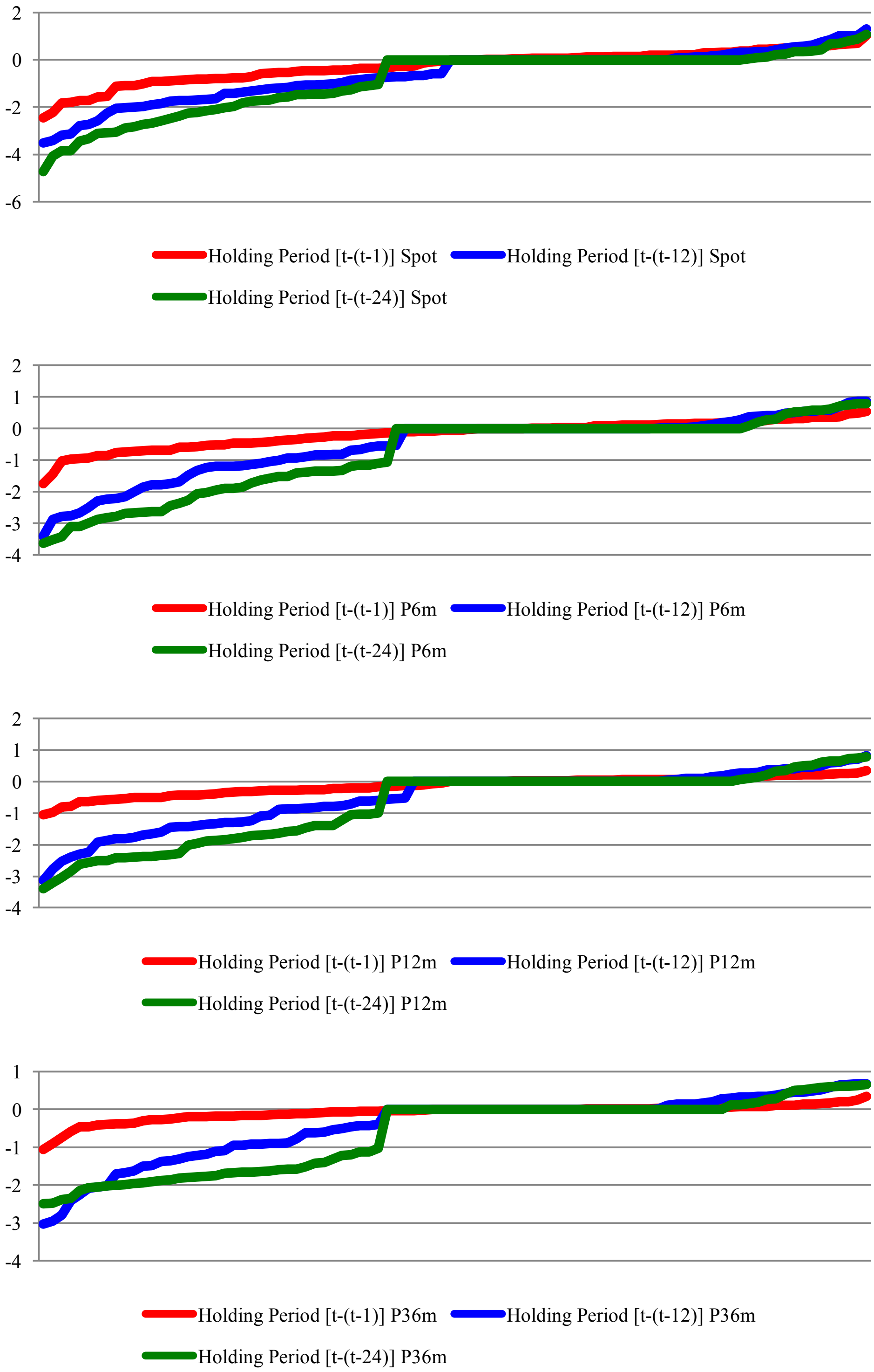


Figure 4.6: Utility (Value) Functions – Subsample period D for a Capesize vessel



The shape of the utility functions which is based on historical freight rate values suggests that a future real experiment that will investigate the way ship-owners make decisions will enhance the robustness of these value functions. Being able to prove that ship-owners preferences follow the aforementioned pattern is of great importance for the shipping literature since it could explain the way shipping investments are formulated under different market conditions, provide useful information in terms of investment timing, while also assist investors in the creating an optimal portfolio asset portfolio.

4.4 Conclusion

The empirical analysis investigates the nature of the relationship between risk and returns in shipping investments over different time periods, market conditions and risk attitudes using multiple risk and return measures. The returns resulting from operating in the physical market based on four different types of contracts (i.e. spot, P6m, P12m and P36m) is measured over three holding period horizon. The Simple Variance Approach (SVA), the Exponentially Weighted Moving Average Variance (EWMAV), GARCH, eGARCH, gjrGARCH and Value at Risk approaches are used to determine the existence, nature and significance of a risk-return trade off in the dry bulk freight market.

The financial theory supports the existence of a positive relationship between risk and returns while the management theory suggests that there are instances where the relationship can also be negative. The empirical analysis demonstrates that the relationship can be both positive and negative depending on the time period, market conditions and the type of contract. The empirical analysis shows that the relationship is sensitive in most of the aforementioned scenarios. For instance, the relationship between the freight rate returns and the risk measures can be either positive or negative depending on the sample period.

For instance, the risk and return relationship is positive in the first 2 subsamples but negative in subsample C (i.e. January 2002 to December 2008) and D (i.e. January 2009 to June 2016) because of the market conditions during these periods. For instance, subsample D can be considered as a weak market period recovering from the financial Credit Crisis of 2008. On the other hand, subsample A and B can be considered as bull markets and thus the positive association between risk and return was expected.

Additionally, the relationship between risk and returns changes when longer holding periods are used. For instance, when the holding period is set to 12- or 24-months, the relationship is mostly negative indicating that shipping investments should not only consider current conditions in order to make an optimal decision but should equally assess future expectations.

The study also examines whether the inclusion of other predictive variable affects the relationship between risk and return and the results show that the addition of control variables do not affect the relationship.

In addition, the empirical findings support the fact that some of the utility functions of 12- or 24-months holding periods are concave for gains (implying risk aversion) and convex for losses (risk seeking). In other words, ship-owners seem to prefer the high (low) risk – high (low) return investments when the freight market is prosperous. On the other hand, when the market is in a downward trend, ship-owners tend to look for high (low) return – low (high) risk investments. That asymmetric risk-return relationship can be attributed to risk attitudes governed by Prospect Theory's framework. However at this point it is important to mention that although the utility functions can be used as a tool to explain why the risk and return relationship is negative or positive, further analysis is required to explicitly understand the ship-owners' risk preferences.

These empirical findings suggest that shipping investment, under specific circumstances, present a paradoxical relationship between risk and return which is not due to inconsistencies in the data since the outcome can be replicated even with different risk and return measures. This is called a paradoxical relationship since it contradicts the financial theory and especially the Capital Asset Pricing Model.

Future research can focus on identifying and understanding ship-owners' preferences and behaviour drivers in instances where there is a negative association between risk and returns. Additionally, further research could investigate whether shipping investments require a different (riskier) framework in order to be priced accurately, such as one that will support the existence of a negative association between risk and return under specific circumstances.

Appendix 4.A: The Risk Measures in Detail

Table A.4.9: List of Risk Measures

	Risk Measure		Description	Equation
1	**SVA12**	**spot**	Simple Variance Approach of 12 months rolling window	Equation 4.5
2		**P6m**		
3		**P12m**		
4		**P36m**		
5	**SVA24**	**spot**	Simple Variance Approach of 24 months rolling window	
6		**P6m**		
7		**P12m**		
8		**P36m**		
9	**EWMA12**	**spot**	Exponentially Weighted Moving Average Variance Approach od 12 months rolling window	Equation 4.6
10		**P6m**		
11		**P12m**		
12		**P36m**		
13	**EWMA24**	**spot**	Exponentially Weighted Moving Average Variance Approach od 24 months rolling window	
14		**P6m**		
15		**P12m**		
16		**P36m**		
17	**eGARCH**	**spot**	Exponential GARCH model	Equation 4.3
18		**P6m**		
19		**P12m**		
20		**P36m**		
21	**GARCH**	**spot**	an autoregressive moving average model for conditional variances, with p GARCH coefficients associated with lagged variances and q ARCH coefficients associated with squared innovations.	Equation 4.7
22		**P6m**		
23		**P12m**		
24		**P36m**		
25	**gjrGARCH**	**spot**	Glosten, Jagannathan and Runkle (1993) GARCH –gjrGARCH model	Equation 4.8
26		**P6m**		
27		**P12m**		
28		**P36m**		
29	**t SVA12**	**spot**	Estimating the Value at Risk based on the SVA12, SVA24, EWMA 12 and EWMA 24 risk measures using equation 4.10, 4.11 and 4.12	Equations 4.11, 4.12 and 4.13
30		**P6m**		
31		**P12m**		
32		**P36m**		
33	**t SVA24**	**spot**		
34		**P6m**		
35		**P12m**		
36		**P36m**		
37	**t EWMA12**	**spot**		
38		**P6m**		
39		**P12m**		
40		**P36m**		
41	**t EWMA24**	**spot**		
42		**P6m**		
43		**P12m**		
44		**P36m**		
45	**t eGARCH**	**spot**	estimating the GARCH, eGARCH and gjrGARCH risk measures under the assumption that the residuals series follow a t- Student distribution	Equations 4.3, 4.7 and 4.8
46		**P6m**		
47		**P12m**		
48		**P36m**		
49	**t GARCH**	**spot**		
50		**P6m**		
51		**P12m**		
52		**P36m**		
53	**t gjrGARCH**	**spot**		
54		**P6m**		
55		**P12m**		
56		**P36m**		
57	**VaR t eGARCH**	**spot**	Estimating the Value at Risk based on the eGARCH, GARCH and gjrGARCH risk measures. Equation 4.10 is used to estimate the Value at Risk using the variance-covariance method. Equation 4.11 and 4.12 measure the dowside and the upside Value at Risk.	Equation 4.11, 4.12 and 4.13
58		**P6m**		
59		**P12m**		
60		**P36m**		
61	**VaR t GARCH**	**spot**		
62		**P6m**		
63		**P12m**		
64		**P36m**		
65	**VaR t gjrGARCH**	**spot**		
66		**P6m**		
67		**P12m**		
68		**P36m**		

Table A.4.9 presents all the risk measures used in the empirical analysis along with a brief description and the equation used to measure each of them.

Appendix 4.B: AR(1) Regressions of the Risk Measures

Tables B.4.10 and B.4.12 present the AR(1) Regressions of the Risk Measures for the period from January 1990 to June 2016.

Table B.4.10: AR(1) Regressions of the GARCH approach Risk Measures

	eGARCH				GARCH				gjrGARCH			
h = 1m	**spot**	**P6m**	**P12m**	**P36m**	**spot**	**P6m**	**P12m**	**P36m**	**spot**	**P6m**	**P12m**	**P36m**
Constant	0.004	0.022	0.028	0.020	0.003	0.012	0.016	0.003	0.004	0.012	0.018	0.005
se	0.004	0.007	0.011	0.002	0.003	0.007	0.005	0.002	0.004	0.007	0.006	0.003
pvalue	0.117	0.000	0.014	0.000	0.132	0.006	0.001	0.075	0.124	0.007	0.003	0.070
AR(1)												
Coefficient	0.946	0.554	0.172	-0.321	0.951	0.760	0.423	0.807	0.949	0.761	0.421	0.743
se	0.065	0.169	0.072	0.061	0.055	0.185	0.154	0.209	0.068	0.193	0.156	0.222
pvalue	0.000	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.900	0.305	0.026	0.100	0.914	0.576	0.177	0.650	0.903	0.577	0.174	0.550
h = 12m												
Constant	0.173	0.133	0.112	0.095	0.190	0.102	0.044	0.027	0.190	0.099	0.044	0.028
se	0.058	0.041	0.039	0.032	0.050	0.040	0.025	0.014	0.051	0.040	0.026	0.015
pvalue	0.000	0.000	0.000	0.000	0.000	0.004	0.025	0.084	0.000	0.006	0.030	0.103
AR(1)												
Coefficient	0.623	0.573	0.511	0.420	0.660	0.779	0.873	0.888	0.661	0.788	0.874	0.891
se	0.133	0.135	0.174	0.171	0.118	0.135	0.106	0.090	0.119	0.135	0.109	0.093
pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.386	0.327	0.258	0.174	0.434	0.606	0.761	0.788	0.436	0.620	0.764	0.793
h = 24m												
Constant	0.128	0.053	0.021	0.015	0.078	0.098	0.037	0.028	0.081	0.101	0.037	0.028
se	0.042	0.018	0.007	0.006	0.029	0.032	0.013	0.011	0.031	0.033	0.013	0.011
pvalue	0.000	0.006	0.047	0.048	0.010	0.004	0.055	0.057	0.009	0.003	0.056	0.057
AR(1)												
Coefficient	0.795	0.893	0.937	0.934	0.887	0.847	0.922	0.918	0.883	0.842	0.923	0.918
se	0.072	0.048	0.028	0.035	0.063	0.059	0.032	0.042	0.065	0.059	0.032	0.042
pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.631	0.798	0.879	0.872	0.786	0.716	0.852	0.842	0.779	0.709	0.853	0.842

Notes: Table B.4.10 presents the summary statistics of the *A(1)* regression that assesses whether the GARCH, eGARCH and gjrGARCH risk measures can proxy the expected volatility of the dry bulk freight market for the period between January 1990 to June 2016.

Table B.4.11: AR(1) Regressions of the VaR GARCH approach Risk Measures

	VaR t eGARCH				VaR t GARCH				VaR t gjrGARCH			
h = 1m	**spot**	**P6m**	**P12m**	**P36m**	**spot**	**P6m**	**P12m**	**P36m**	**spot**	**P6m**	**P12m**	**P36m**
Constant	-0.089	-0.047	-0.036	-0.077	-0.090	-0.054	-0.027	-0.013	-0.084	-0.050	-0.027	-0.012
se	0.017	0.010	0.007	0.034	0.017	0.014	0.007	0.006	0.016	0.012	0.007	0.006
pvalue	0.000	0.000	0.000	0.012	0.000	0.000	0.002	0.066	0.000	0.000	0.002	0.085
AR(1) Coefficient	0.535	0.491	0.437	0.690	0.405	0.422	0.410	0.560	0.476	0.491	0.381	0.597
se	0.077	0.108	0.105	0.164	0.080	0.108	0.101	0.146	0.079	0.103	0.093	0.140
pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.285	0.239	0.187	0.474	0.162	0.176	0.165	0.312	0.225	0.239	0.142	0.354
h = 12m												
Constant	-0.032	-0.014	-0.008	-	-0.028	-0.016	-0.007	-0.008	-0.028	-0.016	-0.007	-0.008
se	0.020	0.017	0.014	-	0.020	0.017	0.014	0.012	0.020	0.017	0.014	0.012
pvalue	0.165	0.377	0.513	-	0.216	0.359	0.539	0.495	0.215	0.359	0.540	0.495
AR(1) Coefficient	0.896	0.919	0.939	-	0.891	0.908	0.939	0.927	0.890	0.906	0.939	0.928
se	0.043	0.040	0.035	-	0.045	0.050	0.037	0.051	0.045	0.053	0.036	0.050
pvalue	0.000	0.000	0.000	-	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.806	0.842	0.878	-	0.797	0.824	0.880	0.861	0.796	0.820	0.880	0.862
h = 24m												
Constant	-0.055	-	-0.011	-	-0.027	-0.013	-0.004	-0.003	-0.027	-0.013	-0.004	-0.003
se	0.035	-	0.017	-	0.022	0.017	0.013	0.012	0.021	0.017	0.013	0.012
pvalue	0.110	-	0.588	-	0.298	0.512	0.760	0.792	0.294	0.512	0.758	0.794
AR(1) Coefficient	0.822	-	0.896	-	0.894	0.922	0.948	0.951	0.893	0.922	0.947	0.951
se	0.083	-	0.071	-	0.036	0.038	0.030	0.026	0.036	0.038	0.033	0.025
pvalue	0.000	-	0.000	-	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.678	-	0.805	-	0.804	0.849	0.901	0.906	0.802	0.849	0.900	0.907

Notes: Table B.4.11 presents the summary statistics of the *A(1)* regression that assesses whether the Value at Risk GARCH, eGARCH and gjrGARCH risk measures can proxy the expected volatility of the dry bulk freight market for the period between January 1990 to June 2016.

Table B.4.12: AR(1) Regressions of the VaR SVA and EWMA approach Risk Measures

	VaR SVA12				**VaR SVA24**				**VaR EWMA12**				**VaR EWMA24**			
h = 1m	**spot**	**P6m**	**P12m**	**P36m**	**spot**	**P6m**	**P12m**	**P36m**	**spot**	**P6m**	**P12m**	**P36m**	**spot**	**P6m**	**P12m**	**P36m**
Constant	0.010	0.008	0.004	0.046	0.004	0.003	0.002	0.003	0.005	0.004	0.001	0.003	-0.161	-0.112	-0.071	-0.039
se	0.004	0.006	0.003	0.021	0.002	0.003	0.002	0.002	0.003	0.004	0.002	0.002	0.026	0.023	0.013	0.011
pvalue	0.017	0.002	0.003	0.006	0.073	0.070	0.029	0.038	0.068	0.055	0.033	0.039	0.000	0.000	0.000	0.000
AR(1) Coefficient	0.895	0.822	0.894	0.650	0.937	0.939	0.924	0.788	0.931	0.926	0.937	0.770	0.611	0.648	0.681	0.755
se	0.071	0.165	0.127	0.187	0.047	0.081	0.120	0.163	0.057	0.101	0.098	0.182	0.061	0.076	0.072	0.079
pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.811	0.672	0.783	0.420	0.895	0.882	0.854	0.619	0.875	0.857	0.878	0.592	0.371	0.417	0.461	0.568
h = 12m																
Constant	0.011	0.005	-0.003	87.710	0.010	0.014	0.003	0.008	0.010	0.015	0.002	0.008	-0.065	-0.042	-0.029	-0.020
se	0.005	0.005	0.004	64.500	0.005	0.006	0.003	0.003	0.006	0.007	0.003	0.003	0.028	0.022	0.016	0.010
pvalue	0.035	0.045	0.017	0.136	0.022	0.001	0.084	0.001	0.022	0.000	0.118	0.001	0.028	0.068	0.114	0.185
AR(1) Coefficient	0.934	0.947	1.097	0.984	0.920	0.826	0.960	0.730	0.919	0.804	0.967	0.731	0.922	0.944	0.954	0.960
se	0.048	0.097	0.109	0.001	0.062	0.120	0.094	0.131	0.063	0.121	0.088	0.130	0.039	0.036	0.032	0.032
pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.870	0.828	0.894	1.000	0.846	0.673	0.854	0.525	0.845	0.639	0.860	0.527	0.848	0.891	0.911	0.921
h = 24m																
Constant	0.065	-	0.035	2.306	0.021	0.026	0.019	0.010	0.022	0.026	0.019	0.009	-0.053	-0.030	-0.015	-0.011
se	0.028	-	0.010	7.417	0.008	0.007	0.005	0.003	0.009	0.007	0.006	0.003	0.026	0.020	0.016	0.013
pvalue	0.000	-	0.000	0.798	0.010	0.000	0.000	0.002	0.010	0.000	0.000	0.002	0.073	0.183	0.367	0.436
AR(1) Coefficient	0.625	-	0.325	0.977	0.847	0.695	0.588	0.675	0.842	0.695	0.585	0.679	0.924	0.949	0.963	0.969
se	0.156	-	0.117	0.001	0.083	0.087	0.133	0.116	0.091	0.087	0.137	0.117	0.030	0.027	0.022	0.025
pvalue	0.000	-	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.391	-	0.102	1.000	0.725	0.478	0.334	0.447	0.716	0.478	0.331	0.452	0.854	0.901	0.928	0.937

Notes: Table B.4.12 presents the summary statistics of the *A(1)* regression that assesses whether the Value at Risk SVA and EWMA risk measures can proxy the expected volatility of the dry bulk freight market for the period between January 1990 to June 2016.

Appendix 4.C: Regression Coefficients of the Risk Measures

Tables C.4.13 to C.4.19 present the beta coefficients of Tables 4.5, 4.6, 4.7 and 4.8 presented in section 4.3.2.

Table C.4.13: Beta coefficients of risk and return relationship (GARCH approach)

		h = 1m				h = 12m				h = 24m			
		Spot	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**
FULL	eGARCH	0.022	-0.063	-0.227	-0.043	-0.165	-0.231	-0.227	-0.264	0.050	0.095	0.035	-0.047
	pvalue	0.369	0.019	0.003	0.000	0.002	0.000	0.000	0.000	0.299	0.015	0.268	0.078
	GARCH	0.014	-0.020	-0.079	-0.041	-0.367	-0.494	-0.418	-0.556	0.137	0.115	0.058	-0.069
	pvalue	0.503	0.514	0.018	0.097	0.000	0.000	0.000	0.000	0.028	0.070	0.309	0.185
	gjrGARCH	0.026	-0.023	-0.107	-0.079	-0.386	-0.546	-0.474	-0.657	0.101	0.073	0.071	-0.068
	pvalue	0.280	0.462	0.011	0.011	0.000	0.000	0.000	0.000	0.106	0.249	0.215	0.191
No Crisis	eGARCH	-0.016	0.012	0.006	0.007	-0.026	-0.028	-0.020	-0.044	0.104	0.151	0.077	-0.016
	pvalue	0.340	0.309	0.828	0.470	0.404	0.163	0.260	0.017	0.015	0.000	0.006	0.436
	GARCH	0.110	0.198	0.118	0.060	0.018	-0.045	-0.011	-0.120	0.247	0.248	0.174	0.013
	pvalue	0.285	0.088	0.364	0.695	0.691	0.251	0.776	0.002	0.000	0.000	0.002	0.760
	gjrGARCH	0.128	0.203	0.117	0.060	-0.016	-0.066	-0.010	-0.121	0.196	0.218	0.126	0.006
	pvalue	0.218	0.083	0.365	0.696	0.732	0.100	0.791	0.002	0.002	0.000	0.022	0.875

Notes: Table C.4.13 presents the beta coefficients of the risk and return relationship for the full and no-crisis samples using the GARCH approach. The values highlighted in blue indicate a negative significant relationship at a 5% significance level.

Table C.4.14: Beta coefficients of risk and return relationship (GARCH approach)

		h = 1m				h = 12m				h = 24m			
		Spot	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**
A	eGARCH	0.003	0.017	-0.007	-0.005	-0.010	0.062	0.006	0.093	0.112	0.272	0.135	0.275
	pvalue	0.439	0.001	0.002	0.207	0.717	0.026	0.863	0.000	0.000	0.000	0.000	0.126
	GARCH	0.001	0.004	-0.001	0.006	-0.107	0.072	0.006	0.114	0.169	0.435	0.280	0.183
	pvalue	0.647	0.203	0.059	0.338	0.091	0.076	0.887	0.001	0.002	0.000	0.000	0.000
	gjrGARCH	-0.001	0.012	-0.001	0.010	-0.070	0.108	0.034	0.168	0.162	0.353	0.260	0.212
	pvalue	0.857	0.012	0.022	0.083	0.242	0.008	0.403	0.000	0.003	0.000	0.000	0.000
B	eGARCH	0.009	0.001	0.003	0.002	-0.046	-0.048	-0.039	-0.020	0.195	0.109	0.088	-0.136
	pvalue	0.381	0.971	0.083	0.659	0.333	0.208	0.143	0.211	0.000	0.002	0.001	0.000
	GARCH	0.050	0.256	0.310	0.093	-0.008	-0.055	-0.043	-0.038	0.294	0.172	0.177	-0.056
	pvalue	0.850	0.344	0.154	0.407	0.930	0.447	0.400	0.235	0.000	0.005	0.001	0.085
	gjrGARCH	0.002	-0.005	-0.002	0.009	-0.102	-0.125	-0.095	-0.051	0.340	0.198	0.112	-0.133
	pvalue	0.877	0.713	0.760	0.183	0.245	0.093	0.068	0.111	0.000	0.002	0.019	0.000
C	eGARCH	-0.139	-0.213	-0.080	-0.089	-0.363	-0.425	-0.387	-0.377	1.147	1.355	1.773	0.523
	pvalue	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.068	0.059	0.072	0.016
	GARCH	-0.115	-0.324	-0.249	-0.293	-0.708	-0.472	-0.300	-0.277	0.369	0.564	0.630	0.572
	pvalue	0.067	0.002	0.027	0.000	0.000	0.000	0.029	0.007	0.009	0.000	0.000	0.000
	gjrGARCH	-0.218	-0.337	-0.391	-0.463	-1.066	-0.690	-0.490	-0.496	0.347	0.581	0.679	0.495
	pvalue	0.045	0.001	0.020	0.000	0.000	0.000	0.001	0.000	0.015	0.000	0.000	0.000
D	eGARCH	0.004	0.008	0.005	-0.006	-0.181	-0.242	-0.215	-0.206	-0.601	-0.525	-0.240	-0.243
	pvalue	0.716	0.301	0.168	0.305	0.010	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	GARCH	-0.014	0.028	0.084	0.069	-0.149	-0.320	-0.306	-0.429	-0.572	-0.613	-0.536	-0.312
	pvalue	0.903	0.858	0.697	0.855	0.052	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	gjrGARCH	0.058	0.044	0.088	0.067	-0.216	-0.375	-0.347	-0.458	-0.667	-0.826	-0.621	-0.312
	pvalue	0.576	0.789	0.696	0.863	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table C.4.14 presents the beta coefficients of the risk and return relationship for all the sub-samples using the GARCH approach. The values highlighted in blue indicate a negative significant relationship at a 5% significance level.

Table C.4.15: Beta coefficients of risk and return relationship (SVA and EWMA)

		h = 1m				h = 12m				h = 24m			
		Spot	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**
FULL	SVA12	-0.003	-0.009	-0.060	-0.051	-0.080	-0.126	-0.140	-0.166	-0.084	-0.062	-0.043	-0.064
	pvalue	0.938	0.786	0.064	0.193	0.000	0.000	0.000	0.000	0.000	0.001	0.017	0.002
	SVA24	-0.010	-0.013	-0.044	-0.041	-0.079	-0.107	-0.124	-0.156	-0.076	-0.074	-0.083	-0.136
	pvalue	0.741	0.659	0.138	0.263	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	EWMA12	-0.001	0.000	-0.048	-0.028	-0.123	-0.184	-0.191	-0.226	-0.135	-0.099	-0.065	-0.089
	pvalue	0.964	0.994	0.003	0.120	0.001	0.000	0.000	0.000	0.000	0.000	0.002	0.000
	EWMA24	-0.014	-0.014	-0.041	-0.027	-0.148	-0.183	-0.189	-0.215	-0.124	-0.125	-0.131	-0.191
	pvalue	0.472	0.423	0.001	0.040	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	EWMA12	-0.003	-0.015	-0.005	-0.008	-0.029	-0.140	-0.143	-0.128	-0.062	-0.045	-0.037	-0.021
	pvalue	0.839	0.151	0.561	0.403	0.253	0.000	0.000	0.000	0.000	0.001	0.005	0.217
	EWMA24	-0.007	-0.013	-0.004	-0.008	-0.014	-0.150	-0.178	-0.158	-0.076	-0.106	-0.101	-0.080
	pvalue	0.424	0.092	0.465	0.357	0.554	0.000	0.000	0.001	0.026	0.004	0.007	0.029
No Crisis	SVA12	-0.015	-0.038	-0.064	-0.072	-0.037	-0.082	-0.083	-0.083	-0.004	0.013	0.005	-0.016
	pvalue	0.631	0.189	0.047	0.045	0.009	0.000	0.000	0.000	0.775	0.329	0.711	0.302
	SVA24	-0.020	-0.032	-0.052	-0.062	-0.008	-0.045	-0.072	-0.107	0.030	0.040	0.036	0.011
	pvalue	0.483	0.195	0.064	0.049	0.529	0.002	0.000	0.000	0.058	0.013	0.031	0.585
	EWMA12	-0.011	-0.025	-0.042	-0.044	-0.034	-0.079	-0.078	-0.088	0.009	0.029	0.017	-0.009
	pvalue	0.523	0.052	0.002	0.000	0.010	0.000	0.000	0.000	0.488	0.020	0.146	0.349
	EWMA24	-0.015	-0.024	-0.037	-0.036	-0.006	-0.051	-0.073	-0.106	0.061	0.062	0.043	0.000
	pvalue	0.328	0.016	0.000	0.000	0.671	0.001	0.000	0.000	0.004	0.001	0.012	0.992

Notes: Table C.4.15 presents the beta coefficients of the risk and return relationship for the full and no-crisis sample using the SVA and EWMAV risk measures. The values highlighted in blue indicate a negative significant relationship at a 5% significance level.

Table C.4.16: Beta coefficients of risk and return relationship (SVA and EWMA)

		h = 1m				h = 12m				h = 24m			
		Spot	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**
A	SVA12	0.104	0.013	-0.072	0.115	0.036	0.039	-0.068	0.125	0.248	0.244	0.240	-0.158
	pvalue	0.001	0.579	0.091	0.098	0.262	0.235	0.138	0.048	0.000	0.000	0.000	0.000
	SVA24	0.020	0.016	-0.049	-0.009	-0.097	-0.012	-0.092	-0.127	0.307	0.196	0.147	0.037
	pvalue	0.176	0.221	0.198	0.904	0.024	0.600	0.109	0.269	0.000	0.000	0.004	0.344
	EWMA12	0.022	0.005	-0.009	0.021	0.028	0.032	-0.038	0.072	0.136	0.146	0.114	-0.030
	pvalue	0.000	0.203	0.164	0.008	0.276	0.110	0.165	0.006	0.000	0.000	0.000	0.003
	EWMA24	0.007	0.005	-0.004	0.005	-0.049	0.007	-0.050	-0.056	0.203	0.119	0.075	0.014
	pvalue	0.017	0.040	0.458	0.562	0.148	0.599	0.116	0.194	0.000	0.000	0.001	0.259
B	SVA12	0.051	0.077	0.017	0.045	0.000	-0.036	-0.047	0.058	-0.054	-0.008	0.052	-0.039
	pvalue	0.189	0.112	0.676	0.458	0.991	0.106	0.046	0.072	0.178	0.851	0.162	0.126
	SVA24	0.053	0.093	0.097	0.112	-0.032	-0.019	0.048	0.070	0.017	0.056	0.112	0.092
	pvalue	0.016	0.001	0.000	0.014	0.329	0.464	0.046	0.006	0.598	0.144	0.019	0.006
	EWMA12	0.014	0.019	0.005	0.003	-0.005	-0.029	-0.027	0.015	-0.035	0.001	0.036	-0.016
	pvalue	0.181	0.095	0.453	0.691	0.825	0.086	0.050	0.209	0.308	0.969	0.072	0.058
	EWMA24	0.016	0.025	0.017	0.007	-0.040	-0.022	0.036	0.030	0.030	0.063	0.100	0.039
	pvalue	0.015	0.000	0.000	0.180	0.226	0.403	0.058	0.007	0.352	0.071	0.004	0.008
C	SVA12	-0.116	-0.182	-0.166	-0.231	-0.191	-0.168	-0.133	-0.133	-0.154	-0.142	-0.153	-0.161
	pvalue	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SVA24	-0.071	-0.117	-0.105	-0.149	-0.100	-0.080	-0.064	-0.071	-0.091	-0.066	-0.059	-0.027
	pvalue	0.003	0.000	0.000	0.000	0.000	0.001	0.008	0.004	0.000	0.002	0.005	0.118
	EWMA12	-0.104	-0.145	-0.127	-0.128	-0.356	-0.286	-0.197	-0.190	-0.250	-0.186	-0.135	-0.133
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000
	EWMA24	-0.082	-0.108	-0.097	-0.088	-0.251	-0.193	-0.130	-0.127	-0.162	-0.098	-0.048	-0.007
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.008	0.098	0.796
D	SVA12	0.001	-0.023	-0.010	-0.018	-0.006	-0.115	-0.138	-0.118	-0.006	-0.005	0.002	0.021
	pvalue	0.935	0.293	0.714	0.674	0.773	0.000	0.000	0.003	0.713	0.752	0.912	0.423
	SVA24	-0.005	-0.016	-0.007	-0.013	-0.001	-0.112	-0.162	-0.135	-0.020	-0.054	-0.056	-0.055
	pvalue	0.601	0.267	0.713	0.719	0.966	0.000	0.000	0.005	0.348	0.043	0.072	0.158
	EWMA12	-0.003	-0.015	-0.005	-0.008	-0.029	-0.140	-0.143	-0.128	-0.062	-0.045	-0.037	-0.021
	pvalue	0.839	0.151	0.561	0.403	0.253	0.000	0.000	0.000	0.000	0.001	0.005	0.217
	EWMA24	-0.007	-0.013	-0.004	-0.008	-0.014	-0.150	-0.178	-0.158	-0.076	-0.106	-0.101	-0.080
	pvalue	0.424	0.092	0.465	0.357	0.554	0.000	0.000	0.001	0.026	0.004	0.007	0.029

Notes: Table C.4.16 presents the beta coefficients of the risk and return relationship for all sub-samples using the SVA and EWMAV risk measures. The values highlighted in blue indicate a negative significant relationship at a 5% significance level.

Table C.4.17: Beta coefficients of risk and return relationship (VaR GARCH)

		h = 1m				h = 12m				h = 24m			
		Spot	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**
FULL	VaR_eGARCH	0.993	1.007	1.013	1.747	1.140	1.061	1.030	-	1.048	-	1.040	-
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-	0.000	-	0.000	-
	VaR_GARCH	0.988	0.976	1.003	1.042	1.119	1.068	1.053	1.067	1.087	1.050	1.012	1.022
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	0.978	0.980	1.004	1.067	1.115	1.079	1.043	1.062	1.075	1.050	1.018	1.020
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A	VaR_eGARCH	0.985	0.985	0.997	1.075	0.998	4.092	1.576	-	1.941	-0.745	1.368	1.018
	pvalue	0.000	0.000	0.000	0.000	0.000	0.039	0.000	0.022	0.003	0.915	0.000	0.000
	VaR_GARCH	0.995	0.999	1.013	1.002	0.991	1.007	1.054	-0.260	0.978	1.015	1.006	0.996
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.927	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	0.985	0.988	0.993	0.997	0.991	0.976	1.028	0.942	0.981	1.006	1.009	0.990
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
B	VaR_eGARCH	1.008	1.020	1.026	0.993	1.024	1.054	1.035	1.023	0.948	-1.754	-	-
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.196	-	-
	VaR_GARCH	0.997	0.989	0.992	0.939	0.997	1.000	1.343	1.008	1.015	1.001	1.009	1.009
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.510	0.000	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	0.995	1.001	0.983	0.971	0.986	0.997	1.016	1.026	1.015	1.000	1.006	1.013
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C	VaR_eGARCH	1.298	4.432	1.455	-	-	-	1.021	-	2.841	1.316	-	-0.842
	pvalue	0.000	0.000	0.000	-	-	-	0.000	-	0.001	0.000	-	0.626
	VaR_GARCH	1.130	1.513	1.492	1.303	1.307	1.268	1.071	1.146	0.793	0.897	1.009	1.045
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	1.244	1.760	1.497	1.476	1.461	1.389	1.163	1.177	0.968	1.023	0.984	1.081
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.010	0.000	0.000	0.000	0.000	0.000
D	VaR_eGARCH	0.913	0.966	0.979	0.984	-1.110	0.987	0.994	1.063	1.085	-	-	-
	pvalue	0.000	0.000	0.000	0.000	0.005	0.000	0.000	0.000	0.000	-	-	-
	VaR_GARCH	0.999	0.998	0.999	1.032	1.116	1.000	1.000	1.002	0.999	1.127	0.996	0.993
	pvalue	0.000	0.000	0.000	0.000	0.504	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	1.033	1.011	1.000	1.001	0.879	0.980	0.990	1.037	1.511	1.144	1.112	1.000
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
NoCrisis	VaR_eGARCH	1.723	1.511	1.012	0.966	1.078	1.035	1.025	-	0.993	-	1.023	-
	pvalue	0.084	0.008	0.000	0.000	0.000	0.000	0.000	-	0.000	-	0.000	-
	VaR_GARCH	1.030	1.014	1.006	1.006	1.082	1.033	1.036	1.022	1.060	1.020	1.024	1.014
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	1.025	1.012	1.009	1.000	1.070	1.040	1.039	1.019	1.035	1.012	1.024	1.012
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table C.4.17 presents the beta coefficients of the risk and return relationship for all samples using the Value at Risk GARCH risk measures. The values highlighted in blue indicate a negative significant relationship at a 5% significance level.

Table C.4.18: Beta coefficients of risk and return relationship (VaR SVA and EWMA)

		Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m
FULL	VaR_SVA12	0.987	0.969	1.013	1.009	1.149	1.227	1.257	1.307	1.116	1.101	1.081	1.135
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	0.999	0.988	1.016	1.020	1.082	1.158	1.197	1.279	1.082	1.116	1.142	1.266
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	0.987	0.978	1.011	1.002	1.223	1.336	1.342	1.414	1.189	1.153	1.110	1.163
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	1.004	0.997	1.013	1.009	1.198	1.289	1.303	1.362	1.156	1.192	1.212	1.338
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
No-Crisis	VaR_SVA12	1.024	1.013	1.005	0.964	1.068	1.129	1.138	1.152	0.992	0.984	1.000	1.051
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	1.032	1.031	1.053	1.059	0.976	1.056	1.107	1.205	0.919	0.942	0.955	1.029
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	1.029	1.013	1.000	0.999	1.053	1.118	1.120	1.152	0.973	0.961	0.979	1.023
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	1.027	1.021	1.019	1.015	0.985	1.067	1.107	1.174	0.883	0.911	0.939	1.015
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table C.4.18 presents the beta coefficients of the risk and return relationship for the full and no-crisis samples using the Value at Risk SVA and EWMA risk measures. The values highlighted in blue indicate a negative significant relationship at a 5% significance level.

Table C.4.19: Beta coefficients of risk and return relationship (VaR SVA and EWMA)

		Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m
A	VaR_SVA12	0.877	0.832	0.933	0.767	1.012	0.936	1.119	0.933	0.634	0.627	0.656	1.407
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	0.960	0.938	1.109	1.124	0.537	0.675	0.782	1.098	0.494	0.585	0.614	1.400
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	0.981	0.982	1.005	0.981	0.988	0.960	1.066	0.958	0.836	0.816	0.858	1.062
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	0.995	0.993	1.013	1.011	0.800	0.879	0.934	1.024	0.772	0.829	0.878	1.062
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
B	VaR_SVA12	0.954	0.945	0.959	0.824	1.072	1.158	1.164	1.073	0.976	0.894	0.818	1.006
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	0.981	0.961	0.945	0.873	1.020	0.938	0.787	0.852	0.661	0.567	0.519	0.489
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	0.985	0.990	0.996	0.975	1.027	1.072	1.061	1.004	0.987	0.940	0.913	1.014
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	0.988	0.988	0.989	0.981	1.035	0.981	0.898	0.952	0.803	0.756	0.774	0.881
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C	VaR_SVA12	1.152	1.219	1.148	1.284	1.322	1.279	1.225	1.153	1.303	1.290	1.296	1.284
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	1.131	1.190	1.144	1.214	1.295	1.266	1.257	1.185	1.280	1.231	1.263	1.176
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	1.067	1.133	1.074	1.128	1.409	1.300	1.234	1.168	1.275	1.214	1.188	1.147
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	1.049	1.095	1.061	1.085	1.331	1.251	1.214	1.143	1.278	1.193	1.185	1.063
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D	VaR_SVA12	1.057	1.087	1.067	1.079	1.063	1.233	1.286	1.279	0.918	0.929	0.926	0.939
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	1.031	1.036	1.033	1.069	0.932	1.007	1.068	1.098	0.698	0.744	0.761	0.813
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	1.034	1.026	1.009	1.007	1.065	1.234	1.249	1.256	1.014	1.022	1.022	1.018
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	1.024	1.012	1.004	1.007	0.964	1.091	1.141	1.164	0.845	0.918	0.940	0.958
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table C.4.19 presents the beta coefficients of the risk and return relationship for all the sub-samples using the Value at Risk SVA and EWMA risk measures. The values highlighted in blue indicate a negative significant relationship at a 5% significance level.

Appendix 4.D: Regressions of the Upside and Downside VaR Risk Measures

The study also analyses the relationship between the above (below) target returns and their risk measures for each sub-sample. The results show that the relationship between the risk and returns is negative for the below the target returns and positive for the above the target ones however the relationship appears to be mainly insignificant at the 5% significance level.

Table D.4.20: Beta coefficients of risk and ABOVE target return relationship **(VaR SVA and EWMA)**

		Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m
FULL	VaR_SVA12	1.148	1.117	1.087	1.107	1.148	1.122	1.164	1.188	1.247	1.294	1.312	1.277
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	1.133	1.098	1.080	1.072	1.130	1.135	1.184	1.203	1.257	1.309	1.343	1.321
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	1.055	1.051	1.014	1.020	1.124	1.082	1.109	1.101	1.254	1.261	1.251	1.185
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	1.044	1.033	1.012	1.013	1.131	1.113	1.140	1.115	1.311	1.313	1.299	1.228
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
No Crisis	VaR_SVA12	1.101	1.087	1.076	1.133	1.187	1.188	1.185	1.240	1.243	1.261	1.269	1.236
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	1.102	1.095	1.078	1.104	1.165	1.163	1.145	1.152	1.273	1.283	1.311	1.291
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	1.030	1.020	1.012	1.014	1.125	1.116	1.119	1.123	1.253	1.235	1.215	1.147
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	1.028	1.018	1.011	1.011	1.143	1.128	1.119	1.094	1.332	1.290	1.268	1.184
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table D.4.20 presents the beta coefficients of the above the target risk and return relationship for the full and no-crisis samples using the Value at Risk SVA and EWMA risk measures. The values highlighted in blue indicate a negative significant relationship at a 5% significance level.

Table D.4.21: Beta coefficients of risk and ABOVE target return relationship (VaR SVA and EWMA)

		Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m
A	VaR_SVA12	0.974	0.991	1.016	1.053	1.369	1.164	0.856	1.089	1.273	1.260	1.331	0.701
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	1.105	1.103	0.937	0.897	1.327	1.263	0.871	0.749	0.967	1.057	1.150	0.523
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.006
	VaR_EWMA12	0.997	1.002	1.000	1.002	1.134	1.078	0.994	1.065	1.174	1.155	1.130	0.972
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	1.008	1.008	0.998	0.996	1.123	1.099	0.989	0.959	1.028	1.056	1.064	0.929
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
B	VaR_SVA12	1.024	1.014	0.993	1.043	1.432	1.396	1.365	1.105	1.410	1.406	1.428	1.315
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	1.115	1.034	1.022	1.044	1.351	1.237	1.243	1.012	1.486	1.409	1.385	1.276
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	1.006	1.005	1.000	1.003	1.219	1.173	1.117	1.034	1.194	1.164	1.150	1.050
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	1.015	1.001	1.000	1.001	1.166	1.117	1.088	1.014	1.232	1.171	1.137	1.044
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C	VaR_SVA12	0.957	1.008	1.061	1.148	0.813	0.964	1.163	1.355	0.748	0.888	1.125	1.504
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	0.978	1.005	1.072	1.082	0.703	0.810	0.923	0.905	0.833	0.940	0.929	1.443
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	0.991	1.001	1.006	1.012	0.983	1.057	1.139	1.209	0.882	1.003	1.171	1.397
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	0.997	1.001	1.008	1.006	0.894	0.967	0.994	0.999	0.928	1.027	1.031	1.399
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D	VaR_SVA12	0.861	0.816	0.857	0.977	1.074	1.196	1.242	1.336	1.166	1.250	1.234	1.206
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	0.880	0.872	0.981	0.983	0.981	1.096	1.177	1.286	1.112	1.163	1.169	1.139
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	0.958	0.972	0.986	0.999	1.048	1.096	1.108	1.123	1.091	1.143	1.126	1.099
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	0.966	0.982	1.002	0.999	1.010	1.061	1.082	1.103	1.052	1.085	1.084	1.065
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table D.4.21 presents the beta coefficients of the above the target risk and return relationship for all the sub-samples using the Value at Risk SVA and EWMA risk measures. The values highlighted in blue indicate a negative significant relationship at a 5% significance level.

Table D.4.22: Beta coefficients of risk and BELOW target return relationship (VaR SVA and EWMA)

		Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m
FULL	VaR_SVA12	-0.607	-0.660	-0.740	-0.670	-0.512	-0.438	-0.361	-0.318	-0.529	-0.530	-0.607	-0.660
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	-0.614	-0.725	-0.833	-0.848	-0.707	-0.651	-0.571	-0.531	-0.511	-0.424	-0.389	-0.360
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	-0.825	-0.843	-0.894	-0.882	-0.282	-0.204	-0.265	-0.311	-0.492	-0.517	-0.628	-0.704
	pvalue	0.000	0.000	0.000	0.000	0.002	0.008	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	-0.843	-0.885	-0.931	-0.937	-0.511	-0.460	-0.466	-0.509	-0.478	-0.414	-0.437	-0.475
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
No-Crisis	VaR_SVA12	-0.625	-0.776	-0.865	-0.976	-0.731	-0.701	-0.566	-0.479	-0.659	-0.646	-0.644	-0.621
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	-0.603	-0.764	-0.868	-0.965	-0.912	-0.850	-0.737	-0.590	-0.668	-0.629	-0.613	-0.575
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	-0.878	-0.944	-0.968	-0.996	-0.814	-0.765	-0.711	-0.658	-0.692	-0.703	-0.720	-0.770
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	-0.883	-0.943	-0.969	-0.993	-0.881	-0.832	-0.778	-0.709	-0.692	-0.673	-0.678	-0.717
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table D.4.22 presents the beta coefficients of the below the target risk and return relationship for the full and no-crisis samples using the Value at Risk SVA and EWMA risk measures. The values highlighted in blue indicate a negative significant relationship at a 5% significance level.

Table D.4.23: Beta coefficients of risk and BELOW target return relationship (VaR SVA and EWMA)

		Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m
A	VaR_SVA12	-0.963	-1.025	-0.969	-1.105	-0.477	-0.666	-0.659	-1.079	-1.459	-0.715	-0.755	-0.869
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.005	0.003	0.004
	VaR_SVA24	-0.782	-0.955	-0.990	-1.151	-1.717	-1.266	-1.251	-1.165	-1.266	-0.763	-0.793	-1.486
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.000
	VaR_EWMA12	-0.998	-1.007	-0.997	-1.002	-0.730	-0.886	-0.889	-0.998	-1.057	-0.940	-0.941	-0.971
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	-0.992	-1.004	-0.997	-1.004	-1.226	-1.040	-1.037	-1.006	-1.040	-0.957	-0.968	-1.020
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
B	VaR_SVA12	-0.753	-0.759	-0.981	-0.960	-0.604	-0.577	-0.394	-0.383	-0.554	-0.631	-0.650	-0.653
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.005	0.003	0.001	0.000	0.000	0.000
	VaR_SVA24	-0.702	-0.877	-1.021	-1.076	-0.701	-0.799	-0.949	-1.046	-0.664	-0.887	-1.120	-1.205
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	-0.971	-0.977	-1.002	-1.005	-0.731	-0.770	-0.786	-0.867	-0.841	-0.865	-0.903	-0.926
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	-0.976	-0.990	-1.002	-1.009	-0.795	-0.862	-0.958	-0.984	-0.891	-0.957	-1.021	-1.029
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C	VaR_SVA12	-0.687	-0.716	-0.871	-0.632	-0.649	-0.670	-0.644	-0.651	-0.771	-0.857	-0.930	-1.040
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	-0.767	-0.821	-0.919	-0.754	-0.775	-0.767	-0.756	-0.732	-0.891	-0.974	-1.018	-1.042
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	-0.808	-0.824	-0.913	-0.851	-0.450	-0.586	-0.599	-0.702	-0.661	-0.811	-0.879	-0.971
	pvalue	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	-0.858	-0.888	-0.939	-0.900	-0.611	-0.709	-0.717	-0.782	-0.773	-0.896	-0.937	-0.971
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D	VaR_SVA12	-1.096	-1.126	-1.018	-0.880	-0.924	-0.702	-0.527	-0.466	-0.860	-0.643	-0.569	-0.214
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.001	0.306
	VaR_SVA24	-1.052	-1.116	-1.030	-0.865	-1.154	-1.108	-0.950	-0.740	-1.156	-0.706	-0.579	-0.412
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.166
	VaR_EWMA12	-1.052	-1.031	-1.008	-0.991	-0.925	-0.725	-0.636	-0.543	-0.838	-0.681	-0.628	-0.555
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	-1.051	-1.029	-1.011	-0.995	-1.031	-0.967	-0.881	-0.734	-1.043	-0.741	-0.645	-0.619
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table D.4.23 presents the beta coefficients of the below the target risk and return relationship for all the sub-samples using the Value at Risk SVA and EWMA risk measures. The values highlighted in blue indicate a negative significant relationship at a 5% significance level.

Table D.4.24: Beta coefficients of risk and ABOVE target return relationship (VaR GARCH)

		Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m
FULL	VaR_eGARCH												
	pvalue												
	VaR_GARCH	1.107	1.144	1.032	1.091	1.501	1.177	1.101	1.084	1.212	1.154	1.049	1.027
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	1.072	1.144	1.031	1.092	2.120	1.404	1.742	1.084	1.075	1.050	1.040	1.795
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A	VaR_eGARCH									2.301			
	pvalue									0.004			
	VaR_GARCH	1.001	1.069	1.013	0.999	1.069	1.311	1.083	1.140	1.107	0.988	1.044	1.026
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	1.001	1.047	1.013	0.999	1.314	1.159	1.201	1.585	1.117	0.986	0.988	1.039
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
B	VaR_eGARCH	2.521	1.277	0.991			0.946			1.129			
	pvalue	0.000	0.000	0.000			0.000			0.000			
	VaR_GARCH	1.369	0.997	0.984	1.010	1.057	1.403	1.009	1.030	1.010	1.842	1.641	1.106
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	1.016	0.989	0.984	1.011	1.007	1.091	1.052	1.022	1.015	1.105	1.023	1.151
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C	VaR_eGARCH	1.063	2.142	1.053	7.157		1.013	1.242	1.079				8.861
	pvalue	0.000	0.000	0.000	0.101		0.000	0.000	0.000				0.670
	VaR_GARCH	0.976	1.003	1.001	1.019	1.016	1.016	0.988	0.963	1.803	1.821	1.518	1.210
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	0.989	1.004	0.997	1.026	1.172	1.183	1.029	1.014	1.788	1.833	1.264	1.102
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D	VaR_eGARCH	1.096	1.063	1.003	1.004							7.063	0.769
	pvalue	0.000	0.000	0.000	0.000							0.154	0.000
	VaR_GARCH	1.000	1.000	1.001	0.997	1.280	1.434	1.567	1.026	1.219	1.489	1.014	1.002
	pvalue	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	1.000	0.999	1.002	0.997	1.282	1.434	1.570	1.303	1.220	1.505	1.352	1.472
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
NoCrisis	VaR_eGARCH									1.295			
	pvalue									0.190			
	VaR_GARCH	1.032	1.037	1.024	1.032	1.094	1.292	1.098	1.293	1.039	1.038	1.116	1.100
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	1.050	1.038	1.016	1.032	1.152	1.634	1.349	1.044	0.998	2.086	1.053	1.418
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table D.4.24 presents the beta coefficients of the above the target risk and return relationship for all samples using the Value at Risk GARCH risk measures. The values highlighted in blue indicate a negative significant relationship at a 5% significance level.

Table D.4.25: Beta coefficients of risk and BELOW target return relationship (VaR GARCH)

		Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m
	VaR_eGARCH							-0.680					
	pvalue							0.000					
FULL	VaR_GARCH	-0.585	-0.592	-0.659	-0.486	0.039	-0.206	-0.327	-0.642	-0.368	-0.746	-0.853	-0.928
	pvalue	0.000	0.000	0.000	0.000	0.700	0.002	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	-0.345	-0.290	-0.402	-0.237	1.739	0.742	1.732	0.547	1.250	-0.071	-0.645	-0.880
	pvalue	0.008	0.084	0.042	0.133	0.000	0.000	0.000	0.000	0.000	0.456	0.000	0.000
	VaR_eGARCH	-1.957	-1.105	13.152							-1.536		-1.001
	pvalue	0.482	0.000	0.532							0.000		0.000
A	VaR_GARCH	-1.032	-1.029	-0.977	-0.987	-1.035	-0.277	-0.183	-0.528	-1.001	-0.858	-0.717	-0.763
	pvalue	0.000	0.000	0.000	0.000	0.000	0.035	0.252	0.000	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	-0.987	-1.049	-0.965	-0.980	-1.006	-0.561	0.198	-0.600	-0.991	-0.491	-0.747	-0.687
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.395	0.000	0.000	0.005	0.000	0.000
	VaR_eGARCH		-0.826	0.085	-0.324							1.543	
	pvalue		0.076	0.961	0.656							0.976	
B	VaR_GARCH	-0.897	-0.953	-0.952	-0.999	-0.911	-0.892	-0.870	-0.912	-0.651	-0.949	-1.000	-0.880
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	-0.847	-0.904	-0.920	-0.998	-0.784	-0.812	-0.505	-0.909	0.445	-0.902	-0.080	-0.924
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.188	0.000	0.519	0.000
	VaR_eGARCH		-4.910	-1.753									
	pvalue		0.535	0.931									
C	VaR_GARCH	0.309	-0.156	-0.369	-0.244	1.246	-0.456	-0.230	0.973	0.519	-0.570	-0.556	-0.889
	pvalue	0.068	0.737	0.459	0.454	0.004	0.003	0.220	0.001	0.049	0.000	0.000	0.000
	VaR_gjrGARCH	0.957	0.254	-0.069	0.131	0.017	0.515	1.099	-0.216	0.558	-0.535	-0.515	-0.325
	pvalue	0.000	0.713	0.925	0.787	0.891	0.014	0.004	0.170	0.034	0.000	0.000	0.001
	VaR_eGARCH	-0.793	-0.270	-0.823	-1.597						-1.462		
	pvalue	0.000	0.289	0.000	0.158						0.087		
D	VaR_GARCH	-1.228	-0.964	-1.052	-0.023	-0.201	-0.578	-0.880	-0.873	-0.620	-0.596	-0.785	-1.011
	pvalue	0.000	0.000	0.000	0.990	0.472	0.000	0.000	0.000	0.034	0.001	0.000	0.000
	VaR_gjrGARCH	-0.925	-0.986	-0.996	-1.014	0.658	0.903	-0.876	0.214	1.272	-0.080	-0.547	-0.960
	pvalue	0.000	0.000	0.000	0.000	0.241	0.002	0.000	0.078	0.078	0.707	0.004	0.000
	VaR_eGARCH												
	pvalue												
No-Crisis	VaR_GARCH	-0.830	-0.953	-0.920	-0.906	0.052	-0.502	-0.758	-0.823	-0.438	-0.753	-0.777	-0.975
	pvalue	0.000	0.000	0.000	0.000	0.700	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	-0.724	-0.916	-0.861	-0.856	0.513	-0.248	-0.577	-0.730	0.563	0.260	-0.639	-0.939
	pvalue	0.000	0.000	0.000	0.000	0.010	0.001	0.000	0.000	0.000	0.015	0.000	0.000

Notes: Table D.4.25 presents the beta coefficients of the below the target risk and return relationship for all samples using the Value at GARCH risk measures. The values highlighted in blue indicate a negative significant relationship at a 5% significance level.

Appendix 4.E: Regressions of the Control Variables

Table E.4.26: Beta coefficients of risk and return relationship with control variables (SVA and EWMA)

		Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m
FULL	SVA12	0.020	0.022	0.020	0.034	-0.277	-0.625	-0.790	-0.613	-0.432	-0.283	-0.189	-0.286
	pvalue	0.744	0.755	0.776	0.609	0.029	0.000	0.000	0.000	0.008	0.107	0.308	0.077
	SVA24	0.035	0.011	0.008	-0.005	-0.352	-0.506	-0.599	-0.437	-0.580	-0.534	-0.578	-0.642
	pvalue	0.599	0.889	0.915	0.946	0.006	0.000	0.000	0.000	0.001	0.002	0.001	0.000
	EWMA12	0.008	0.055	0.054	0.094	-0.134	-0.363	-0.639	-0.706	-0.326	-0.289	-0.298	-0.458
	pvalue	0.927	0.613	0.718	0.532	0.081	0.000	0.000	0.000	0.003	0.024	0.072	0.005
	EWMA24	0.033	0.030	-0.030	0.012	-0.203	-0.322	-0.475	-0.473	-0.371	-0.388	-0.501	-0.710
	pvalue	0.761	0.835	0.876	0.953	0.006	0.000	0.000	0.000	0.001	0.001	0.000	0.000
No Crisis	SVA12	-0.007	-0.016	-0.035	-0.007	-0.460	-1.154	-0.870	-0.448	0.064	0.481	0.235	-0.176
	pvalue	0.921	0.848	0.639	0.920	0.047	0.000	0.000	0.002	0.805	0.076	0.367	0.446
	SVA24	0.008	-0.034	-0.062	-0.051	-0.015	-0.514	-0.659	-0.464	0.283	0.419	0.292	0.014
	pvalue	0.920	0.736	0.488	0.554	0.955	0.030	0.001	0.001	0.244	0.077	0.206	0.940
	EWMA12	-0.035	-0.026	-0.016	-0.081	-0.463	-1.201	-1.022	-0.899	0.258	0.781	0.520	-0.322
	pvalue	0.774	0.894	0.928	0.748	0.061	0.000	0.000	0.000	0.344	0.008	0.102	0.388
	EWMA24	-0.017	-0.129	-0.146	-0.274	-0.010	-0.547	-0.737	-0.707	0.385	0.464	0.341	-0.156
	pvalue	0.906	0.614	0.576	0.451	0.965	0.013	0.000	0.000	0.035	0.019	0.135	0.536

Notes: Table E.4.26 presents the beta coefficients of the risk and return relationship for the full and no-crisis samples using the SVA and the EWMA risk measures after controlling for macroeconomic variables. The values highlighted in blue indicate a negative significant relationship at a 5% significance level.

Table E.4.27: Beta coefficients of risk and return relationship with control variables (SVA and EWMA)

		Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m
A	SVA12	0.426	0.046	-0.044	0.571	0.134	0.632	-0.686	0.704	3.183	2.959	2.624	-2.231
	pvalue	0.324	0.926	0.910	0.032	0.848	0.368	0.159	0.037	0.000	0.000	0.000	0.000
	SVA24	-0.306	-0.826	-0.265	0.276	-0.425	1.130	-0.374	-0.101	1.838	2.161	1.821	1.033
	pvalue	0.738	0.469	0.588	0.390	0.588	0.481	0.520	0.725	0.000	0.002	0.025	0.308
	EWMA12	2.941	1.158	0.503	6.668	0.226	1.501	-0.955	2.268	5.052	4.642	5.399	-6.787
	pvalue	0.196	0.683	0.841	0.004	0.795	0.176	0.243	0.004	0.000	0.000	0.000	0.013
	EWMA24	0.028	-2.659	-0.038	4.547	0.090	4.106	-0.676	-0.500	2.732	4.100	4.689	4.031
	pvalue	0.995	0.639	0.991	0.112	0.929	0.089	0.510	0.507	0.000	0.000	0.007	0.227
B	SVA12	0.188	-0.937	-1.602	0.857	0.188	-0.937	-1.602	0.857	-0.818	-0.015	1.088	-1.498
	pvalue	0.796	0.292	0.053	0.207	0.796	0.292	0.053	0.207	0.263	0.984	0.152	0.178
	SVA24	0.001	-0.075	1.724	1.749	0.001	-0.075	1.724	1.749	1.467	2.165	2.530	3.576
	pvalue	0.999	0.943	0.109	0.115	0.999	0.943	0.109	0.115	0.316	0.062	0.005	0.004
	EWMA12	0.032	-1.332	-2.674	1.507	0.032	-1.332	-2.674	1.507	-0.818	0.092	2.444	-5.852
	pvalue	0.971	0.252	0.064	0.400	0.971	0.252	0.064	0.400	0.350	0.928	0.082	0.069
	EWMA24	-0.315	-0.220	2.281	4.206	-0.315	-0.220	2.281	4.206	1.789	2.565	3.600	7.830
	pvalue	0.725	0.829	0.090	0.088	0.725	0.829	0.090	0.088	0.218	0.039	0.002	0.007
C	SVA12	0.970	-0.398	0.223	-0.404	-2.275	-2.319	-1.409	-1.306	-1.736	-1.720	-1.804	-2.146
	pvalue	0.000	0.135	0.295	0.083	0.000	0.000	0.008	0.007	0.001	0.001	0.000	0.000
	SVA24	2.041	-0.869	0.880	-1.372	-1.630	-1.798	-1.191	-1.660	-3.260	-3.500	-3.253	-1.342
	pvalue	0.000	0.112	0.099	0.008	0.006	0.003	0.060	0.009	0.001	0.004	0.011	0.456
	EWMA12	1.475	-1.204	0.270	-1.693	-1.014	-1.243	-0.962	-1.274	-1.175	-1.149	-1.346	-1.684
	pvalue	0.000	0.014	0.581	0.007	0.000	0.000	0.020	0.001	0.001	0.003	0.005	0.002
	EWMA24	2.598	-2.922	-0.800	-3.551	-1.180	-1.424	-1.142	-1.791	-1.857	-1.717	-1.266	0.800
	pvalue	0.000	0.001	0.401	0.002	0.000	0.000	0.021	0.001	0.003	0.022	0.219	0.529
D	SVA12	-0.373	-0.435	0.063	0.100	-0.235	-2.409	-1.863	-0.817	0.205	0.651	0.824	0.701
	pvalue	0.425	0.367	0.884	0.782	0.719	0.000	0.000	0.029	0.877	0.611	0.444	0.317
	SVA24	-0.477	-1.216	-0.441	0.000	0.163	-1.075	-1.153	-0.645	-1.277	-1.743	-1.123	-0.471
	pvalue	0.660	0.150	0.550	0.999	0.857	0.045	0.006	0.110	0.291	0.061	0.159	0.494
	EWMA12	-0.509	-1.359	-0.174	-0.271	-0.614	-2.371	-2.040	-1.299	-3.489	-3.553	-2.882	-0.792
	pvalue	0.338	0.174	0.897	0.861	0.264	0.000	0.000	0.002	0.001	0.011	0.043	0.485
	EWMA24	-0.819	-3.227	-2.334	-1.575	-0.116	-1.216	-1.310	-0.947	-1.549	-1.723	-1.473	-1.077
	pvalue	0.446	0.038	0.290	0.477	0.865	0.005	0.001	0.017	0.031	0.007	0.020	0.129

Notes: Table E.4.27 presents the beta coefficients of the risk and return relationship for all the sub-samples using the SVA and the EWMA risk measures after controlling for macroeconomic variables. The values highlighted in blue indicate a negative significant relationship at a 5% significance level.

Table E.4.28: Beta coefficients of risk and return relationship with control variables (VaR SVA and EWMA)

		Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m
FULL	VaR_SVA12	0.216	0.269	0.271	0.239	0.539	0.543	0.556	0.491	0.709	0.738	0.756	0.685
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	0.224	0.284	0.288	0.268	0.496	0.484	0.495	0.429	0.684	0.680	0.669	0.592
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	0.379	0.478	0.644	0.636	0.353	0.398	0.491	0.473	0.568	0.637	0.728	0.694
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	0.463	0.602	0.749	0.762	0.329	0.355	0.431	0.411	0.557	0.575	0.606	0.576
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
No Crisis	VaR_SVA12	0.287	0.335	0.296	0.290	0.777	0.747	0.720	0.621	0.889	0.912	0.886	0.813
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	0.305	0.359	0.331	0.334	0.763	0.704	0.681	0.560	0.855	0.844	0.828	0.737
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	0.580	0.736	0.708	0.818	0.827	0.789	0.780	0.728	0.925	0.958	0.948	0.920
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	0.637	0.804	0.804	0.880	0.817	0.761	0.756	0.667	0.833	0.857	0.877	0.850
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table E.4.28 presents the beta coefficients of the risk and return relationship for the full and no-crisis samples using the Value at Risk SVA and the EWMA risk measures after controlling for macroeconomic variables. The values highlighted in blue indicate a negative significant relationship at a 5% significance level

Table E.4.29: Beta coefficients of risk and return relationship with control variables **(VaR SVA and EWMA)**

		Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m	Spot	P6m	P12m	P36m
A	VaR_SVA12	0.639	0.621	0.676	0.682	0.636	0.741	0.622	0.751	1.438	1.308	1.050	0.670
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	0.543	0.473	0.562	0.606	0.498	0.647	0.541	0.666	1.783	1.232	0.891	0.599
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	0.998	1.008	0.992	1.010	0.868	0.985	0.871	1.000	1.165	1.206	1.149	0.940
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	0.990	1.000	0.983	0.992	0.992	1.033	0.939	0.945	1.284	1.200	1.120	0.928
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
B	VaR_SVA12	0.724	0.721	0.707	0.700	0.724	0.721	0.707	0.700	0.825	0.875	0.985	0.771
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	0.570	0.565	0.548	0.519	0.570	0.565	0.548	0.519	0.930	0.987	1.103	0.791
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	0.883	0.887	0.908	0.969	0.883	0.887	0.908	0.969	0.927	0.983	1.060	0.975
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	0.786	0.840	0.954	0.976	0.786	0.840	0.954	0.976	1.087	1.150	1.185	1.090
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C	VaR_SVA12	0.323	0.467	0.355	0.447	0.635	0.649	0.632	0.663	0.690	0.685	0.678	0.678
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	0.314	0.441	0.376	0.478	0.539	0.531	0.509	0.534	0.585	0.586	0.596	0.600
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	0.942	0.853	1.036	0.855	0.548	0.663	0.671	0.739	0.686	0.733	0.752	0.799
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	1.135	0.956	1.112	0.936	0.570	0.622	0.638	0.721	0.617	0.637	0.682	0.771
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D	VaR_SVA12	0.625	0.688	0.700	0.614	0.706	0.642	0.640	0.605	0.787	0.865	0.895	0.869
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	0.475	0.574	0.640	0.568	0.572	0.495	0.497	0.481	0.659	0.702	0.712	0.705
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	0.836	0.956	0.982	0.992	0.783	0.708	0.706	0.686	0.844	0.913	0.932	0.934
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	0.829	0.955	0.985	0.983	0.730	0.647	0.649	0.610	0.773	0.792	0.817	0.857
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table E.4.29 presents the beta coefficients of the risk and return relationship for all the sub- samples using the Value at Risk SVA and the EWMA risk measures after controlling for macroeconomic variables. The values highlighted in blue indicate a negative significant relationship at a 5% significance level

Table E.4.30: Beta coefficients of risk and return relationship with control variables (GARCH)

		h = 1m				h = 12m				h = 24m			
		Spot	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**
FULL	eGARCH	0.107	0.129	0.092	-0.933	-0.119	-0.352	-0.448	-0.407	0.055	0.181	0.122	-0.142
	pvalue	0.195	0.134	0.002	0.009	0.019	0.000	0.000	0.000	0.407	0.023	0.225	0.233
	GARCH	0.085	0.073	0.220	0.064	-0.099	-0.177	-0.247	-0.343	0.105	0.081	0.056	-0.055
	pvalue	0.362	0.346	0.001	0.546	0.001	0.000	0.000	0.000	0.038	0.098	0.304	0.366
	gjrGARCH	0.132	0.082	0.190	0.052	-0.102	-0.186	-0.261	-0.350	0.077	0.052	0.067	-0.054
	pvalue	0.114	0.276	0.000	0.534	0.001	0.000	0.000	0.000	0.128	0.294	0.216	0.375
A	eGARCH	2.467	1.257	-1.568	-2.418	-0.298	1.186	0.140	2.824	2.260	2.481	3.170	0.239
	pvalue	0.416	0.053	0.035	0.541	0.609	0.051	0.776	0.000	0.003	0.000	0.000	0.023
	GARCH	-0.017	0.012	0.079	0.270	-0.352	0.962	0.368	1.722	1.007	1.360	1.685	2.778
	pvalue	0.687	0.869	0.356	0.030	0.181	0.026	0.411	0.000	0.018	0.000	0.000	0.000
	gjrGARCH	2.838	1.044	-1.599	1.379	-0.361	1.139	0.606	1.960	0.965	1.519	1.628	2.599
	pvalue	0.058	0.007	0.268	0.190	0.170	0.007	0.176	0.000	0.026	0.000	0.000	0.000
B	eGARCH	-0.346	-0.421	-0.622	-1.537	-0.346	-0.421	-0.622	-1.537	1.801	1.611	2.090	-1.660
	pvalue	0.302	0.298	0.304	0.125	0.302	0.298	0.304	0.125	0.000	0.007	0.004	0.001
	GARCH	-0.047	-0.134	-0.200	-0.748	-0.047	-0.134	-0.200	-0.748	0.923	0.829	1.231	-1.090
	pvalue	0.799	0.529	0.527	0.141	0.799	0.529	0.527	0.141	0.000	0.018	0.002	0.100
	gjrGARCH	-0.226	-0.307	-0.481	-0.928	-0.226	-0.307	-0.481	-0.928	0.948	0.911	0.918	-1.970
	pvalue	0.209	0.133	0.112	0.061	0.209	0.133	0.112	0.061	0.000	0.006	0.041	0.000
C	eGARCH	0.943	0.816	-0.083	-0.177	-0.196	-0.232	-0.131	-0.252	0.043	0.037	0.024	0.157
	pvalue	0.000	0.000	0.862	0.613	0.085	0.074	0.297	0.066	0.071	0.088	0.136	0.032
	GARCH	0.594	0.357	0.365	0.255	-0.094	-0.181	-0.033	-0.171	0.328	0.556	0.700	0.741
	pvalue	0.000	0.000	0.000	0.013	0.068	0.025	0.691	0.116	0.001	0.000	0.000	0.000
	gjrGARCH	0.371	0.401	0.253	0.178	-0.103	-0.232	-0.106	-0.281	0.314	0.561	0.702	0.749
	pvalue	0.000	0.000	0.000	0.008	0.011	0.001	0.163	0.003	0.002	0.000	0.000	0.000
D	eGARCH	-0.840	-1.773	-1.870	-1.272	-0.478	-1.004	-1.241	-1.565	-0.635	-0.936	-0.846	-1.580
	pvalue	0.203	0.151	0.509	0.566	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	GARCH	-0.004	0.042	0.033	0.000	-0.375	-0.632	-0.574	-0.599	-0.518	-0.584	-0.621	-0.807
	pvalue	0.946	0.447	0.459	0.996	0.009	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	gjrGARCH	0.023	0.041	0.031	0.000	-0.502	-0.651	-0.603	-0.600	-0.480	-0.525	-0.606	-0.807
	pvalue	0.740	0.437	0.472	0.988	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
NoCrisis	eGARCH	-0.019	-0.066	-0.081	-0.420	-0.165	-0.373	-0.233	-0.414	0.142	0.333	0.292	-0.154
	pvalue	0.877	0.744	0.358	0.101	0.106	0.018	0.182	0.015	0.085	0.000	0.018	0.361
	GARCH	0.011	0.033	0.010	-0.004	-0.058	-0.184	-0.067	-0.275	0.176	0.194	0.170	0.006
	pvalue	0.589	0.096	0.566	0.782	0.421	0.021	0.429	0.001	0.001	0.001	0.007	0.941
	gjrGARCH	0.014	0.034	0.010	-0.004	-0.107	-0.219	-0.065	-0.276	0.133	0.169	0.119	-0.006
	pvalue	0.491	0.084	0.567	0.783	0.130	0.006	0.439	0.001	0.018	0.003	0.060	0.941

Notes: Table E.4.30 presents the beta coefficients of the risk and return relationship for all samples using the GARCH risk measures after controlling for macroeconomic variables. The values highlighted in blue indicate a negative significant relationship at a 5% significance level

Table E.4.31: Beta coefficients of risk and return relationship with control variables (VaR GARCH)

		h = 1m				h = 12m				h = 24m			
		Spot	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**
FULL	VaR_eGARCH	0.292	0.546	0.744	0.012	0.704	0.899	0.963	0.000	0.685	0.000	0.887	0.000
	pvalue	0.000	0.000	0.000	0.129	0.000	0.000	0.000	0.008	0.000	0.000	0.000	0.000
	VaR_GARCH	0.446	0.589	0.820	0.608	0.760	0.852	0.934	0.896	0.793	0.895	0.966	0.956
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	0.392	0.543	0.865	0.570	0.762	0.842	0.943	0.900	0.796	0.895	0.961	0.958
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A	VaR_eGARCH	1.007	1.011	0.997	0.838	1.002	0.699	0.401	0.004	0.046	0.000	0.168	0.065
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.016	0.039	0.980	0.000	0.122
	VaR_GARCH	0.995	1.002	0.992	0.994	1.003	0.992	0.929	0.003	1.018	0.989	0.994	1.011
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.457	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	0.996	1.011	1.002	1.002	1.004	1.010	0.958	1.049	1.017	0.988	0.999	1.012
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
B	VaR_eGARCH	0.915	0.935	0.956	0.960	0.915	0.935	0.956	0.960	1.051	-0.005	0.000	0.000
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.380	0.005	0.838
	VaR_GARCH	0.988	1.000	0.000	0.979	0.988	1.000	0.000	0.979	0.969	0.987	0.994	0.977
	pvalue	0.000	0.000	0.983	0.000	0.000	0.000	0.983	0.000	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	0.997	1.003	0.993	0.967	0.997	1.003	0.993	0.967	0.969	0.987	0.997	0.973
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C	VaR_eGARCH	0.015	-0.007	0.043	0.000	0.000	0.000	0.990	0.000	0.028	0.329	0.000	-0.010
	pvalue	0.893	0.514	0.370	0.855	0.128	0.007	0.000	0.581	0.150	0.000	0.299	0.296
	VaR_GARCH	0.136	0.052	-0.144	0.493	0.682	0.704	0.955	0.891	0.330	0.527	0.620	0.836
	pvalue	0.258	0.429	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	-0.219	-0.061	-0.148	0.239	0.620	0.629	0.002	0.866	0.496	0.575	0.646	0.853
	pvalue	0.000	0.192	0.000	0.000	0.000	0.000	0.264	0.000	0.000	0.000	0.000	0.000
D	VaR_eGARCH	0.512	0.854	0.985	0.942	-0.063	1.001	1.001	0.872	0.801	0.000	0.003	0.004
	pvalue	0.000	0.000	0.000	0.000	0.032	0.000	0.000	0.000	0.000	0.388	0.001	0.088
	VaR_GARCH	0.999	1.000	1.000	0.765	-0.001	0.999	1.000	0.968	0.339	0.721	0.965	0.969
	pvalue	0.000	0.000	0.000	0.000	0.841	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	0.792	0.932	0.984	0.966	1.078	1.014	1.008	0.938	0.376	0.709	0.836	0.990
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
NoCrisis	VaR_eGARCH	0.001	0.006	0.733	0.144	0.859	0.956	0.962	0.000	0.564	0.000	0.906	0.000
	pvalue	0.697	0.116	0.000	0.000	0.000	0.000	0.000	0.005	0.000	0.000	0.000	0.000
	VaR_GARCH	0.595	0.807	0.796	0.689	0.858	0.953	0.943	0.970	0.855	0.946	0.930	0.960
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	0.567	0.782	0.862	0.772	0.869	0.947	0.941	0.973	0.861	0.955	0.930	0.964
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table E.4.31 presents the beta coefficients of the risk and return relationship for all samples using the Value at Risk GARCH risk measures after controlling for macroeconomic variables. The values highlighted in blue indicate a negative significant relationship at a 5% significance level.

Table E.4.32: Beta coefficients of risk and BELOW target return relationship with control variables (SVA and EWMA)

		h = 1m				h = 12m				h = 24m			
		Spot	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**
FULL	VaR_SVA12	-0.276	-0.286	-0.264	-0.220	-0.421	-0.487	-0.471	-0.594	-0.527	-0.738	-0.803	-0.727
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	-0.293	-0.333	-0.295	-0.258	-0.384	-0.412	-0.376	-0.398	-0.489	-0.687	-0.817	-0.776
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	-0.763	-0.719	-0.634	-0.757	-0.134	-0.227	-0.470	-0.837	-0.607	-0.902	-1.077	-1.011
	pvalue	0.000	0.000	0.000	0.000	0.082	0.016	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	-0.876	-0.835	-0.736	-0.815	-0.268	-0.338	-0.435	-0.558	-0.654	-0.962	-1.312	-1.311
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
No Crisis	VaR_SVA12	-0.357	-0.333	-0.250	-0.256	-0.613	-0.588	-0.558	-0.595	-0.698	-0.971	-1.032	-0.975
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	-0.397	-0.404	-0.287	-0.324	-0.579	-0.578	-0.524	-0.568	-0.645	-0.852	-0.980	-1.004
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	-0.897	-0.856	-0.756	-0.801	-0.912	-0.937	-1.023	-1.122	-1.002	-1.231	-1.266	-1.220
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	-0.937	-0.945	-0.861	-0.893	-0.889	-0.905	-0.950	-1.051	-0.993	-1.161	-1.255	-1.256
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table E.4.32 presents the beta coefficients of below the target risk and return relationship for the full and no-crisis samples using the Value at Risk SVA and EWMA risk measures after controlling for macroeconomic variables. The values highlighted in blue indicate a negative significant relationship at a 5% significance level.

Table E.4.33: Beta coefficients of risk and BELOW target return relationship with control variables (SVA and EWMA)

		h = 1m				h = 12m				h = 24m			
		Spot	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**
A	VaR_SVA12	-0.573	-0.532	-0.553	-0.761	-0.794	-0.744	-0.688	-0.697	-0.794	-0.744	-0.688	-0.697
	pvalue	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.001	0.000	0.000	0.000
	VaR_SVA24	-0.520	-0.585	-0.543	-0.609	-0.458	-0.541	-0.530	-0.637	-0.458	-0.541	-0.530	-0.637
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	-0.999	-0.982	-0.995	-0.996	-1.233	-1.070	-1.046	-0.993	-1.233	-1.070	-1.046	-0.993
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	-1.001	-0.988	-0.991	-0.991	-0.757	-0.918	-0.906	-0.986	-0.757	-0.918	-0.906	-0.986
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
B	VaR_SVA12	-1.207	-0.919	-0.716	-0.722	-1.207	-0.919	-0.716	-0.722	-1.207	-0.919	-0.716	-0.722
	pvalue	0.000	0.000	0.019	0.008	0.000	0.000	0.019	0.008	0.000	0.000	0.019	0.008
	VaR_SVA24	-0.957	-0.750	-0.575	-0.513	-0.957	-0.750	-0.575	-0.513	-0.957	-0.750	-0.575	-0.513
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	-1.393	-1.278	-1.237	-1.140	-1.393	-1.278	-1.237	-1.140	-1.393	-1.278	-1.237	-1.140
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	-1.280	-1.168	-1.028	-1.004	-1.280	-1.168	-1.028	-1.004	-1.280	-1.168	-1.028	-1.004
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C	VaR_SVA12	-0.394	-0.554	-0.464	-0.381	-1.155	-1.474	-1.615	-1.821	-1.151	-1.100	-1.015	-0.871
	pvalue	0.000	0.000	0.000	0.035	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_SVA24	-0.525	-0.726	-0.563	-0.685	-1.020	-1.269	-1.247	-1.552	-0.823	-0.804	-0.790	-0.833
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA12	-0.836	-0.817	-0.632	-0.905	-0.296	-1.825	-1.557	-1.465	-0.930	-1.234	-1.147	-1.038
	pvalue	0.000	0.000	0.000	0.000	0.369	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	-0.915	-0.894	-0.714	-0.969	-0.951	-1.487	-1.431	-1.337	-1.010	-1.076	-1.055	-1.033
	pvalue	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D	VaR_SVA12	-0.588	-0.623	-0.603	-0.612	-0.530	-0.604	-0.596	-0.570	-0.477	-0.504	-0.457	-0.124
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.002	0.382
	VaR_SVA24	-0.510	-0.575	-0.572	-0.715	-0.479	-0.456	-0.396	-0.353	-0.475	-0.448	-0.306	-0.103
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.004	0.000	0.001	0.035	0.295
	VaR_EWMA12	-0.828	-0.915	-0.968	-0.983	-0.755	-0.906	-0.981	-1.000	-0.657	-0.867	-0.961	-0.908
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_EWMA24	-0.831	-0.935	-0.971	-0.990	-0.740	-0.737	-0.749	-0.745	-0.629	-0.733	-0.737	-0.548
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001

Notes: Table E.4.33 presents the beta coefficients of below the target risk and return relationship for all the sub-samples using the Value at Risk SVA and EWMA risk measures after controlling for macroeconomic variables. The values highlighted in blue indicate a negative significant relationship at a 5% significance level.

Table E.4.34: Beta coefficients of risk and BELOW target return relationship with control variables (GARCH approach)

		h = 1m				h = 12m				h = 24m			
		Spot	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**	**Spot**	**P6m**	**P12m**	**P36m**
FULL	VaR_eGARCH							-0.621					
	pvalue							0.000					
	VaR_GARCH	-0.298	-0.292	-0.233	-0.223	0.017	-0.371	-0.410	-1.002	-0.282	-0.851	-0.997	-1.011
	pvalue	0.000	0.000	0.000	0.000	0.770	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	-0.143	-0.128	-0.116	-0.122	0.126	0.195	0.263	0.377	0.167	-0.079	-0.872	-1.007
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.303	0.000	0.000
A	VaR_eGARCH	-0.005	-0.581	-0.001							0.002		0.000
	pvalue	0.636	0.000	0.701							0.323		0.124
	VaR_GARCH	-0.935	-0.920	-0.969	-0.916	-0.941	-0.571	-0.292	-0.864	-0.941	-0.571	-0.292	-0.864
	pvalue	0.000	0.000	0.000	0.000	0.000	0.039	0.267	0.000	0.000	0.039	0.267	0.000
	VaR_gjrGARCH	-1.009	-0.818	-0.900	-0.811	-0.977	-0.824	0.123	-0.925	-0.977	-0.824	0.123	-0.925
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.507	0.000	0.000	0.000	0.507	0.000
B	VaR_eGARCH		0.000	0.000	0.000							0.000	
	pvalue		0.644	0.954	0.653							0.954	
	VaR_GARCH	-1.042	-1.041	-1.062	-1.073	-1.042	-1.041	-1.062	-1.073	-1.042	-1.041	-1.062	-1.073
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	-1.147	-1.086	-1.181	-1.066	-1.147	-1.086	-1.181	-1.066	-1.147	-1.086	-1.181	-1.066
	pvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C	VaR_eGARCH		0.000	0.000									
	pvalue		0.901	0.739									
	VaR_GARCH	-0.106	-0.230	-0.163	-0.173	0.225	-0.672	-0.411	0.533	0.031	-0.837	-0.916	-0.927
	pvalue	0.092	0.000	0.000	0.011	0.001	0.000	0.024	0.000	0.858	0.000	0.000	0.000
	VaR_gjrGARCH	-0.049	-0.150	-0.114	-0.101	0.048	0.326	0.400	-0.563	0.042	-0.812	-0.931	-1.598
	pvalue	0.265	0.001	0.000	0.041	0.869	0.151	0.000	0.001	0.814	0.000	0.000	0.001
D	VaR_eGARCH	-0.472	-0.074	-0.998	-0.034						-0.055		
	pvalue	0.000	0.403	0.000	0.161						0.154		
	VaR_GARCH	-0.236	-0.440	-0.851	-0.007	-0.026	-0.727	-0.954	-1.073	-0.140	-0.386	-0.689	-0.571
	pvalue	0.000	0.000	0.000	0.652	0.768	0.000	0.000	0.000	0.150	0.004	0.000	0.000
	VaR_gjrGARCH	-1.006	-1.019	-1.003	-0.554	0.062	0.262	-0.915	0.393	0.117	-0.012	-0.314	-0.547
	pvalue	0.000	0.000	0.000	0.000	0.147	0.003	0.000	0.072	0.004	0.932	0.024	0.000
No Crisis	VaR_eGARCH												
	pvalue												
	VaR_GARCH	-0.297	-0.301	-0.159	-0.130	0.064	-0.825	-1.006	-1.089	-0.386	-0.896	-1.002	-0.887
	pvalue	0.000	0.000	0.000	0.000	0.215	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	VaR_gjrGARCH	-0.136	-0.121	-0.044	-0.046	0.114	-0.267	-0.776	-1.034	0.189	0.180	-0.899	-0.948
	pvalue	0.000	0.000	0.062	0.071	0.001	0.003	0.000	0.000	0.000	0.007	0.000	0.000

Notes: Table E.4.34 presents the beta coefficients of below the target risk and return relationship for all samples using the Value at Risk GARCH risk measures after controlling for macroeconomic variables. The values highlighted in blue indicate a negative significant relationship at a 5% significance level

Appendix 4.F: Back testing the Value at Risk approach

Table F.4.35 presents the loglikelihood ratio of each Value at Risk (VaR) model used. According to Kupiec (1995) the forecasting power of the VaR models is anticipated to be reliable at a 99% confidence interval.

Table F.4.35: LogLikelihood Ratio Values of the VaR models

		FULL			**A**			**B**			**C**			**D**			**No Crisis**		
Risk Measure	**h =**	**1m**	**12m**	**24m**	**1m**	**12m**	**24m**	**1m**	**12m**	**24m**	**1m**	**12m**	**24m**	**1m**	**12m**	**24m**	**1m**	**12m**	**24m**
t SVA12	**spot**	5.991	5.991	5.991	5.991	5.991	5.991	2.378	5.991	5.991	2.378	5.991	5.991	3.321	5.991	5.991	5.991	5.991	5.991
	P6m	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	3.321	5.991	5.991	5.991	5.991	5.991
	P12m	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	1.801	5.991	5.991	3.321	5.991	5.991	5.991	5.991	5.991
	P36m	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	3.321	5.991	5.991	5.991	5.991	5.991
t SVA24	**spot**	5.991	5.991	5.991	5.991	5.991	5.991	2.378	5.991	5.991	2.378	5.991	5.991	3.321	5.991	5.991	5.991	5.991	5.991
	P6m	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	2.378	5.991	5.991	3.321	5.991	5.991	5.991	5.991	5.991
	P12m	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	1.801	5.991	5.991	3.321	5.991	5.991	5.991	5.991	5.991
	P36m	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	1.398	5.991	5.991	3.321	5.991	5.991	5.991	5.991	5.991
t EWMA12	**spot**	5.991	5.991	5.991	5.991	5.991	5.991	2.378	5.991	5.991	2.378	5.991	5.991	3.321	5.991	5.991	5.991	5.991	5.991
	P6m	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	2.378	5.991	5.991	3.321	5.991	5.991	5.991	5.991	5.991
	P12m	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	1.801	5.991	5.991	3.321	5.991	5.991	5.991	5.991	5.991
	P36m	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	1.398	5.991	5.991	3.321	5.991	5.991	5.991	5.991	5.991
t EWMA24	**spot**	2.378	5.991	5.991	5.991	5.991	5.991	5.991	5.991	0.000	1.398	5.991	5.991	3.321	5.991	5.991	5.991	2.378	0.000
	P6m	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	1.398	5.991	5.991	3.321	5.991	5.991	5.991	5.991	0.000
	P12m	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	1.398	5.991	5.991	3.321	5.991	5.991	2.378	2.378	0.000
	P36m	5.991	2.378	2.378	2.378	2.378	5.991	5.991	2.378	2.378	5.991	5.991	5.991	3.321	5.991	5.991	5.991	5.991	0.000
VaR t eGARCH	**spot**	2.378	5.991	5.991	5.991	5.991	2.378	5.991	5.991	5.991	5.991	2.378	5.991	3.321	5.991	2.378	5.991	5.991	0.000
	P6m	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	2.378	5.991	2.378	3.321	5.991	5.991	2.378	2.378	5.991
	P12m	5.991	1.801	5.991	1.801	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	3.321	5.991	5.991	5.991	5.991	5.991
	P36m	1.801	2.378	5.991	2.378	2.378	5.991	5.991	5.991	1.801	5.991	5.991	5.991	3.321	5.991	5.991	5.991	2.378	2.378
VaR t GARCH	**spot**	2.378	5.991	5.991	5.991	5.991	5.991	5.991	0.000	2.378	5.991	1.801	2.378	3.321	5.991	0.000	1.801	5.991	5.991
	P6m	5.991	5.991	2.378	5.991	5.991	2.378	2.378	5.991	2.378	5.991	2.378	5.991	3.321	5.991	5.991	1.801	2.378	5.991
	P12m	5.991	5.991	5.991	2.378	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991	3.321	5.991	5.991	2.378	5.991	5.991
	P36m	5.991	5.991	5.991	5.991	2.378	5.991	5.991	1.801	0.000	5.991	5.991	5.991	3.321	5.991	1.801	5.991	5.991	2.378
VaR t gjrGARCH	**spot**	2.378	2.378	1.801	5.991	5.991	1.801	5.991	2.378	0.000	1.801	5.991	1.801	3.321	5.991	2.378	5.991	5.991	5.991
	P6m	5.991	5.991	5.991	5.991	5.991	2.378	5.991	2.378	0.000	2.378	5.991	2.378	3.321	5.991	1.801	5.991	5.991	5.991
	P12m	5.991	5.991	5.991	5.991	1.801	5.991	2.378	5.991	0.000	1.398	5.991	5.991	3.321	5.991	2.378	5.991	5.991	1.801
	P36m	5.991	1.801	1.801	5.991	2.378	5.991	5.991	0.000	0.000	1.398	5.991	5.991	3.321	5.991	5.991	5.991	5.991	2.378

Chapter 5

Concluding Remarks and Future Research

The purpose of this chapter is to summarise the main empirical findings of each chapter and their contributions whilst also outline future research ideas.

5.1 Summary and Conclusion

During an unstable period, the necessity to provide robust, innovative and resourceful financial solutions is crucial for the success of any shipping company and the level of freight rates is the most important factor that affects their profitability. Freight rates are determined by supply and demand which are subject to complex interactions (e.g. events in the Middle East, country-specific policies etc.) as well as money flows. Therefore, finding reliable and consistent models that can assess and understand important characteristics of the freight market is of great importance.

These models are also essential tools for market participants wishing to comprehend the evolution of freight rates, volatilities, correlation and economic relationships in order to develop profitable policies. The empirical properties of the freight rates series are assessed using the data outlined in Chapters 2, 3 and 4 and the results show that the freight rate distributions present heavy tails and that their volatilities and correlations are asymmetric and time dependent. This suggest that there potential extreme and adverse outcomes in the market. Therefore, these facts also highlight the need for the construction of advanced quantitative techniques to describe their conditional distributions.

To sum up, the aim of this thesis is to provide results that will enhance our understanding of how the freight and ship markets move in the dry bulk sector of the shipping industry. In order to achieve this, three important areas are examined i) the construction of chartering strategies based on multiple technical trading indicators, ii) the dynamic interactions between the term structure of freight rates and the macroeconomy and iii) the dynamic relationships between freight rate returns and freight rate volatilities. The next sections review the main findings of the thesis and suggest potential future areas to expand the research.

5.1.1 Chartering Strategies

Chapter 2 focuses on how to construct and assess chartering strategies. Multiple parameterisations (30,046) of technical trading rules (e.g. trend, momentum, volatility, moving average envelopes and a complex strategy) are applied to the physical market for three vessel types (i.e. Capesize, Panamax and Handymax vessels) and different contract durations (i.e. spot, 6-, 12- and 36-month contracts) in order to identify the best types of contract at each point in time.

Existing studies tend to only consider a small number of contracts (i.e. exclusively spot or spot and period time charter without specifying the exact duration of a period charter contract when the latter is identified as the most profitable choice), limited sets of technical trading rules, short sample periods, simple performance metrics and basic testing methods which may be subject to data-snooping bias. Therefore, there was room to develop a comprehensive study of technical analysis in the freight market that will investigate if technical analysis can beat the freight market on a large-scale with an accurate empirical design.

Technical trading rules have been widely criticised in the literature therefore, in order to enhance the robustness of the analysis, the following actions were performed: extending the analysis to include alternative vessels types and sizes, exclude the turbulent financial period and use two different outperformance criteria (i.e. maximum mean and risk-adjusted returns). All robustness tests conclude that the active strategies present superior performance compared to the passive ones. In addition, the bootstrap analysis and the estimation of the White's Reality Check *p-value* indicated that the empirical findings are not the result of the data-snooping bias effect.

The empirical analysis of several parameterisations of active trading strategies show that these can be applied to the physical market in order to increase the profitability of the chartering operations. The results also highlight the fact that active strategies are less risky compared to passive ones so ship owners can use technical trading rules as a heuristic approach when making chartering decisions.

Additionally, since the active chartering strategies are more profitable than the passive ones, it can be concluded that the dry bulk freight market rejects the Efficient Market Hypothesis for the period between January 1992 and June 2016. Additionally, during the same period, the freight rates fail to retain the Liquidity Theory Hypothesis since the empirical findings indicated that the liquidity spread does not increase monotonically. Therefore, the chartering strategies cannot rely on these two term structure theories in order to propose profitable strategies since the trend, momentum, volatility and complex strategies suggest that a ship-owner can earn on average higher returns compared to passive strategies and to a *"simple spread strategy"*.

Overall, market timing rules can provide reliable hedging strategies that enable participants to operate under profitable freight rate over a period of time and maintain that hedge if the market moves in the desired direction or switch if the market moves against them.

5.1.2 Term Structure of Freight Rates and the Macroeconomy

In the shipping freight market, the freight rates (i.e. long-term and short-term rates) are determined by the demand for trade, supply of ships and other macroeconomic factors (Hawdon, 1978; Beenstock and Vergottis, 1989a,b; Evans and Marlow, 1990; Beenstock and Vergottis, 1993). The fleet supply function works by moving ships in and out of service in response to freight rates meaning that it is elastic when the freight rates are low and inelastic when these are high (Stopford, 2009). On the other hand, the fleet demand function is almost vertical and shows how charterers react to changes in freight rate. Chapter 3 proposes a model which, for the first time, includes a very large dataset consisting of both demand and supply variables whose influence is then assessed using two methodological approaches that have never been applied to the shipping industry previously.

Chapter 2 showed that the level of freight rates is the most important factor when determining the profitability of chartering strategies and therefore identifying the factors that drive the movement in the freights rates is crucial. A large demand and supply macroeconomic dataset with variables that are directly related to the shipping industry is constructed to provide a more robust and accurate view of the freight rates' behaviour. The goal is to be able to apply for the first time the FAVAR (Bernanke et al 2005) and a dynamic latent factor model (Diebold and Li, 2006) to the shipping industry in order to accurately analyse the reasons behind the freight rate movements since both models (which have been proven to be accurate tools for assessing the dynamic interactions between the macroeconomic variables and the freight rates) have only been used in the financial sector.

The empirical analysis of the FAVAR model shows that the macroeconomic factors explain a high proportion (up to 70%) of the movements of the freight rate curve and that the effects of the demand and supply shocks are stronger at the long end of the freight rate curve. Additionally, the impulse response functions allow the assessment of the effect on freight rates caused by one standard deviation shock to the macroeconomic variable series. The robustness of the FAVAR model is confirmed through a series of regression models (e.g. unrestricted regressions, latent factor regressions, etc.). The results indicate that multiple factors can better explain the freight rate variability. Additionally, when regressing the demand and supply factors with the log differences of the freight rates series, the supply factors seem to explain a larger variation (up to 60%) of the term structure of freight rates compared to the demand factors.

Finally, the latent factors of the dynamic latent freight rate model are regressed against the supply and demand factors. The results show that a significant proportion of the level, slope and curvature factors are attributed to the macroeconomic supply factors. On the other hand, except from the slope factor, the latent factors do not explain the demand factors to a significant degree. Overall, the empirical findings indicate that the supply factors can explain a bigger portion of the freight rate variability compared to the demand variables.

5.1.3 Risk and Return Relationship

The last empirical part of the thesis in Chapter 4 focuses on the nature of the risk and return relationship in the dry bulk freight market in order to understand the firms' competitive behaviour. The results show that the market may be affected by changes in the variables over a longer period. Analysing the nature of the risk and return relationship using multiple holding period horizon, there are cases where this connection is negative.

Although a negative risk and return trade off is considered as a paradoxical finding based on the financial theory, there is evidence in the literature supporting the existence of this phenomenon. Therefore, this study contributed to the literature on finance and management by investigating the nature of the relationship between risk and returns in the shipping industry through several dimensions such as time; multiple (i.e. bull and bear) market conditions as well as using multiple valuation models. The risk and return relationship was analysed using multiple risk and return measures since various studies support the fact that the negative association between risk and return may be due to statistical errors (Denrell, 2004; Ruefli, 1990; Ruefli and Wiggins, 1994) or to the choice of risk and return measures used (Baucus, Golec and Cooper, 1993).

The purpose of the study was to prove that the risk and return relationship is robust and unaffected by risk and return measures, subsamples, market conditions and controlling variables associated with the business cycle. Additionally, this study attempted to examine whether a negative association between risk and returns in the past is due to the attitudes toward risk as conceptualised by the Prospect Theory. Therefore, the analysis used behavioural decision theory and *Prospect Theory* (Kahneman and Tversky, 1979) that support the fact that decision makers become risk seekers or risk averse depending on if the performance has been below or above a specific target level.

Overall, the asymmetric risk-return relationship in the up- and down-markets of shipping freight rates is analysed and the result indicated that the risks are positively correlated with the returns in a bull market and negatively associated in a bear market. Additionally, there is evidence that decision makers are risk seekers when performance has been below a specific target level and risk averse when the performance has been above a certain point. This examination of past performance could potentially explain the relationship between risk and return in shipping investments.

5.2 Directions for Further Research

Overall, the empirical findings of this thesis have important implications for the freight market trading and risk management as well as chartering operations. Chapter 2 reveals that the use of technical trading indicators can help identify profitable strategies. Additionally, Chapter 3 demonstrates significant dynamic interactions between the macroeconomy and the term structure of freight rates whilst the results of Chapter 4 offer a better understanding of the nature of the risk and return relationship.

Based on the empirical findings, the analysis can be extended to additional vessel types but also to the tanker market to study, compare and identify characteristics of the entire bulk shipping industry. Chapter 2 focuses on the construction of optimal chartering strategies using the current and future level of freight rates. The analysis and the assessment of these chartering strategies is based on a series of assumptions which in the future could be relaxed in order to be able to propose more realistic and dynamic chartering strategies. For instance, the use of real life scenarios could serve as an ideal alternative to explore how the risk attitudes are affected under specific circumstances (e.g. market conditions, fleet size, etc.).

Furthermore, future research could also incorporate multiple vessels in the proposed model as well as additional options, such as the *"lay-up"*, *"wait"*, *"exit"* and the *"purchase option"* in a period charter (Alizadeh and Nomikos, 2009). Also, since the dry bulk freight market failed to retain the Efficient Market Hypothesis and the Liquidity Theory Hypothesis, future research could test if other term structure theories such as the *Market Segmentation Theory* (Culbertson, 1957) or the *Preferred Habitat Theory* (Modigliani and Sutch, 1966) can explain the way the freight rates are formulated.

The empirical analysis of Chapter 3 could be a good starting point for extending the VAR framework by including additional VAR models to assess and compare its forecasting performance in the freight rate market. Given that the proposed model explains a sufficient percentage of the freight rate variability, it could be tested in the future to confirm its forecasting ability.

The empirical findings of Chapter 4 suggest shipping investments, under specific circumstances, present a paradoxical (negative) relationship between risk and return, that is not due to inconsistencies in the data since the outcome can be replicated using various risk and return measures. The relationship is considered as paradoxical since it contradicts the financial theory and especially the Capital Asset Pricing Model. Therefore, future research can focus on identifying and understanding ship-owners' preferences and behaviour drivers in situations when there is a negative association between risk and returns. Additionally, further research could study whether shipping investments require a different (riskier) framework (i.e. a pricing model that will consider the existence of a negative association between risk and return under different scenarios) to be assessed accurately.

Therefore, future research could also focus on the development of dynamic models that will also incorporate multiple real life scenarios to tackle more complex problems of the industry in the most accurate way. Overall, the shipping industry is a very complex and dynamic business that makes the formulation of problems a challenging task due to the dimensionality and the dynamic nature of almost every variable required in a model. In order to be able to tackle shipping problems accurately, one of the most commonly used approaches is the development of scenarios that allow the examination of variables or areas where quantitative data is not available.

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