Quantitative analysis of the dry bulk freight market, including forecasting and decision making

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ABSTRACT

This thesis provides a quantitative analysis of the dry bulk freight market and investigates a number of crucial issues associated with ship chartering. To this end, it analyzes the dynamics of spot and period freight markets separately and leads to insightful conclusions.

At the outset, a theoretical discussion of the market fundamentals sets the scene and is followed by a thorough exploration of the key determinants of freight rates. At this point a new composite indicator is constructed -the Dry Bulk Economic Climate Index (DBECI)-, which is tailored to the dry cargo market and mirrors the aggregate impact of some carefully selected economic variables. As opposed to conventional approaches, the structure and the weighting scheme of this index are based on extensive exploratory and numerical analysis. This enhances the credibility of the DBECI and ultimately gives rise to more meaningful analyses. The next step is to carry out Co-integration analysis, Granger Causality tests and Impulse Response analysis in order to identify possible linkages between this new indicator and the freight market. In parallel, a similar numerical analysis is performed for some equally important determinants, such as the Chinese steel production, the average bunker prices, the port congestion, and the price of the most traded bulk commodities. The results reveal significant lead-lag relationships for the cases of DBECI, bunker prices, Chinese steel production, and commodity prices, while the port congestion appears to lead the freight rates only in the Capesize sector.

The subsequent section is devoted to the development of parsimonious multivariate forecasting models (VAR/VECM and VARX). In this respect, the preceding theoretical and empirical analysis constitutes the groundwork for the selection of the most appropriate explanatory variables. Specifically, the Chinese steel production and the fleet development are used as endogenous variables, while the DBECI and the fuel prices are treated as exogenous. Next, a univariate framework (ARIMA) for the freight rates of Panamax and Capesize vessels is developed and serves as a benchmark for comparison of the forecasting accuracy of the proposed multivariate models. The findings show that the VARX model outperforms both of the alternative approaches, suggesting that the incorporation of these two exogenous variables (DBECI and average bunker prices) can significantly enhance the robustness of simpler models and ultimately result in more accurate forecasts.

The last part of this thesis involves the investigation of excess return opportunities in the spot market. For this purpose the dynamics between trip charters and their corresponding voyage charters are studied. The thesis first examines the existence of a long-run equilibrium relationship and then develops a new methodology based on technical analysis so as to identify excess return signals and formulate a suitable chartering strategy. The results reveal that this approach outperforms the ‘naïve’ strategy of always chartering in vessels on trip time charters and perform the underlying voyage charters.

Overall, the present thesis is of interest to academics and maritime practitioners alike. It fills significant gaps in the literature, while at the same time it can serve as a powerful decision support tool for shipping companies.

ΠΕΡΙΛΗΨΗ

Η παρούσα διδακτορική διατριβή παρέχει μία ποσοτική ανάλυση της ναυλαγοράς ξηρού χύδην φορτίου και διερευνά μία σειρά κρίσιμων θεμάτων που συνδέονται με τις ναυλώσεις πλοίων. Σε αυτό το πλαίσιο, αναλύονται οι ναυλαγορές spot και περιόδου ξεχωριστά και εξάγονται κατάλληλα συμπεράσματα.

Σε πρώτο στάδιο παρέχεται μία θεωρητική ανάλυση των θεμελιωδών μεγεθών της συγκεκριμένης αγοράς και ακολουθεί μία ενδελεχής αναζήτηση των σημαντικότερων παραγόντων που επηρεάζουν τις τιμές των ναύλων ξηρού φορτίου. Παράλληλα, κατασκευάζεται ένας νέος σύνθετος δείκτης, ο δείκτης οικονομικού κλίματος της αγοράς ξηρού φορτίου (Dry Bulk Economic Climate Index or DBECI), ο οποίος ο οποίος περικλείει ένα σύνολο προσεκτικά επιλεγμένων οικονομικών μεταβλητών και αντανακλά τη συνολική επίδρασή τους στη ναυλαγορά ξηρού φορτίου. Σε αντίθεση με άλλες απλουστευμένες προσεγγίσεις που αποδίδουν ίσα βάρη στις παραμέτρους, ο υπολογισμός των βαρών του συγκεκριμένου δείκτη βασίζεται σε ένα συνδυασμό θεωρητικής έρευνας και εφαρμογής μίας προσαρμοσμένης μεθόδου γραμμικού προγραμματισμού. Αυτή η προσέγγιση βελτιώνει την αξιοπιστία του δείκτη και επιτρέπει τη διενέργεια πιο ουσιαστικής ανάλυσης. Το επόμενο βήμα περιλαμβάνει ανάλυση συν-ολοκλήρωσης (Co-integration analysis), εξέταση της Granger αιτιότητας (Granger causality) και ανάλυση κρουστικής απόκρισης (impulse response analysis), ώστε να ανιχνευτεί πιθανή σύνδεση ανάμεσα σε αυτό το νέο δείκτη και τη ναυλαγορά. Παράλληλα εφαρμόζεται μία παρόμοια προσέγγιση για κάποιους εξίσου σημαντικούς εξωτερικούς παράγοντες, όπως η συνολική παραγωγή χάλυβα στην Κίνα, η μέση τιμή υγρών καυσίμων πλοίου, η συμφόρηση λιμένων ως ποσοστό του συνολικού στόλου της κάθε κατηγορίας πλοίων, και οι τιμές των κύριων εμπορευμάτων της αγοράς ξηρού χύδην φορτίου (σίδηρος, γαιάνθρακας, σιτηρά). Τα αποτελέσματα καταδεικνύουν στατιστικά σημαντικές σχέσεις αιτιότητας για τις περιπτώσεις του DBECI, των τιμών καυσίμων πλοίου, του ύψους παραγωγής χάλυβα, και των τιμών των κύριων εμπορευμάτων, ενώ στην περίπτωση της συμφόρησης λιμένων αντίστοιχες σχέσεις εντοπίζονται μόνο για τις τιμές ναύλων των πλοίων τύπου Capesize.

Στο επόμενο στάδιο της διατριβής αναπτύσσονται μοντέλα πρόβλεψης των μελλοντικών τιμών των ναύλων, κάνοντας χρήση της προηγούμενης ανάλυσης. Πιο συγκεκριμένα αναπτύσσονται πολύ-μεταβλητά μοντέλα τύπου VAR / VECM, για τα οποία επιλέγονται ως ενδογενείς μεταβλητές η παραγωγή χάλυβα στην Κίνα και το μέγεθος του στόλου κάθε τύπου φορτηγών πλοίων. Παράλληλα δημιουργούνται

πολύ-μεταβλητά μοντέλα που εμπεριέχουν και εξωγενείς μεταβλητές τύπου VARX, στα οποία προστίθενται ως εξωγενείς μεταβλητές ο νέος δείκτης που κατασκευάστηκε σε προηγούμενο τμήμα της διατριβής (DBECI), καθώς και η μέση τιμή τιμών υγρών καυσίμων για πλοία. Τέλος κατασκευάζονται και αυτό-παλινδρομικά μοντέλα τύπου ARIMA για τη διεξαγωγή συγκρίσιμων προβλέψεων. Τα αποτελέσματα καταδεικνύουν την ανωτερότητα των VARX μοντέλων έναντι των δύο εναλλακτικών προσεγγίσεων. Αυτό δείχνει ότι η χρήση των δύο νέων αυτών μεταβλητών που δημιουργήθηκαν στην παρούσα εργασία (DBECI και μέσες τιμές καυσίμων), μπορούν να βελτιώσουν σε σημαντικό βαθμό την ακρίβεια προβλέψεων των τιμών ναύλων.

Το τελευταίο κομμάτι της διατριβής επικεντρώνεται στη spot ναυλαγορά και διερευνά τη δυνατότητα υπερβάλλουσας απόδοσης μέσω της κατάλληλης χρήσης και συντονισμού χρονοναύλωσης ταξιδίου (trip time charter) και ναύλωσης κατά ταξίδι (voyage charter). Αρχικά γίνεται χρήση co-integration analysis και αποδεικνύεται η ύπαρξη μιας μακροπρόθεσμης σχέσης ισορροπίας ανάμεσα στους δύο τρόπους ναύλωσης στη spot αγορά όταν αυτοί αφορούν την ίδια διαδρομή. Σε αυτό το πλαίσιο, εντοπίζονται βραχυπρόθεσμες αποκλίσεις τις οποίες εκμεταλλεύεται η παρούσα ανάλυση για τη δημιουργία μίας νέας στρατηγικής ναυλώσεων, που βασίζεται σε αρχές Τεχνικής Ανάλυσης. Τα αποτελέσματα δείχνουν ότι η προτεινόμενη προσέγγιση παρέχει υψηλότερες αποδόσεις συγκριτικά με συμβατικές στρατηγικές.

Συνολικά, η παρούσα διατριβή έχει τόσο θεωρητική όσο και πρακτική χρησιμότητα. Συμπληρώνει σημαντικά κενά στη διεθνή βιβλιογραφία και παράλληλα μπορεί να ενισχύσει τη διαδικασία λήψης αποφάσεων σε ναυτιλιακές εταιρίες.

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Table of Contents

List of Tables

List of Figures

1. INTRODUCTION

1.1. Scope of Research

Managerial decision analysis using quantitative techniques is an important and continuously growing area in shipping. Traditionally, most shipping companies over-rely on experience and 'gut feeling'. Many shipowners feel confident that a combination of experience of past cycles, personal insights, and up-to-date information can always lead them to the correct decision and drive their business forward. However, this kind of intuitive decisions is subject to cognitive and behavioural biases. Very often they tend to interpret data and market developments in ways that verify their initial hypothesis, even if it is invalid. Moreover, the shipping industry has undergone enormous changes over the past few years and the new complex landscape poses unprecedented challenges to decision makers. The shipping market variability is further magnified by the immense impact of its economic environment.

In this volatile context, decision support tools can assist maritime practitioners in decision making and reinforce the competitive dimensions of their businesses. The majority of companies that embraced advanced analytics and embedded them into their operations have seen a substantial growth of their profitability in the long term. However this presumes that they can make proper use of those quantitative techniques and adopt a pragmatic approach to interpreting the results.

In spite of the long history of forecasts and the increasing sophistication of modelling techniques, their reliability remains questionable. In fact, as Drucker (1977) argued, every attempt to accurately predict the market is doomed to fail. After all, this is in line with the Efficient Market Hypothesis, which is analyzed in great detail in the ensuing chapters. Nevertheless, this does not merit a reason to give up on forecasting. To the contrary, forecasting is absolutely essential in shipping, as long as the decision makers put it into the right perspective and interpret the results accordingly. As the shipping industry is getting more and more complex, the need for quantitative management has become even direr than in the past.

The key is that forecasts should be viewed as a tool that enables managers to deal with uncertainty and enhance the decision making process. The prime goal of forecasters is not to come up with precise predictions of the future values of freight rates, but to specify the appropriate variables and feed them into a suitable model that can generate sensible predictions and identify market trends. In a nutshell, this is merely described in the words of Box (1979) who states that "all models are wrong but some are useful" (p. 202).

Certain sophisticated techniques, such as data mining, use huge datasets and perform numerous statistical tests to uncover hidden correlations which are often unfounded and difficult to interpret. Unlike those methods, the current analysis is more targeted and aims to deliver practical insights that can substantially improve the decision making process. In particular, the thesis sets out the modelling process by positing the key factors that affect freight rates and then builds appropriate forecasting models. These are based on the ARMA and VAR/VECM modelling categories. Thereafter, this study focuses on the spot freight market and examines the effectiveness of a novel technique for making informed chartering decisions.

The structure of this thesis is as follows: Chapter 2 introduces the dry bulk market and provides the necessary theoretical background, Chapter 3 presents a comprehensive review of the relevant literature, Chapter 4 describes the modelling framework and the related statistical tools, Chapter 5 focuses on the construction of a new index which will be used in the subsequent analysis, Chapter 6 explores the relationship between certain external factors and the freight market, Chapter 7 presents and evaluates the results of different forecasting models, Chapter 8 elaborates more on the spot freight market and introduces a new methodology that enhances decision making, and finally Chapter 9 concludes the thesis.

1.2. Contribution

The contribution of the present thesis to the existing literature is evident on many levels. The study begins with a comprehensive theoretical analysis of the freight market fundamentals and continues with a sound quantitative assessment of the impact of certain elements of the external environment. Next, the most critical of those factors are incorporated into a forecasting model whose performance is compared to alternative techniques. Finally, the thesis concentrates on the spot freight market and formulates a novel decision making tool.

It is worth noting that another important contribution is that the various methods developed in this thesis are applied to different vessel sizes in both the spot and the period freight markets. This sheds some additional light on the unique characteristics of each market segment and explains their distinctive reaction to external influences. The only exception is Chapter 8, which delves into the spot market and explores the related dynamics.

The analysis of Chapter 6 provides statistical evidence in support of the view, widely held in the dry industry, that there is a lead-lag relationship between Chinese steel production and dry bulk freight rates, while it also explores the direction of this relationship. In addition, this study investigates the relationship between the dry bulk freight market and the price of 'major bulks'. The interaction between dry commodity prices and freight rates has not warranted much attention in the maritime literature so far. Yet, given that these are the most traded bulk cargoes and their dynamics actually determine the level of freight rates for the entire dry cargo market, it turns out that the impact of those commodity prices deserves further attention. Hence, this examination is put forward and is followed by a theoretical interpretation. It arises that this relationship is not always straightforward; that is, high commodity prices do not necessarily correspond to high freight rates. Importantly, one of the main contributions of this study is the statistical confirmation and depiction of this relationship. Specifically, the findings demonstrate that commodity price spikes may boost freight rates in the short run, but the high price impedes trading activity going forward. Additionally, a similar analysis is performed for port congestion and bunker prices. Despite the plethora of studies on micro- and macro- economic determinants of freight rates, there have been no studies addressing those issues. The results are generally in line with industry expectations and contribute to the understanding of freight market movements.

Along these lines, a new index is constructed, named DBECI, which captures the impact of several economic factors on the dry cargo freight market. In fact, it is a leading composite indicator and consists of a set of carefully selected macroeconomic metrics. The aggregation of those variables forms an index which is directed at the dry bulk market and corresponds to the specific influence of the economic environment. The very idea of setting up a bespoke index of that type for the shipping market has never been documented before, as it is discussed in the literature review of this thesis (Chapter 3). Unlike other indices which are assigned equal weights, the weighting of the DBECI is based on an extension of a linear programming technique ('Benefit of the doubt' approach). The usefulness of this indicator is verified by causality and impulse response analyses for a variety of vessel sizes. The respective results point to significant causation running from the DBECI to the freight rates of each vessel category.

The next step is to use the findings of the preceding analysis in order to build parsimonious forecasting models. To this extent, the study formulates multivariate VARX models using the DBECI and the average bunker prices as exogenous variables. Both of these variables are being used for the first time as explanatory variables in a forecasting model. In addition, the VAR/VECM and the VARX models factor in the fleet development and the Chinese steel production and treat them as endogenous variables. The former metric corresponds to ship supply and the latter to the demand for bulk carriers. This is another innovation of the current thesis and draws on the fact that the selection of the explanatory variables is based on the preceding analysis. The predictive power of these VARX models is assessed by means of comparison of the forecast errors with two alternative modelling approaches; i.e. the VAR/VECM and the univariate ARIMA. The numerical results suggest that VARX models outperform their counterparts in almost all cases. This provides sufficient evidence that the utilization of those two newly constructed metrics can substantially improve the forecasting accuracy of freight rates.

Finally, the thesis concentrates on the spot market and investigates the excess return dynamics between trip charters and their corresponding voyage charters. First, it establishes the existence of a long-run equilibrium between time charter (t/c) trips and their underlying voyages, through co-integration testing. In this context, the focus shifts to the short-term deviations, which are exploited for the construction of a technical analysis based chartering strategy. In particular, a new methodology is developed, the Modified Momentum Trading Model (MMTM). This is used for the formulation of a suitable chartering strategy, which is eventually tested against the simple rule of entering into a voyage charter every week. The results show that the proposed approach outperforms the benchmark strategy, suggesting that the appropriate exploitation of rate deviations in the spot market can yield considerable excess returns.

The relevant literature review (3.3 – 3.4) reveals that there have not been any studies investigating the relationship between trip charters and their underlying voyages. The body of the literature makes no distinction between trip charters and the (Time Charter Equivalent) TCE of voyages. These are rather used interchangeably to represent the spot market rates for purposes of comparison with the time charter period rates and FFAs. However, they constitute two different methods of chartering a vessel and it is interesting to study their dynamics. Hence this study extends the analysis to a new area of research, filling a critical gap in the literature.

2. THEORETICAL BACKGROUND

2.1. Economies and Diseconomies of Scale in Shipping

The cost of transporting a ton of cargo on a voyage is given by the following formula:

$$Unit\ Cost = \frac{C + OPEX + H}{Q} \tag{2.1}$$

where C denotes the capital expenses, OPEX the operating expenses of the ship, H the cargo handling costs, and Q the parcel size (consignement).

The above formula implies that as the size of a vessel increases, the unit transport cost goes down. This occurs because the numerator - which reflects the costs -, does not rise proportionally to the parcel size. Technological advancements and automation have contributed significantly to the minimization of transport costs for large vessels. In particular, modern megaships are cost efficient, consuming less fuel than older ships and keeping insurance and staffing costs to the minimum. In addition, the new megaships are highly automated and usually require approximately the same number of crew members as smaller ships.

All in all, the cost increase is not in line with the increase in size. This provides a cost benefit on a 'per ton' basis and gives rise to the concept of economies of scale which largely explains the tendency towards larger ships.

Another factor that has favoured the increase in ship size is the progress in delivery systems and logistical processes that facilitated the storage and movement of goods, and enabled businesses to handle larger cargo parcels. In addition, the last years' upgrade of port facilities and equipment has given many ports the means to serve giant vessels.

However, there are limitations to this trend, which create diseconomies of scale. In particular, there is a threshold beyond which the cost per unit stops to fall and begins to rise. This threshold is not fixed for all vessels and mainly depends on the ship type and its trading pattern.

A major reason for diseconomies of scale is the port depth of most ports, which is too shallow to accommodate those behemoth vessels that have disproportionately deep draughts. The only solution is to attempt to dredge the port seabed and deepen it, but this is usually uneconomical or even unfeasible. Furthermore, some of the megaships will be too large to cross the Panama Canal, even after the expansion. On top of that, in many cases, a small parcel - relative to the ship's carrying capacity - may require special stowing and securing, raising the cargo handling costs.

Additional limitations are imposed by port terminals, whose depths can accommodate megaships in the first place. However, they do not always have the appropriate infrastructure and equipment to handle massive amounts of goods efficiently. One of the main problems is caused by reduced land for temporary warehousing, as the sophisticated equipment (such as larger shore cranes) occupies more space. Moreover, the inland transport of large cargo quantities may require a huge number of trucks which have to arrive at the port gates simultaneously, creating congestion.

2.2. Demand for shipping services

Demand for ships is not a direct, but a derived demand. This implies that the customers are not after the ship itself. They are actually looking to use a ship in order to transport their cargo. It is the cargo space that is of interest to them. In this sense, the demand for shipping services derives from the demand for the carried commodities.

The most appropriate unit of measurement of ship demand is the ton miles. This measure is defined as:

$$\text{Ton-miles} = \text{Seaborne Trade x Average Haul} \qquad (2.2)$$

According to the above formula, a ton-mile is defined as a ton of cargo moved one mile. This measure is preferable to the total deadweight (dwt) of ships needed, as it accounts for the distance too. In fact, the cargo volume alone does not provide an accurate picture of ship demand. This requires the addition of an indication of how long the ships are going to be occupied. The latter can be expressed by the average haul over which the goods are carried.

2.2.1. Factors affecting demand

Demand for shipping services is affected by a variety of factors, which eventually play a vital part in the determination of shipowner's profitability.

First of all, subsequent to the above discussion about 'ton-miles', it has been clear that the average haul is essential for the ship demand. Specifically, the higher the average distance, that is the longer the ships are occupied, the higher the demand for tonnage.

The world economy plays a major role in the determination of ship demand. Weak economic activity reduces the level of consumption and drags down the volume of seaborne trade. Conversely, a vibrant economy may contribute to trade growth and spur the demand for shipping. At the same time, consumer sentiment is closely related to those dynamics. The expectations of consumers as to the future state of the market constitute an important driver of the ship demand, given that they largely determine investment decisions and consumer spending.

Another critical factor is the level of transport costs. High transport costs may put a cap on trading activities, as they tend to increase the total commodity costs. Therefore, many transactions may completely break off or they may be held back till the market turns in charterers' favour. On the other hand, low transport costs may act as an incentive for buyers of commodities, encouraging them to exploit the market momentum and increase their imports. This in turn will escalate the trade of goods by sea, marking a growing demand.

Taking a closer look at the components of seaborne trade, it turns out that the developments in certain commodity trades could shape or change the ship demand fundamentals. For instance, the level of steel production may modify the trends in the entire dry cargo market, given that iron ore is the main ingredient of steel and at the same time the most traded dry bulk commodity. Also, the broad volume of dry bulk trade is tied to the attractiveness of substitutes. For example, coal is in direct competition with other commodities, such as oil and Liquefied Natural Gas (LNG). A preference of importing countries to an alternative source of energy, instantly translates into higher demand for other ship types (e.g. tankers or LNG carriers) and lower demand for bulk carriers.

Finally, demand for shipping services is largely affected by miscellaneous external factors and unexpected events which occur as random shocks and take their toll. These include political events, weather conditions, technological innovations, regulatory changes etc. Political turmoil and wars occur in an unpredictable fashion and their effect on shipping is usually quite severe. For example the war between Egypt and Israel led to the closure of the Suez Canal and this gave a boost to the shipping demand. In other cases, an armed conflict may cause uncertainty and trigger extensive stockpiling in other parts of the world (e.g. the Korean war in early 1950s). However, even smaller scale or localized events may have implications for the ship demand, such as strikes or trade restrictions.

Furthermore the weather element can be highly influential to the seaborne trade. For example a drought may destroy the crops and compel a grain self-sufficient country to cut down on exports or even start importing (e.g. droughts in Russia and Ukraine). Likewise, a flood may cause severe disruptions, like the Queensland floods that impacted coal production and exports.

2.3. The supply of ships

The supply of sea transport is inelastic and does not promptly respond to changes in demand given that the construction and delivery of new vessels may take between 1 and 3 years and the life expectancy of ships is about 15-30 years. Thus, the supply side cannot immediately catch up with an increase in demand. Conversely, when the demand plummets, the supply cannot easily follow suit if the fleet is of relatively young average age.

The supply of shipping services expresses the available seaborne carrying capacity in the market. In this respect it embodies the active fleet and is divided in different segments depending on the ship type and size. Supply is measured either in total deadweight tonnes or in total number of vessels trading in the freight market. In essence, it reflects the total capacity or the number of ships that are readily available for the carriage of goods.

There are certain decision makers whose actions may determine the level of ship supply. First of all, shipowners have the most direct influence on supply, as their decisions to scrap or lay-up their vessels, or order newbuildings, automatically reshape the available carrying capacity. At the other end of the spectrum, charterers or shippers effectively seek transport space and occupy the existing fleet, while they may also affect the short term supply by negotiating the vessel speed when the market favours them. Bankers offer financing and thereby control the liquidity of shipping companies. Thus when financiers provide easy lending shipowners raise capital to purchase new ships, while when financing gets tight and the market is in distress many shipowners resort to scrapping. Finally, regulators also play a part in supply of shipping services, considering that new legislation (environmental or safety) is likely to push non-compliant ships out of the market.

2.3.1. Factors affecting supply

Supply is subject to change both in the short and the long run. In the short term, the impact of a number of factors on the supply of shipping services is examined under the assumption of a constant stock of vessels. Those factors include lay-up, speed, time spent in port and so on. From this perspective, it is important to identify the primary factors that cause fluctuations to the active stock of ships and then interpret the underlying dynamics. On the other hand, the long-run development of supply is driven by changes in the stock of vessels which are substantiated by new deliveries, scrapping, and losses.

Considering first the long term horizon, it turns out that new-building deliveries are the primary contributor to supply. The vessels that 'hit the water' add up to the existing tonnage and increase the supply of shipping services. The rate of new orders mainly depends on the access to financing and on the freight market expectations. The latter is conditional on the market information at the time of placing the order. Furthermore, the new-building prices and the availability of construction space (slots) within shipyards also influence the ordering decision.

Demolition (or scrapping) refers to the breaking up of uneconomical ships by designated scrap yards. This process is vital for the shipping market as it removes the surplus of ships, alleviating the tonnage supply. This decision is usually made when the running costs of an old ship exceed the income for a long period of time or when it has to undergo costly repairs. The rate of scrapping is mainly tied to the levels of demolition prices, the average age of the world fleet and the market conditions and expectations.

Turning to the short term, the prime factor reducing the number of ships available for trading (therefore the supply) is the practice of lay-up. This commercial decision is made by a shipowner when the vessel's revenues are well below the operating expenses for a prolonged period of time. Under such circumstances, the vessel is placed in a safe anchorage until the freight market bounces back. In this way, the shipowner accepts to forgo the (squeezed) revenues so that they can minimize the running costs.

There are two types of lay-up, the hot and the cold lay-up. The former enables the ship to return to service more promptly and requires minimum safe manning, as well as heating to the main engine. The ship remains functional but the secondary systems may shut down. In contrast, the latter type of lay-up refrains from the need for heating to engine and generally reduces the operational costs to the minimum. Even so, a minimum crew is still necessary to stand watch and take care of the basic maintenance of the ship. Over the last few years, shipowners tend to opt for hot lay-up, particularly when they expect a market upturn in the short term. Besides, they reduce the risk for undesirable effects such as corrosion and hull fouling. The selection of a suitable location is not clear-cut. The shipowner has to take into account several factors, such as the cost of the lay-up berth, the accessibility to supplies, the favourable positioning upon reactivation and the weather conditions.

Another critical factor is the average operating speed of the world fleet. High speed corresponds to shorter journey times which result in greater carrying capacity at a given point in time. On the other hand, when vessels slow steam (usually as a response to a stagnating freight market), the short run supply drops due to lower availability of vessels at the loading zones.

Time spent in port is another major determinant of short-term supply and it has to be noted that this is outside shipowner’s control. Nevertheless, congestion is often beneficial for shipowners as it reduces the active stock of vessels. In contrast, when port turnaround times are reduced, vessels become available faster and this ultimately shortens the short-term supply of shipping services.

In general, port time is considered ‘unproductive’ time for a ship. Even less ‘productive’ is the time the ship spends ballasting or being off-hire. Thus, the proportion of laden to ballast journeys is of interest in terms of supply. A possible reduction in ballast legs, which might be a result of more ‘return’ cargoes, minimizes the ballast legs and allows a rise in laden days at sea.

Lastly, some vessels may occasionally be converted to floating storage facilities either offshore or in port. For example large bulk carries may be used as floating silos to store grain. This decision reduces supply in the short run, but the reactivation process is not easy due to possible corrosion and damages.

2.4. The dry bulk commodities

The dry bulk cargoes split into 'major' and 'minor' bulks. The major bulks comprise iron ore, coal and grains, while the minor bulks include steel products, nickel ore, forest products, fertilizers, sugar, scrap, pig iron, cement, bauxite/alumina, petroleum coke, phosphate rock, etc.

The trade of major bulks accounts for over 50% of the total dry trade. Iron ore is one of the main ingredients (along with coking coal) for the production of steel. The largest consumer of this raw material is China and the main exporters include Australia, Brazil and South Africa. Coal is divided into steam (or thermal) coal which is used in electricity production and coking (or metallurgical) coal which is bought by steel plants. The main coal importers are China, South Korea, Japan and European Union, while it is massively exported by Australia, Indonesia and Russia. Grains encompass a variety of products, but the most traded of them include coarse grains, wheat, and soyabeans. The prime grain importers are Japan, Mexico, Egypt, Saudi Arabia, South Korea, China, Brazil, Algeria, Indonesia and Brazil, while some important exporters include US, Argentina, Australia, Russia, EU and Ukraine.

2.5. Types of bulk carriers

- ***Handysize (20-39,999 dwt)***

The small size of Handysize ships enables them to comply with the restrictions of a variety of ports and transport a wide range of goods. In addition, they are equipped with on board cargo handling gear, which allows them to load and discharge cargo at ports with poor facilities.

Those features render Handysize vessels overly versatile. Thus instead of following specific trade patterns, they are involved in the majority of dry bulk trades across the world. However, they are mainly deployed in minor bulk trades.

- ***Handymax (40-49,999 dwt)***

Handymax ships have similar specifications to Handysize. What differentiates them is is their larger dimensions. They are primarily engaged in the movement of all major and some of the minor bulks, such as scrap, steel and forest products.

- ***Supramax (50-56,999 dwt)***

Supramax vessels have a greater carrying capacity than their Handysize – Handymax counterparts. Their cranes allow them to operate in ports with poor infrastructure, such as certain Asian ports. Hence, they are particularly suitable for Asian trades.

- ***Ultramax (57-64,999 dwt)***

This ship type has a higher loading capacity than the smaller Handysize, Handymax and Supramax vessels. In particular Ultramax bulk carriers can load around 10-20% more cargo than the conventional Supramax ships.

The dimensions of a typical Ultramax vessel are slightly smaller than a Panamax's, but the Ultramax is equipped with on board cranes. This is why those vessels are highly desirable for Asian trades. Many Asian ports have very poor port facilities and they require vessels having their own cargo handling equipment. Furthermore, their smaller draft (13-14 meters) compared to the Panamax's enables them to comply with the draft restrictions of a larger number of ports.

As a final point, it is worth mentioning that the eco design of the modern Ultramax vessels makes them fuel efficient offering substantial fuel savings.

- ***Panamax-Kamsarmax (65-84,999 dwt)***

The Panamax (65-79,999 dwt) and the larger Kamsarmax (80-84,999) ships are mainly gearless and participate in iron ore, coal and grain trades. They typically have seven holds and they commonly carry phosphates, bauxite, fertilizers, forest products and steels.

- ***Capesize (100-199,999 dwt)***

Capesize ships have nine holds, while they are gearless and rely on shore facilities for loading and discharging. Their large dimensions and deep draughts make them so reliant on port infrastructure, that port restrictions and facilities play a critical part in the determination of their trade routes. In fact, very few ports around the world have the capacity to accommodate this size and as a result Capesize vessels are highly dependent on certain trades.

These large vessels focus almost exclusively on iron ore and coal long-haul runs and to a lesser extent on grain trade – usually only the smaller Capesizes transport grain cargoes.

- ***Very Large Bulk Carriers (200,000+ dwt)***

These behemoth vessels are gearless and equipped with strengthened tank-tops, so that they can safely carry large quantities of iron ore. They can only approach ports which have berths specially designed for those megaships.

The first Valemax vessels were ordered by the Brazilian mining company Vale S.A. They intended to exploit the economies of scale and carry iron ore from Brazil to European and Asian ports at a lower transport cost. In this manner, they expected to enhance their competitiveness over Australian ore producers who are based closer to major Asian customers.

2.6. The dry bulk freight market

The freight market is a market place where the shipowners sell sea transport and earn revenue in the form of freight or hire payments. A distinctive characteristic of this market is that it contributes to the total amount of cash held by the shipping industry through cash inflows from merchants, traders etc.

The freight market is divided into different market segments, according to the ship size and type, while the level of freight rates depends on a variety of factors, such as market conditions, cargo quantity, cargo type, location, ship age, ship specification etc.

At the same time, there exist different types of contractual agreements. The main methods of ship employment include voyage charters, time charters, contracts of affreightment, consecutive voyages and bareboat charters. Each of these categories will be discussed in great detail in the following sections.

2.7. Ship chartering

A ship is chartered after a series of negotiations between principals (shipowner and charterer) through their respective brokers (exclusive, competitive or in-house). The negotiation process includes various stages, such as indications, firm offers, counter offers, negotiation of the main terms, agreement on the clauses details and eventually the fixture.

The charterer is in search of a suitable vessel to carry a specific cargo or charter it in for a period of time. On the other edge, the shipowner is looking to secure employment for their ship ahead of the delivery of the carrying cargo, if possible. These two parties contact each other and negotiate the deal through one or more shipbrokers that liaise and conclude the deal in exchange for a commission.

Initially, the (owners') shipbrokers circulate information about the (estimated) dates and areas that the vessels become available, along with a description of their main technical characteristics. Simultaneously, the charterers' brokers place cargoes on the market, providing details about the size, timing, type of cargo and loading/discharging rates. The above-mentioned orders and ship positions may be sent to competitive brokers, who will further circulate them to additional channels, aiming to be involved in the deal.

When one of the two parties identifies an appealing ship (or cargo) the brokers get in contact and seek some additional information or clarifications to contemplate if the business can be beneficial (e.g. 'freight ideas'). These 'indications' may be followed by counter indications, but none of these is binding. In fact, there is the flexibility of discussing potential business and exchange data with various parties concurrently at this stage.

The next step is to request the principal's authority to make an opening offer. This marks the official beginning of negotiations which may be quite lengthy and involve numerous offers and counter offers. The first and more critical round of negotiations focuses on the main terms of the contract. Should they reach a deal on the main terms, the charterer usually sends the suggested pro-forma charter party to the shipowner (and their broker) and then they proceed to the 'subject details' stage.

The elements of the main terms differ depending on the type of contractual agreement. In the case of voyage charter, the focus is on the date, the cargo type and quantity, the load/discharge ports, the freight rate, demurrage and despatch etc. For time charters, the main terms usually concentrate on the hire rate, the charter period, the delivery date, the place of delivery and redelivery, trading limits, cargo exclusions etc.

Every charterer's offer and counter-offer is usually made with subjects (e.g. 'subject receiver's approval). Occasionally even shipowners put subjects on negotiations, especially in cases of unknown or unnamed charterers. Thereby they make the offers subject to ‘approval of charterers by owners’.

Under English Law, the fixture occurs only when the two parties have agreed on ‘all and every detail’. Therefore, all ‘subjects’ must have been lifted in order for a fixture to take effect.

It should be noted that only one firm offer at a time can be made. This implies that a ship cannot be under offer for more than one cargo at the same time (unless they are part cargoes). Likewise the charterer cannot offer the same cargo to more than one vessels simultaneously. The rationale is that neither a ship could possibly move two (or more) full cargoes on a single voyage, nor a particular cargo could be carried by more than one ships at a given time.

Another important point is that while it is legal to withdraw or alter an offer any time during the negotiations, it is not professionally ethical to do so until it expires or until it is accepted (or rejected or countered) by the other party.

2.8. Types of contractual agreements and analysis of their main characteristics

The following sections describe the main methods of chartering a ship and point out their distinctive characteristics.

2.8.1. Voyage Charter

The voyage charter is a method of ship chartering where the ship is employed for a single voyage, loading cargo from a designated port for discharge at a specific port in an agreed area. It is also known as ‘spot contract’. The Shipowner is paid a fixed freight either per ton of cargo carried or lump sum (more rarely), which is normally payable at the destination (or on signing the bills of lading). The quantity of cargo to be loaded is agreed in advance.

Under a voyage charter, the shipowner incurs all ship running costs (crew costs, stores and provisions, insurance of vessel, spares etc.), as well as the additional voyage expenses (bunker expenses, port disbursements, canal tolls, insurance of cargo etc.). The shipbroker’s commission is payable on freight, and may also be payable on demurrage, depending on the agreement.

2.8.2. Time Charter (T/C)

A time charter is a contract between a shipowner and a charterer for hire of a ship for a certain period of time. The shipowner remains responsible for the technical operation of the ship, with particular regard to crewing, maintenance, insurance of vessel, repairs, classification etc., but the time charterer (or disponent owner) takes over the commercial control of the vessel, including the appointment and payment of port agents, the purchase of bunkers, the canal tolls, the insurance of cargo etc. That is to say that the shipowner pays the operating expenses, while the charterer the voyage costs. The time charterer has the freedom to select trade routes and cargoes for the chartered vessel, but they have to conform to the pre-agreed trading limits and cargo exclusions.

However, if the ship fails to perform properly or suffers mechanical breakdowns, she may be considered ‘off-hire’, during which period the charterer stops remunerating the shipowner.

Under a t/c the shipowner instead of earning freight, is entitled for a hire at an agreed daily rate. This fee is normally paid monthly or semi-monthly in advance. The time charterer may decide to operate the ship in the spot market, carrying cargoes under voyage charters or alternatively sublet the vessel to other charterers on a t/c basis.

A trip time charter is a short t/c, in which the ship is contracted for the duration of a specific trip only. On the contrary, under a standard or period time charter the time charterer has the freedom to trade the vessel for an agreed period (3 months / 6 months/ 1 year/ 3 years etc.) within some pre-specified trading areas.

2.8.3. Contract of Affreightment (CoA)

The contract of affreightment (CoA) occurs when the shipowner (or ship operator) agrees to carry a large quantity of cargo between specified ports over a series of voyages for a fixed rate per ton. The chartering terms are pre-agreed and the carrier may use their own ship or charter-in outside tonnage in order to meet their contractual obligations. However, the exact cargo size and timing are usually not known from the beginning.

2.8.4. Consecutive Voyage Charter

The consecutive voyage charter is essentially a variation of voyage charters where the ship is employed for a series of voyages which are made one after the other. The agreement may state that the vessel is placed at the disposal of charterer for an agreed period and is obligated to perform as many voyages as possible within this timeframe or alternatively that the ship is required to make a certain number of individual voyages. Each voyage is governed by separate terms, with respect to freight rate, demurrage etc.

2.8.5. Bareboat charter

A bareboat charter occurs when the charterer assumes both the commercial and the operational control of a vessel for a typically long period of time. This implies that the charterer pays the voyage costs of the vessel, as well as the operating expenses. The shipowner remains responsible only for the capital costs and receives a fixed hire over the period of the charter. This contractual agreement is practically a finance tool that allows charterers to manage and operate ships without proceeding to direct purchases. On the other hand, bareboat charters are preferred by entities with little experience or expertise in shipping, such as financial institutions, who decide to invest in shipping but avoid any involvement in ship operation.

2.9. The Baltic Exchange

The Baltic Exchange traces its origins in 1774 when it operated as a meeting place of maritime practitioners, known as 'The Virginia and Baltic Coffee House'. In 1860s, the deployment of the cable system changed the fundamentals of communication in shipping and this in turn transformed the role of the Baltic Exchange. Even though the cable network facilitated trade and eliminated speculative ballast legs, it had some serious weaknesses as it was cumbersome and too expensive. Therefore, there was a pressing need for a central market place where brokers could meet shipowners and merchants and make deals for the carriage of cargoes. Shipbrokers were able to dispatch the related terms to their principals who could then send on voyage instructions to the ship's Master by cable. Therefore, the Baltic Exchange took up the role of a global clearing house and enhanced the efficiency of communication in shipping.

Information technology noted significant progress in 1970s, with the advent of fax, telex, telephone and later email and computer networks. Shipbrokers could now use those new communication systems to circulate business and conduct negotiations much faster and cheaper. Therefore, the Baltic Exchange lost its status as the central maritime market place in which deals were struck verbally.

Nevertheless, the Baltic Exchange remains the ‘guardian’ of ethics in shipping business. This is reflected in its motto ‘our word our bond’ which symbolizes the gravity of integrity and trust in shipping. Even today, the main terms of many contracts are first agreed upon verbally and only later are confirmed in writing.

2.9.1. The Baltic Exchange indices

ROUTE	DETAILS	WEIGHTING	CARGO
C2	160,000 lt Tubarao/Rotterdam	10%	Iron ore
C3	160,000 mt Tubarao/Qingdao	15%	Iron ore
C4	150,000 mt Richards Bay/Rotterdam	5%	Coal
C5	160,000 mt W Australia/Qingdao	15%	Iron ore
C7	150,000 mt Bolivar/Rotterdam	5%	Coal
C8_03	172,000 mt Gibraltar-Hamburg trans Atlantic RV	10%	Iron ore/Coal
C9_03	172,000 mt Amsterdam-Rotterdam-Antwerp or passing Passero/China-Japan	5%	Iron ore
C10_03	172,000 mt Pacific RV	20%	Iron ore/Coal
C11_03	172,000 mt China-Japan/Amsterdam-Rotterdam-Antwerp or passing Passero	15%	Coal

Table 1: Baltic Capesize Index route definitions

ROUTE	DETAILS	WEIGHTING	CARGO
P1A_03	74,000 mt Trans Atlantic (including ECSA) round	25%	Grain, Ore, Coal, or similar
P2A_03	74,000 mt Skaw-Gibraltar via ECSA, US Gulf or USEC/Far East	25%	Grain, Ore, Coal, or similar
P3A_03	74,000 mt trans Pacific RV via Australia or Pacific	25%	Grain, Ore, Coal, or similar
P4_03	74,000 mt Japan-South Korea via USWC or Australia, redelivery Skaw-Passero	25%	Grain, Petcoke, Coal or similar

Table 2: Baltic Panamax Index route definitions

ROUTE	DETAILS	WEIGHTING	CARGO
1A	52,454 mt Antwerp-Skaw/Singapore-Japan	12.5%	MOP/Petcoke
1B	52,454 mt Canakkale/Singapore-Japan	12.5%	MOP/Petcoke/Iron ore/Steels
2	52,454 mt SK-Japan for 1 Australian or trans Pacific RV	25.0%	Coal/Grains/Sulphur
3	52,454 mt SK-Japan/Gibraltar-Skaw	25.0%	Coal/Steels/PKE/Nickel ore
4A	52,454 mt USG/Skaw–Passero	12.5%	Grains/Phosphate/Scrap/Petcoke
4B	52,454 mt Skaw–Passero/USG	12.5%	Bauxite/MOP
5	52,454 mt Dakar-Douala via ECSA/Singapore-Japan	0.0%	Grains/Sugar
9	52,454 mt Dakar-Douala via ECSA/Skaw-Passero	0.0%	Grains/Sugar

Table 3: Baltic Supramax Index route definitions

ROUTE	DETAILS	WEIGHTING	CARGO
1	28,000 mt Skaw–Passero/Recalada–Rio	12.50%	Phosphate/MOP
2	28,000 mt Skaw-Passero/Boston–Galveston	12.50%	MOP/Phosphate/Urea
3	28,000 mt Recalada–Rio/Skaw–Passero	12.50%	Grains/Sugar
4	28,000 mt USG via USG or NCSA/Skaw–Passero	12.50%	Grains/Bauxite/Scrap
5	28,000 mt SE Asia via Australia/Singapore–Japan incl China	25%	Coal/Logs/Grains
6	28,000 mt SK–Japan via Nopac/Singapore-Japan incl China	25%	Coal/Sulphur/Grains

Table 4: Baltic Handysize Index route definitions

2.10. Shipping cycles and their history

The shipping market is known for its cyclical nature and this has become evident throughout its history. For instance in 1956 analysts were bullish and (wrongly) predicted that the shipping market boom would last for years. However, the year 1957, which coincided with the reopening of the Suez canal, marked a long lasting recession that only ended in 1967 on account of the second closure of the Suez canal. The positive market expectations of 1955-6 triggered massive orders of new-building ships which were delivered a few years later and deteriorated the already struggling market. The demand side was very weak due to a slowing global economy and the accumulation of abundant commodity stockpiles in Europe.

The 8-year closure of the Suez Canal mainly boosted the tanker market, but it turned out to be beneficial for bulk carriers too. One of the most immense market booms came in 1973, when freight rates and ship prices skyrocketed. However, this was followed by a collapse of the wet market due to the Yom Kippur War. On the contrary, the dry bulk market proved more resilient and went through a period of favourable market conditions that lasted till 1975, when the cycle reversed and the bulk carriers entered a crisis. The trough lasted 3 years and then the market bottomed out. This recovery phase was mainly driven by lower ship ordering that alleviated the surplus of tonnage, combined with rising demand for commodities and especially for coal, which was imported in many cases as a substitute for the inflated oil. The high levels of congestion supported the dry bulk freight market, which remained strong until 1981, when a combination of factors such as weak world economy, mine strikes and falling coal trade turned the boom to a bust.

The dry cargo market recovered in 1986 thanks to improved economic conditions and the freight rates reached a peak in 1989. Thereafter, the shipping market entered a 5-year period of extreme fluctuations that made the identification of the cycle stages vague. Some notable events of that decade include the Asia crisis in 1997 that devastated the freight market, but this recession did not last as long as expected. Thus, the dry cargo market rebounded only to be pushed down again by the stock-market collapse (also known as dot-com bubble) in early 2001.

The most recent cycle started in 2003 and saw the dry bulk freight rates spiking to all time high levels for the next 4-5 years. This unprecedented market boom was mainly driven by the sharp growth of China and its tremendous appetite for raw materials, such as iron ore and coal. This was combined with severe port congestion around the world, easy access to bank financing and relatively low supply of tonnage. However, the US sub-prime mortgage crisis of 2007 spread to the financial markets and the world economy and eventually did not leave the shipping market intact, causing a severe crash in 2008. Since then the freight market has been stagnating and struggling to bottom out, but no signs of a real recovery have been shown yet.

Hence, the existence of cycles is easily identifiable, just by looking at the past market developments and pinpointing repetitive patterns. In this respect, it has been observed that each cycle comprises four consecutive stages: the trough, the recovery, the peak, and the collapse. However, the duration of the cycles is highly unpredictable. The study of the past 50 years has shown that a typical cycle lasts about 7 years on average (Stopford, 2009). However, this length is not fixed and varies from time to time depending on the market fundamentals and the effect of external shocks. Specifically, the longest cycles of that period include 6 cycles which lasted more than 9 years each and had 5-year troughs. The shortest ones include four 5-6 year cycles while there were also two 8-year cycles. If someone goes further back in time, in the sail era, they will come across cycles that lasted nearly 15 years.

In this context, the high degree of market uncertainty makes the prediction of cycles' duration and turning points very difficult or even impossible for some authors (Cufley, 1972). On top of this, market sentiment exacerbates this issue, especially at the extremes of the cycle (troughs and peaks).

Economic and shipping cycles are broadly categorized as long and short term cycles. The former category encompasses cycles determined by major economic, technological, geopolitical or socio-cultural changes. The detection of this kind of cycles is extremely important, but difficult as the effect of such developments is usually diffuse. On the other hand, the short-term cycles (or business cycles) are much more agile and track the ever changing market trends over time.

Every shipping cycle is driven by the supply and demand dynamics, but what causes the most dramatic changes and contributes to volatility is the occurrence of unexpected external events, such as macroeconomic shocks, wars, Canal closures, political turmoil, congestion and stockpiling.

2.11. Seasonal cycles

In addition to the characteristics and the categorization of cycles discussed in 2.10, shipping cycles are frequently shaped by cyclicality. This property refers to the periodic pattern of certain trades that may influence the behaviour of freight rates and form seasonal cycles at times.

Prominent examples involve the agricultural trades, which are subject to the period of harvest. It has also been observed that industrial production falls during the summer months and this reflects negatively on the freight market. Furthermore, the Chinese New Year is usually associated with declining freight rates due to waning market activity.

2.12. The Efficient Market Hypothesis (EMH)

The EMH states that prices at any time fully reflect all available information (Fama, 1970). It follows that for a given set of information, market efficiency is not compatible with profit making on the basis of this specific information set (Jensen, 1978). This concept is extended by Malkiel (1991), who points out that if an information set, X_t, is disclosed to all market participants and the security price does not change, then the market should be deemed efficient. The security prices in such a market would be adjusted according to fully and correctly reflected information.

Following Roberts (1967), Fama (1970) distinguishes into three different forms of market efficiency, depending on the content of the information subsets, and tests whether prices efficiently adjust to the information of each case. The three forms include the weak form, the semi-strong and the strong form. The weak form takes into consideration only historical prices, the semi-strong form expands to all publicly available information, while the strong form includes both public and private information. The latter category involves an extreme form of market efficiency, which considers monopolistic access to information and presumes that the related costs are always zero (Grossman and Stiglitz, 1980). However, this cannot be valid in practice, due to the existence of trading and information costs. Therefore it best serves as a benchmark for the assessment of deviations from efficiency (Fama, 1991). Elaborating more on the access to private information by individual agents, Fama (1991) focuses on the measurement of abnormal returns and discusses the joint-hypothesis problem, according to which the abnormal returns are not necessarily attributed to inefficiency, but they may also occur due to poor model specification or implementation. Finally, he discusses the predictability of returns in the context of the EMH. Fama (1998) focuses on long-term return anomalies, such as over-reaction or under-reaction to information, and provides evidence that they do not contradict the EMH.

Most authors test the weak and the semi-strong form of the EMH. Considering that under the EMH no excess returns are possible, these tests usually attempt to reject the EMH by examining the ability of technical trading techniques to generate excess profits. The information set in such tests contains only past values in the case of weak efficiency, while it is extended to include economic indicators, default premia etc. when semi-strong efficiency is tested. The test of the strong form is not so straightforward, since it is not easy to obtain and measure private and inside information. Thus, this form of efficiency is usually tested indirectly (e.g. by looking at performance indicators and factoring in the cost of obtaining private information).

More recently, there is a tendency in the literature to approach the EMH using behavioural models, which account for the impact of market participant's psychology and beliefs on trading (Barberis, Shleifer, & Vishny, 1998; Shleifer, 2000; Barberis and Thaller, 2003; Shiller, 2003; Papapostolou, Nomikos, Pouliasis, & Kyriakou, 2014; Greenwood and Hanson, 2015; Alizadeh, Yip, & Thanopoulou, 2015). These papers attribute the failure of the EMH to biases coming from the heterogeneous behaviour of investors and attempt to capture the under-reaction and over-reaction.

2.13. The competitive dry cargo market

A market that would satisfy the aforementioned assumptions of efficiency is a perfectly competitive one. In such a market, the participants act in a rational manner and absorb all available information, shaping the rates accordingly.

Specifically, the dry bulk market can be viewed as a perfectly competitive one, if it obeys the following properties:

1. All market practitioners aim to maximize their profits.

2. There is a sufficient number of buyers and sellers of shipping services (and assets) with comparable wealth levels.

3. The dry bulk shipping companies offer the same type of service.

4. There is easy and free entry to and exit from the market.

5. All participants have access to full information.

The first feature is straightforward. The shipowners seek to earn higher freight rates and increase their profit margins, while the charterers press for lower rates in order to reduce the transport costs and maximize their profit. After all, profit making is the very reason for entering this market.

Assumption two is easily satisfied. There is a large number of small and medium sized ship owning companies and many of them own 1-2 vessels. Each of the top shipowners controls a very small percentage of the total bulk carrier fleet (less than 1%). Likewise, there are numerous charterers, ranging from commodity traders to factories and mines. Therefore none of the market participants is capable of influencing the behavior of the freight rates. However, it should be noted that shipowners do have some control over operating expenses and they continuously strive to keep them low, without compromising the working conditions of the crew and the safety of the ship and its cargo. The latter is ensured by international conventions, such as the Maritime Labor Convention (MLC) and Safety of Life At Sea (SOLAS).

Nevertheless, special consideration should be placed on the case of the sale and purchase market, which is dominated by two types of investors; i.e. the operators who make long term investments and the pure speculators who are more interested in the capital gains from speculative sale and purchase activities rather than in the operational profits. Consequently, this heterogeneous behavior of market participants may create a flaw with regard to the application of the EMH.

The third assumption is appropriate in the context of the dry bulk business. The shipowners are essentially sellers of carrying capacity, while the charterers act as buyers of cargo space. Owners are expected to provide a seaworthy vessel, free of any liens and well maintained, ensuring that it complies with the applicable maritime regulations and laws. However, if a shipowner presents a substandard ship, then the cargo space offered is of lower quality due to the higher risk of cargo damage or complete loss. Hence, this would undermine the competitiveness of the dry bulk market, violating the condition of uniformity of services.

The fourth assumption is clearly satisfied. A prospective shipowner can easily enter this market by purchasing either a new-building or a second-hand bulk carrier. As long as the capital has been raised, there are no entry barriers or extra charges for new entrants. Conversely, a shipowner can exit the market by selling their ship in the second-hand or in the demolition market.

Finally, the smooth flow of information is guaranteed by the Baltic Exchange, which is the main source of independent market data and tracks the daily rates for a variety of routes and ship types. In addition, individual shipbrokers act as information transmitters, collecting information and advising their clients on the current rates and characteristics of specific trades, as well as on the most recent market developments and trends.

2.14. The efficiency of freight markets

If the dry bulk market is assumed efficient, then the term structure of the freight rates dictates that the time charter rate should be equal to a weighted average of spot rates and risk premia over the duration of the t/c contract.

In this setting, there are six different theories depending on the nature of the risk premium. The risk premium is assumed zero in the pure expectations theory, constant in the expectations theory, positive or negative in the preferred habitat theory, varying with respect to the term to maturity in the liquidity preference theory, varying with time and term to maturity in the time-varying risk theory and finally dependent on the excess returns of the market t/c portfolio over spot rates, as well as on the covariance between the t/c portfolio of a single shipowner and the market portfolio in the case of the CAPM.

As it is presented in Chapter 3, several authors have tested the EMH in the dry bulk freight market and they mainly consider weak efficiency, while some other authors, such as Adland and Strandenes (2006), assume semi-strong efficiency. At the same time, the consensus is that there is a time-varying risk premium. The critical point for the validity of the expectations theory (and the efficiency of the freight market) is the appropriate adjustment of this risk premium so that is maintains the market efficiency. Thus, everything comes down to the suitable approximation of the related risk. Some examples of such an approximation include the unconditional and conditional variance of past forecast errors, but this is beyond the scope of this study.

2.15. Efficient market hypothesis and forecasting

As it has been discussed thus far, according to the EMH, freight rates reflect all available information. This implies that only new information or market shocks can change them. Therefore, rates are unpredictable given that news or 'force-majeure' events cannot be predicted, by definition. In this regard, if rates were forecastable, then certain market participants, acting as 'profit seekers', would use forecasting techniques to produce unlimited profits. Nevertheless, in practice when new information or new trading rules lead to excess profits in the short-run, more and more market participants try to take advantage and increase their own profitability.

Going forward, the profit opportunity dwindles. Therefore, this suggests that the weak (or semi-strong) form of efficiency is practically maintained in the long-run, whilst there are short-term excess return opportunities.

It follows that efficiency should be viewed as a dynamic condition that is attained in the long-run, rather than one that must be fulfilled at all times. This is demonstrated by the convergence to a long-term equilibrium, after a short period of deviations. To put it in perspective, this behavior of time series is adequately captured by co-integration analysis, which is the framework followed in the present thesis.

In a related study Timmermann and Granger (2004) discuss the implications of forecasting for market efficiency, drawing on the fact that the existence of a robust forecasting model practically violates the EMH.

The mathematical (conditional) expectation of the next period's rate R_{t+1}, given the information available at time t, I_t, is expressed as follows:

$$E(R_{t+1} \mid I_t) = R_{t+1} + \varepsilon_{t+1} \tag{2.3}$$

where ε_{t+1} is a random error which is i.i.d (independently and identically distributed), with zero mean and constant variance.

The above equation is based on rational expectations and actually describes an unbiased forecast. Unbiasedness constitutes one of the three properties of mathematical expectations, along with orthogonality (or informational efficiency) and the law of iterated expectations. Rational expectations should be homogeneous and based on the true model. In general, market participants are supposed to form rational expectations when they produce forecasts using the true model and all available information, and at the same time they follow the three properties of mathematical expectations.

2.16. Risk factors in the dry bulk freight market

The aforementioned time-varying risk premium is based on the fact that the spot market is surrounded by a higher degree of uncertainty compared to the period market. For this reason, following Adland and Cullinane (2005), it is essential to state the different sources of risk in the spot market.

- ***Unemployment risk***

This type of risk pertains to the failure of a vessel to find a suitable cargo in the area of discharge. In this case the operator's options are: a) to remain idle in port until a business comes up in the area, b) to accept a part cargo, hoping to find a supplementary one en route, but this would be subject to first charter's approval, and c) to ballast to another area of higher demand. All of the above options are expected to result in economic losses for the ship owner. Therefore, according to Zannetos (1966) they need to concede to a negative risk premium.

The unemployment risk cannot be completely eliminated as it is associated with the supply-demand dynamics; but it can be managed by closely monitoring and assessing the market fundamentals of each route. Additionally, the unemployment risk is dependent on the ship technical specifications and age, as a more modern design has better chances to secure employment than an obsolete one.

- ***Higher volatility of spot rates compared to t/c rates***

Kavussanos (1996) and Kavussanos and Alizadeh (2002) among others, argue that spot rates fluctuate more than t/c rates. Consequently, a ship owner demands a compensation to go spot, leading to a negative risk premium. This is consistent with the empirical study of Norman (1981) for tankers.

- ***Risk of limited supply of tonnage***

This risk mainly affects charterers. According to Norman (1979), in periods of limited supply the transportation value exceeds the cost. Often various reasons, such as the due date of the letter of credit, push charterers to find a vessel promptly and carry the cargo. Therefore, in such cases the charterers are more likely to accept an overvalued rate as long as they find a suitable vessel on time. In other words, the charterers are willing to pay a positive risk premium in the spot market. This risk premium is closely related to the supply-demand balance in a specific region while at the same time depends on vessel's technical specifications and especially on speed.

- ***Default risk***

In the case of a period charter, if the market moves against the charterers making unviable for them to keep on paying above market rates they might default on the contract. It is apparent that this type of risk is positively correlated with the freight market fluctuations. The more volatile the market, the more defaults may occur. On the contrary, a shipowner is more secured under a voyage charter, since the largest part of the freight (usually 90%) is paid in advance. Therefore, in this context, the risk premium has a positive sign.

- ***Risk of technological or legislative obsolescence***

When a charterer is committed to a long term charter there is always the risk that the vessel will not be efficient in the future, should the regulatory framework change or the bunker prices rise. In such cases, more modern vessels enter the market which comply with new regulations and have improved specifications in terms of design and fuel consumption. Therefore, the chartered vessel will not be able to compete on equal terms with the newcomers, leading to a reasonably negative risk premium.

- ***Risk of strikes and adverse weather conditions at ports***

This risk factor is not included in the categorization of Adland and Cullinane (2005) or any other risk categorization, but in practice it is very important for chartering decisions. Under a voyage charter, if the cargo cannot be loaded or discharged due to strikes or rain, the time typically does not count as lay-time and the ship operator cannot claim demurrage for the time lost. On the contrary, if the vessel is on time charter, then in the above events it remains on-hire and as a result there is no loss of income despite the delays. Thus, if this type of risk is isolated in a similar fashion, the corresponding risk premium should be negative.

3. LITERATURE REVIEW

3.1 The impact of external factors on the freight market

Shipping freight market is generally influenced by both internal and external factors. The shipping demand is a derived demand and as such it is driven by a variety of factors that reflect the demand for the carrying commodities as well as the state of the world economy. In this context, many authors have endeavoured to identify the most critical drivers of the freight market and explore their effect on freight rates.

Zanettos (1966) adopts a structural approach to investigate the relationship between time charter rates and a set of variables, which includes the London Interbank Offered Rate (LIBOR), the oil price, the Air (index for air transportation), the tonnage in lay up, the tonnage scrapped, and the Operating Expenses (OPEX). Strandenes (1984), and later Beenstock and Vergottis (1989, 1993) find that the freight rates are determined by macroeconomic factors such as oil prices, world economic activity, the growth of industrial production, commodities trade, as well as by internal factors, such as newbuilding ship orders, deliveries, and demolitions.

However, there is a gap in the literature, as there have been no comprehensive studies attempting to determine the underlying relationship between steel output and shipping freight rates at an empirical level. The general consensus is that the level of steel production is a bellwether of demand for raw materials and, consequently, of freight rate fluctuations; However, thus far, this only has theoretical grounding. Hence, the current study intends not only to cover this gap, but also to assess the relations in the context of both the spot and period charter market for three different vessel sizes (i.e. Capesize, Panamax and Supramax).

Another strand of the literature has devoted itself to the investigation of the interaction between transport costs and commodity prices. For instance, Goodwin and Schroeder (1991) employ a VAR model and carry out impulse response analysis in order to examine the wheat price dynamics in six different international markets, while they also take account of the influence of both freight rates and exchange rates. Other authors investigate the effect of transport costs on spatial market integration (McNew, 1996; Roehner, 1996; Price-Leadin & Corn, 1999), while Sadorsky (1999) focuses on the oil market and adopts a VAR framework to assess the influence of oil prices on real stock returns.

Haigh and Bryant (2000) focus on the risk of river barge and ocean freight rates, as this is expressed by their time-varying volatility. In particular, they search for potential effects on grain prices. Overall, their findings support the hypothesis of a linkage between transport rates and commodity prices. Bessler and Lee (2002) use Error Correction Models (ECM) (along with directed acyclic graphs) to investigate the relationship among money, income, nominal prices, and wheat prices in the US. Haigh and Bessler (2004) extend this analysis and employ the same methodology to explore the relationship between commodity markets and the transport market. The results show that these two markets are interrelated. Alizadeh and Nomikos (2004) examine the causal relationship between futures and tanker freight rates, while McKenzie (2005) concentrates on the reaction of soybean levels to barge rate shocks and he finds that the basis levels in Gulf drop as a response to a hike in barge rates.

Yu, Bessler, and Fuller (2007) employ co-integration analysis and algorithms of inductive causation on directed acyclic graphs to examine the relationship between US grain and freight markets, and conclude that there is substantial interaction between them. In addition, Poulakidas and Joutz (2009) look into the way by which a spike in oil prices affects tanker rates. Their analysis of the lead-lag relationship between crude oil prices, crude oil inventories and tanker rates is based on co-intergration and Granger causality, and their results are indicative of significant lead-lag relationships.

Chen and Hsu (2012) turn their attention to the fluctuations of oil price and provide evidence that high volatility holds back global trade. Shi, Yang, and Li (2013) use a Structural Vector Autoregressive (SVAR) model to study the effect of crude oil price volatility on tanker freight rates. In addition, they split the oil price shocks into supply and non-supply shocks. On that basis, they apply impulse response analysis and their findings suggest that oil supply shocks impact the freight market, whilst they find no significant effect in the case of non-supply shocks.

Shen and Chou (2015) investigate the existence of causal relationships between the price of West Texas Intermediate (WTI) oil and several Baltic Exchange indices. The empirical results show that there is significant co-integration between WTI and each of the Baltic indices. Furthermore, they perform Granger causality tests and find that WTI causes all of the indices. Therefore, they conclude that crude oil price may serve as a predictor variable in a forecasting model.

In other studies, Kavussanos and Nomikos (2003), and Kavussanos, Visvikis, and

Dimitrakopoulos (2010, 2014) focus on the derivatives markets and examine the volatility spillover effects between shipping freight and commodity future markets. The empirical results show that the futures contracts for commodities such as wheat, corn and soybeans lead the respective FFA markets. Those findings support the assumption of a linkage between certain commodity prices and the underlying freight rates.

3.1.1 Economic determinants of freight rates

Many authors have investigated the role of macroeconomic variables in the formation of freight rates and they conclude that the major determinants of freight rates include global economic activity, industrial production growth, and oil prices (Hawdon, 1978; Strandenes, 1984; Beenstock & Vergottis, 1989; 1993).

In other studies, Tamvakis (1995) and Tamvakis and Thanopoulou (2000) turn their attention to microeconomic variables and assess the impact of ship age on chartering. The motivation of their study came from the implications of the US Oil Pollution Act (OPA1990) which banned single hull tankers from US waters, as well as of the amendment of the MARPOL convention in 1996 which made it mandatory for tankers trading globally to be equipped with double hulls. Their hypothesis is that this would negatively affect the chartering of older, single hulled ships, and create a two-tier market. However, this hypothesis is not confirmed by the empirical analysis.

Grammenos and Arkoulis (2002) investigate the impact of world macroeconomic factors on the stock returns of several listed shipping companies. The factors under consideration include industrial production, oil prices, inflation, exchange rates (against the USD), and laid up tonnage. The results reveal that laid up ships and oil prices have a negative effect on stock returns, whilst the exchange rate is positively related to the returns of stocks. Overall, the authors indentify a strong connection between the shipping industry and the macroeconomic environment. Dikos, Marcus, Papadatos, and Papakonstantinou (2006) use system dynamics modelling and look at causality effects, so as to assess the macroeconomic factors that drive the tanker time charter rates. They estimate the flow of supply of tonnage through entry, exit and lay-up decisions and then they compare it with demand. Finally from their interaction they determine the key factors that affect tanker rates.

Alizadeh and Talley (2011a) focus on microeconomic determinants of dry bulk freight rates. They examine the effect of vessel size, age, length of lay-can, and voyage route on rates using a system of simultaneous equations. The results indicate the existence of significant relationships; therefore, those factors should be taken into considerations during chartering negotiations. In another study, Alizadeh and Talley (2011b) apply a similar methodology in the tanker market and find that the determinants of tanker rates include the ship's hull type (single or double hull), the age, the routes, the lay-can duration and the deadweight (dwt) utilization ratio (cargo / dwt).

Lee (2012) follows a different direction and examines if the global economic conditions can have a significant effect on trade disputes. This paper bears some relevance to the subject matter of this thesis, considering that possible trade disputes may negatively influence the trading activities and reduce the demand for shipping services on certain routes. Moreover, viewing this in a smaller scale, it may impede the chartering negotiations between shipowners and charterers. Tang, Koh, Heng, Soh, and Lim (2013) investigate the macroeconomic determinants of shipping cycles, using the market downturn of 1980s as a point of reference. In this reading, they pinpoint the following macroeconomic factors: the exchange rate of USD, the crude oil price, the inflation, and the globalization.

More recently, several authors have taken into consideration the impact of economic factors with respect to modelling and decision making in the shipping market. For example, Lyridis, Manos, and Zacharioudakis (2014) develop forecasting models for the dry cargo market and incorporate macroeconomic variables. Batrinca and Cojanu (2014), in their attempt to specify the main drivers of the dry cargo freight market, they construct a multiple OLS regression model and endeavour to detect the impact of each explanatory variable on the freight rates. The results verify the apparent negative relationship between freight rates and supply of ships, as well as the positive one between freight rates and demand. They also find that the world GDP has a positive effect on freight rates. However, the authors do not present sufficient evidence that the variables fulfil the Ordinary Least Squares (OLS) assumptions nor do they properly check the model specification. On top of that, they use annual data and inevitably miss out on the short term fluctuations.

3.2 Forecasting freight and time charter rates

The pressing need to obtain reliable forecasts of freight rates has placed shipping forecasting at the forefront of maritime economic research over the past few years. The complex nature of the freight markets calls for the support of contemporary tools and techniques that can reinforce the effectiveness of decision making and significantly reduce the uncertainty.

The research activities in this area have employed a great variety of models, which have dissimilar characteristics and are based on different assumptions. Yet, all these models have a common goal; that is, the generation of accurate forecasts so as to enhance decision making.

At the early stages of research in this area, the majority of authors base their predictions on classical regression analysis. However, this approach entails serious weaknesses, since it is not appropriate for non-stationary time series. On top of that, the consensus among the majority of researchers is that freight rates are non-stationary with unit roots. The related tests in this study confirm this hypothesis and thus the most suitable framework for this type of data is adopted.

The present study proposes three different modelling frameworks: the VAR/VECM the VARX, and the ARIMA. All of them are designed to account for the non-stationarity contribution and overcome the associated weaknesses.

Forecasting had not attracted so much attention in the maritime literature till the 1990s. Although Koopmans (1939) pointed out the necessity for forecasting in the shipbuilding market, very few authors attempted to predict shipping cycles or any other variables pertaining to the freight market. In fact, the bulk of research centred on trade rather than on shipping forecasting. Even so, the forecasting techniques at the time were very simplistic. For instance, it was common for the researchers to use historical average to represent trends.

Going forward, Cullinane (1992) applies the Box-Jenkins approach to forecast the future movements of the Baltic Freight Index (BFI). His data runs from 1985 to 1988 and he uses it to make short-term predictions which he considers more accurate than long-term. Thus, due to the short-term forecasting horizon, the model is utilized as the basis for a speculative BIFFEX investment strategy. The accuracy of the forecasts is evaluated on the basis of: the Mean Sum of Squares of the residuals (MSS), the Mean Absolute Deviation of the residuals (MAD), the Maximum Absolute Deviation of the residuals (MAXAD), and a modification of Theil's inequality coefficient (U).

As the research progresses, some authors point out the linkage of economic variables to the shipping market and discuss the different stages of forecasting in shipping (Beenstock & Vergottis, 1993) and (Stopford, 1997; 2009).

Chang and Chang (1996) use regression analysis to test the explanatory power of (Baltic International Freight Futures Exchange) BIFFEX prices. They test the predictability of BIFFEX and their results suggest that their model can generate one-month forecasts with 90% precision, which drops to 23% for six-month forecasts.

Veenstra and Franses (1997) adopt the VAR / VECM modelling framework in order to obtain forecasts for the spot freight rates of some selected Panamax and Capesize routes. At the same time, they attempt to identify the underlying freight rate trends. The rationale of their approach is that the series are found non-stationary, while they also detect co-integrating relations. A distinctive characteristic of their methodology is that they do not include any additional endogenous or exogenous variables. The justification they provide is that since the EMH suggests that the freight rates incorporate all publicly available information, there is no need to add any extra variables. Their findings reveal that the freight rates are stochastic in nature and they use this feature to explain the inability of their model to produce accurate forecasts. They further claim that the latter results are consistent with the EMH and in this sense they can be interpreted as a verification of its validity.

Li and Parson (1997) introduce a non-linear approach in the form of neural networks and evaluate its short and long term forecasting performance against ARMA models. Their data starts from January 1980 to November 1993 and includes monthly observations on tanker rates, demand, and supply. They estimate the parameters p and q of the ARMA (p,q) model on the basis of the Pandit and Wu approach, where the values of p and q are varied and the F-test, the autocorrelation of residuals, and the cross-correlation between residuals and inputs determine the most appropriate model specification. Then, they conduct freight rate forecasting for the lead time of 1, 2, 5, 12, 18, 20, 23, and 24 months. According to the Mean Squared Error (MSE) criterion the two approaches perform equally well in the short-run (for lead time of 1 month), whilst the neural network framework provides results with lower MSE in the longer term.

Cullinane, Mason, and Cape (1999) examine the effect of a modification in the Baltic

Freight Index (BFI) that took place in 1993, when all handy size routes were struck out. They investigate this by applying ARIMA modelling to the periods prior to and after the revision. The results imply that the change in the composition of the BFI has not affected its behaviour significantly.

Veenstra and Charalambides (2001) adopt a multivariate framework to forecast trade flows of four major commodities; i.e. crude oil, iron ore, grain, and coal. More specifically, they apply a VAR model over main trade routes and produce long-term forecasts. The simulation results are evaluated under the MSE criterion, which yields relatively small forecasting errors.

Jonnala, Fuller, and Bessler (2002) attempt to specify a set of variables which best tracks the behaviour of freight rates in the grain trade. These include the ship size, the distance, the registry, the season, the charter party terms, and the tonnage deployed for the shipment of certain other dry cargoes. On this basis, they build an empirical model using autoregressive conditional heteroskedastic error processes and finally they compare its predictive power with a random-walk process.

Kavussanos and Nomikos (1999, 2003) concentrate on the lead-lag relationship between freight futures and spot prices and assess the forecasting ability of some selected models. The distinct characteristic of their study is that the underlying asset – the freight - is non-storable. The authors first investigate the causal relationship between futures and spot prices carrying out causality tests and impulse response analyses. They find that there is a long-run relationship and significant causality running from futures to spot prices. Therefore, information from the futures can be used to obtain better forecasts of the spot prices, but the opposite is not true. Then, they develop several different models to generate forecasts of the spot and futures prices for several steps ahead. These are the VAR model in first differences, the VECM (and the parsimonious Seemingly Unrelated Regressions (SUR) – VECM), the ARIMA, the Exponential Smoothing and the Random-Walk (RW). According to the RMSE Ratio criterion, the VECM outperforms all other models in the prediction of spot prices, while ARIMA provides better forecasts than the RW model.

Alizadeh and Nomikos (2003) assess the ability of Forward Freight Agreements (FFAs) to forecast the direction of future freight rates on four major routes and find that they are weak predictors and that the forecasting accuracy is inversely related to maturity.

Kavussanos and Visvikis (2004) turn their attention to the forward markets and investigate the predictive ability of Forward Freight Agreements (FFA) in relation to the respective spot freight rates. In this context, they first perform causality and impulse response analysis and subsequently they use some extensions of the VECM framework, such as the VECM-GARCH and the VECM-SURE models in order to capture the volatility spillovers between the two markets. In congruence with that study, Kavussanos, Visvikis, and Menachof (2004) employ co-integration analysis and VECM modelling to examine the FFA predictability in the Panamax freight market. Thus, they select some representative Panamax routes and evaluate whether the unbiasedness hypothesis holds. According to their results, 3-month FFA prices are unbiased predictors of spot freight rates in the Pacific, but not in the Atlantic region. All in all, they find that the results are subject to the distinctive features of each market, to the selection of trade routes, and to the duration of the contract.

Lyridis, Zacharioudakis, Mitrou, and Mylonas (2004) engage in non-linear modelling and use Artificial Neural Networks (ANNs) to predict the spot rates of VLCC (Very Large Crude Carriers). Their analysis is based on the assumption that the past values of freight rates may impact the future values. This implies that in effect they reject the EMH. The first step of their work involves the identification of the most appropriate explanatory variables through the detection of the potential sources of variability. This constitutes the groundwork for the specification of reliable ANN models. Indeed, the results validate the robustness of their approach, especially for longer term forecasts during volatile periods. In particular, ANNs with variables in differential form seem to respond better to quick and extreme changes in the tanker market, minimizing the forecast errors. Notably, the results indicate a substantial improvement over the preceding analysis of Li and Parson (1997).

In his PhD dissertation, Tsolakis (2005) devises the Error Correction Models (ECM) methodology to analyse the freight market (among others), arguing that, in contrast to other models, ECM do not violate the Classical Linear Regression Model (CLRM) assumptions. On this basis, he generates forecasts for different ship sizes. At the same time, he runs ARMA forecasts and compares the results. Overall, the ECM framework provides greater accuracy and therefore it is regarded as more appropriate. In addition, he finds that his approach performs better in the t/c market than in the spot market and he explains this by the stochasticity of the spot rates as opposed to the t/c rates.

Randers and Göluke (2007) construct an aggregate forecasting model which intends to identify turning points in the tanker freight market. However, their model does not account for the different ship sizes and trade routes. Their main assumption is that the cyclicality of the market can be described by the interaction of two balancing loops; i.e. the capacity and the utilization adjustment loops.

Scarsi (2007) questions the reliability of forecasting models, due to the strong connection of the freight market with various external factors. He argues that this handicaps the ability of models to produce accurate forecasts and therefore market practitioners cannot rely on them. Furthermore, he points out that the shipowners' failure to track market trends is largely attributed to poor monitoring of the market developments, as well as to the lack of a solid decision making process.

Batchelor Alizadeh, and Visvikis (2007) test if the spot and forward freight rates can serve as inputs towards the joint prediction of their future values. In this setting, they formulate several different models (VAR, VECM, S-VECM, ARIMA, and Random Walk) and compare their performance on the basis of the Root Mean Squared Error (RMSE). VECM models appear to provide excellent in-sample fit, while they also yield satisfactory out-of-sample forecasts for the spot rates. On the flip side, none of the models perform well when forecasting forward rates.

Thalassinos, Hanias, Curtis, and Thalassinos (2009) also adopt non-linear analysis and apply the False Nearest Neighbours (FNN) method to forecast the future values of an index that tracks the Afframax tanker rates. This method originated from chaos theory.

Goulielmos και Psifia (2009) describe the volatile nature of freight markets and point out the weaknesses of forecasting in shipping. Then they propose certain novel techniques which significantly diverge from the traditional Random Walk processes and aim to introduce a new perspective on the modelling of the freight market. They adopt chaotic, non-linear, and deterministic approaches and their underlying methods involve Power Spectrum Analysis, Rescaled Range Analysis (and the related Hurst Exponent), V-statistic, and BDS Statistic. They come up with both in-sample and out-of-sample forecasts and in this process they use Kernel Density Estimation and Principal Components Regression, both of which handle non-linear series in an appropriate manner.

Duru and Yoshida (2009) explore the utilization of judgmental methods as forecasting tools and advocate the advantages of qualitative methods over quantitative ones. In this respect, they predict the BDI using two judgmental forecasting techniques, the expert-opinion and the Delphi method. The accuracy of their approach is evaluated through a comparison with the following time-series methods: Exponential Smoothing, TRAMO/SEATS algorithms, and X12 ARIMA. The results present the judgmental forecasting methods as superior to the statistical methods; however, this method category incorporates intuition and subjective judgment, while at the same time it has some serious limitations; it is hardly feasible to continuously form groups of maritime experts and ask their opinions. Moreover, Duru, Bulut, and Yoshida (2013) review the performance of Delphi forecasting and conclude that even though it is a useful decision-making tool, at times it might lead to irrational judgments due to its high reliance on human imagination.

Duru (2010) embarks on fuzzy logical modelling and develops appropriate algorithms to forecast the BDI. These are the Fuzzy Integrated Logical Forecasting (FILF) and the Extended FILF (E-FILF). Finally he validates the effectiveness of his proposed methodology by comparing the results with naïve-type methods.

In another study, Goulielmos and Psifia (2011) challenge the popular assumption in the maritime literature that the freight rates are normally distributed and i.i.d (independently and identically distributed). They provide evidence that the Dry Cargo Freight Index, the Dry Cargo Time Charter Index, and the historical t/c rates of a typical Kamsarmax exhibit significant skewness and kurtosis and therefore deviate from normality. In this regard, they argue that the classical forecasting models which are based on this assumption, such as the Random Walk, produce erroneous results. In addition, they attempt to predict shipping cycles and their duration using the V-statistic. However, they estimated that the cycle that started in 2008 was expected to last only two years, but this did not come about.

Bulut, Duru, and Yoshida (2012) revisit the Fuzzy Time Series (FTS) method and build a Vector Autoregressive Fuzzy Integrated Logical Forecasting (VAR-FILF) model to generate predictions for the Handymax and Panamax t/c rates. The robustness of their method is tested against conventional time series approaches, as well as against the Bivariate cFTS (Bi-cFTS) and the Chen's FTS (cFTS) methods. However, their proposed model is very sensitive to the interval length. It should be noted that the applicability of FTS as a forecasting tool in the shipping market has been investigated by many authors and in a variety of settings. For example, Stefanakos and Schinas (2015) use this method to gain insights into the future movements of bunkers prices.

Papailias and Thomakos (2013) are concerned with the identification of cyclical patterns and with BDI forecasting. Their analysis suggests that the shipping cycles last about 3 – 5 years. However, this pattern fails to capture the current cycle, the duration of which has already exceeded this projected time frame. At the next stage of their paper they proceed to the prediction of the annual growth of the BDI. This is carried out through various models which embed explanatory variables and account for cyclicality. Those models include Linear Regressions and Broken Trends, Factor Methods, and Autoregressive models. The latter category serves as the benchmark for the evaluation of the predictive accuracy of the afore-mentioned models, and the results show that they are quite robust.

Nielsen, Jiang, Rytter, and Chen (2014) deal with the assessment of the impact of the forecast horizon and of the number of observations on a freight forecasting model for the liner market. As a first step they formulate a forecast model based on the interaction between market rates and rates offered by individual firms. Within this perspective, they empirically analyze the manner in which the observation fit and the forecasting period affect the performance of the model. They conclude that it is of paramount importance to refrain from over-fitting and the robustness of the model is highly dependent on the balance between the number of explanatory variables and the forecast horizon.

In the study of von Spreckelsen, von Mettenheim, and Breitner (2014), the non-linear forecasting methods of spot freight rates in the liquid market come under scrutiny. Their study spans various forecasting techniques ranging from ANN to linear methods. As a conclusion they note that non-linear models are more appropriate for short term forecasts of spot rates.

Wong (2014) produces short and long term predictions of the BDI using Fuzzy heuristic modeling, Grey System and ARIMA. The latter proves to perform better than the others for longer term forecasts, whilst the GM(1,1) model provides the least accuracy overall.

Zhang, Zeng, and Zhao (2014) analyze the causal relationship between spot freight rates and t/c rates, as well as between spot rates and FFAs. The related series are found co-integrated. Thus a VECM framework is regarded as the most appropriate to model the underlying relationships and provide forecasts of spot rates.

Geomelos and Xideas (2014) produce ex-post and ex-ante forecasts in the dry and wet markets using univariate (ARIMA, GARCH, and E-GARCH) and multivariate models (VAR / VECM and VARX). In parallel, they obtain combined forecasts in the form of an average of future values generated by the afore-mentioned models. The forecast errors show that the latter process outperforms the individual models. Another notable characteristic of this study is the formulation of VARX models using as endogenous variables the spot and t/c rates, the new-building second-hand prices, the scrap prices, and the fleet capacity, and as exogenous the world GDP and the seaborne trade (measured in million tonnes).

Zeng, Qu, Ng, and Zhao (2015) come up with a new forecasting approach, whereby they decompose the BDI into three distinct components representing short term changes, long-run trends, and external shocks respectively. This method is called Empirical Mode Decomposition (EMD). Thereafter, each component is modelled using ANN, which is also applied when the composition takes place. It turns out that this EMD-ANN approach enhances the performance of a single ANN model and at the same time outperforms the conventional VAR.

3.3 Spot and period rates in the context of the Efficient Market Hypothesis (EMH)

The dry bulk market offers its participants the flexibility of entering into a charter party after choosing among a variety of contracts with different maturities. The modelling of the spot and period rates, as well as the examination of their relationship, has been in the forefront of freight market research over the last few years.

An abundance of research has been conducted to investigate the relationship between spot and long-term rates in the context of the Efficient Market Hypothesis (EMH), while several other studies test the validity of the EMH in freight markets. Zannetos (1966) is the first to study the effect of short-term expectations on freight rates. In particular, he presents the bond market concept of term structure as a relationship between spot and period rates. However, he does not take into consideration that in the longer term, regardless of the short-term trends, market expectations cannot be fully reflected in the current t/c rates due to additional costs resulting from delays and so forth. Glen, Owen, and Van der Meer (1981) examine the risk premium in the tanker market, assuming that the t/c income is equal to the present value of a series of spot contracts over the same duration. Their conclusion is that the estimated risk premium is not significantly different from 0. However, while acknowledging the existence of the Expectation Hypothesis they do not check its validity. This is done by Hale and Vanags (1989) who test the Expectation Hypothesis in the dry cargo market and their tests either reject it or lack the necessary statistical significance. However, there are concerns over the validity of their results, as their 6-year period data set may not represent a full cycle, while on top of that they make use of the questionable Mankiw-Summers test. On the other hand, Veenstra (1999) applies the improved Cambell and Shiller test. In his study, he re-examines the term structure between spot and t/c rates employing a present value model and estimates it using a VAR approach. He transforms the period t/c rates into voyage equivalent time charter rates measured in $ per ton (instead of $ per day) so as to be comparable to the voyage spot rates which are quoted in $ per ton. He finds that the rates are non-stationary but co-integrated and concludes that his model adequately describes the relationhip between spot and period rates. Interestingly, he provides a practical application of his model, where he develops a chartering strategy, according to which, when the spread (defined as the difference between period and spot rates) is above its historical mean the operator chooses a period charter, while when it is below, they enter into a spot contract. In this sense, he interprets the historical mean as a risk premium that offsets the loss of flexibility arising out of a period contract. Yet this assumption is rejected from the empirical analysis. Furthermore, he makes some inconsistent simplifications. For instance, the assumption that the time horizon of period charters goes to infinity is flawed, as the duration of most period charters does not exceed 3-5 years. Also, it should be noted that although all these studies identify the existence of a risk premium, they do not attempt to model it.

The study of Kavussanos and Alizadeh (2002) is of great importance for the maritime literature, as they reject the Expectation Hypothesis through a series of statistical tests and they introduce, for the first time, the concept of time-varying risk premium in the shipping market. Along these lines, they view it as the reason for the failure of the Expectation Hypothesis. In fact, they extend Veenstra's (1999) approach to vessels' prices. More specifically, in order to generate excess returns they develop a VAR model using the spread between new-building prices and operating profits, along with the spread between scrap values and operating profits. Their conclusion is that the owners' decision to enter the spot or the t/c market varies in proportion to the spread between spot and t/c values, generating a time-varying risk premium. This time-varying risk premium, during the formation of period rates, reflects the fact that the uncertainty over the direction of freight rates leads shipowners to enter into a period charter and accept a fixed but lower than the spot market rate in order to be secured against a possible market downturn. This lower rate corresponds to a negative risk premium. They also indicate that the longer the duration of a period charter, the lower the rates, as the absolute value of the negative risk premium increases. However, this overlooks the role of market expectations at the time of the deal. When the long-term views of shipowners are bullish and the spot rates are depressed, they might claim higher period rates compared to spot, so that they can recover the lost earnings for committing to a lower rate than what they anticipate in the longer term. Finally, the authors attempt to model the time varying risk premium using the Generalised Autoregressive Conditional Heteroscedasticity in Mean (GARCH-M) model.

In other studies, Wright (2000, 2002) applies co-integration analysis and tests for the existence of an intercept term, while at the same time examines the validity of the rational expectation hypothesis between spot and period rates. The results support the rational expectation hypothesis and reject the presence of an intercept.

In another application, Tsolakis, Cridland, and Haralambides (2003) focus on second-hand ship prices and draw on the concept of co-integration in order to develop an Error Correction Model and compare its results to an Autoregressive Model.

Tvedt (2003) sees the stationarity of dry bulk freight rates and second-hand prices in a new light. He converts the currency denomination data from USD to Japanese yen and illustrates that the transformed observations do not follow a random walk. This contradicts the previous studies which find that the rates and prices are non-stationary in level. He bases the currency change on the influential role of Japan in the dry bulk market, arguing that yen can capture the dynamics of the dry bulk market more adequately. However, the USD remains the prevailing currency in international trade.

The studies of Adland, Koekebakker, and Sodal (2004) and Adland and Cullinane (2006) point to the same direction. These authors argue that spot rates in the liquid market are locally non-stationary, but a non-linear mean-reverting drift at the extremes of the range gives rise to global stationarity. In particular, they claim that the behaviour of spot rates in the largest part of their range resembles a Martingale process and this causes local non-stationarity. Yet this is not the case with the edges, where the authors detect mean-reversion. Finally, it is worth noting that they express the spot rates as TCEs of some selected voyages.

Haigh, Nomikos, and Bessler (2004) adopt alternative approaches and apply Directed Acyclic Graphs (DAG's) and Error Correction Models to investigate the dynamics of the freight rates and the routes that compose the Baltic Panamax Index (BPI). Eventually, they find that the index may not be appropriately weighted.

Another branch of literature related to the present study addresses the relationship between spot rates and Future Freight Agreements (FFAs). For instance, Kavussanos and Visvikis (2004) examine the lead-lag relationship between spot returns and over-the-counter (OTC) FFAs and find a bi-directional causal relationship for all routes. Bessler, Drobetz, and Seidel (2008) test spot rates and FFA prices for autocorrelation and co-integration, and conclude that spot rates are autocorrelated in contrast to FFAs, while spot and forward rates are co-integrated.

There have been a number of pioneering studies that use the principles of technical analysis in a service market like shipping. For example, Norman (1982), Adland (2000), and Adland and Koekebakker (2004) implement technical rules in the second-hand market in order to design investment strategies. In particular, Adland and Koekebakker (2004) test the market efficiency in the second-hand market by arguing that a technical strategy should not generate excess returns in an efficient market. Their strategy fails to produce excess profit; thus it provides some evidence in support of the EMH. However, this is not a sufficient condition for its validity, while at the same time it does not downplay the overall concept of technical trading. In other studies, Alizadeh and Nomikos (2006, 2007) discuss investment and divestment timing decisions for second-hand vessels in the context of a combination between technical and fundamental analysis.

Yet it is not until recently that the principles of technical analysis have been used in freight markets. This stream of literature is initiated by Adland and Strandenes (2006), who implement technical trading rules and examine their profitability. The authors reject the traditional form of the EMH, given that freight rates cannot be stored or traded. Instead, they consider the semi-strong form efficiency as more realistic and test its validity on the basis of the hypothesis that a trading strategy is impossible to yield excess profit in an efficient market. It should be noted that, here, the term 'excess profit' excludes the risk premium. As a final point, the authors suggest that the non-storable and non-tradable features of freight rates call for the utilization of technical analysis, which is indeed an appropriate framework for such cases.

In another study, Alizadeh and Nomikos (2006) use the co-integrating relation between price and earnings in the ship sale and purchase market, as a way to combine technical and fundamental analysis, and eventually determine the optimum investment or divestment timing. For this purpose they make use of P/E ratios (fundamental analysis) and then they look at historical data and implement technical trading rules (technical analysis) for the formation of a suitable trading strategy. The effectiveness of this strategy is then tested against a benchmark strategy (buy and hold) and the results are indicative of its superiority. In parallel, the authors attempted to overcome the data snooping bias by using the bootstrap method.

Alizadeh and Nomikos (2007) extend this approach to the freight market and examine if certain chartering strategies based on technical analysis can generate excess returns. In particular, they apply a Moving Average (MA) trading rule, by which they charter in a vessel on a 12-month period charter and charter it out on a 6-month t/c if the difference between the two rates is higher than the average difference over the previous n-weeks. The study concludes that the MA approach can yield excess profits and provides more robust results when performed in rolling samples. Furthermore, Alizadeh, Adland, and Koekkebaker (2007) use technical trading rules to formulate optimal chartering strategies. In this context they examine the excess return potential.

Adland and Jia (2008) focus on default risk and investigate the way it interacts with the freight market conditions, the charter duration and the financial situation of the charterer. Their results confirm that the default risk premium is positive and can be expressed as an increasing function of freight market conditions and charter duration.

Wright (2011) attempts to model the risk premium using a model initially developed for the financial markets. In particular the risk premium is embedded in a discount rate which is used in combination with several assumptions and simplifications in order to adjust the Expectations Hypothesis in such a way as to account for term risk. However, this model, despite yielding some promising results, is of limited reliability due to the large number of simplifications and assumptions it contains. For instance, the author assumes that risk and equity discount rates are correlated and he also uses a revenue generation technique based on assigned probabilities.

A considerable part of the PhD thesis of Pourkermani (2012) is devoted to the examination of the EMH from the point of view of a ship operating company. In this respect, he evaluates two different chartering decisions, i.e. the selection of a long-term t/c versus the entrance into consecutive voyage charters over the same period. This is done by building a regression model and forecasting the excess freight rate. The explanatory variables include commodity and macroeconomic series. If the EMH held true, there would be no excess returns. The results show that in the case of

Capesize vessels, the spot market can provide higher returns compared to the period market, rejecting the term-structure and the no-arbitrage argument. On the contrary, an operator of the second ship type under consideration (i.e. the Handymax), does not appear able to maximize his profits in the spot market. Therefore, the evidence of this thesis is inconclusive as to the ultimate verification or rejection of the EMH.

Ko (2013) touches upon the term structure of dry freight rates and uses VAR and time-varying coefficient models. The underlying assumptions distinguish between short and long term random shocks. His study reveals that long-term structural shocks have a significant impact on short-term rates, but short-term shocks do not seem to be equally influential with regard to long-term rates. This is interpreted by the author as evidence of market efficiency, since the effect of external (long-term) shocks is reflected in the formation of freight rates. In addition, he measures the (time-varying) adjustment speed of freight rates, using as a reference the long-run equilibrium, which is derived from a VECM model.

In the context of chartering decision making, Axarloglou Visvikis, and Zarkos (2013) examine the choice of ship operators between voyage and time charters. Given the existence of a time-varying spread, they determine its main drivers. These include the business environment and the associated cycles, the market expectations, and the volatility. The above dynamics are empirically analysed using a real options model. The findings indicate that operators ought to take into account the afore-mentioned factors, since they play a major role in the resource allocation process and the related trade-off between flexibility and commitment. In this reading, the occurring 'rule of thump' is that shipowners can maximize their revenue potential if they maintain their flexibility by entering the spot market through a voyage charter when the market is strong, whilst it is in their interest to commit charterers to a long-term t/c during periods of unfavourable (freight) market conditions.

Zhang and Zeng (2015) investigate the lead-lag relationship between spot and t/c rates. In this respect, they first build a VECM model and then use impulse response analysis to describe the effect of external shocks. Their findings point to the existence of significant mutual influence between spot and period rates. Furthermore, they find that the price discovery occurs in the case of long term time charters of average sized bulk carriers, such as Supramax vessels.

3.4 Chartering Strategies

Modern management techniques and mathematically based chartering decision-making have been steadily gaining traction in the shipping industry over the past few years. The competitive nature of the dry bulk market implies that timely and correct chartering decisions are of paramount importance for the viability of shipping companies.

A robust chartering strategy is extremely vital for shipping firms as it can provide a solid competitive advantage and ultimately increase their profitability. Panayides (2003) shows that those ship management companies who formulate and follow appropriate competitive strategies can substantially enhance their performance.

A ship operator is frequently confronted with several alternatives with regard to the commercial management of his vessel and needs to assess them and make the optimum decision. In particular, they have to select among the following main chartering options:

- Perform a voyage charter and receive freight per metric ton.
- Charter out the ship on time charter for a long period of time (period charter).
- Enter into a short-term time charter (or trip t/c) and receive a daily hire throughout the charter period.
- Agree to carry a large quantity of cargo over several voyages (Contract of Affreightment).
- Engage in consecutive voyages.
- Lay-up the vessel and wait for a market improvement.

Practically the most common and simultaneously crucial chartering decision pertains to the choice between the spot and the period market. In a general sense, the key is to trade in the spot market when the freight rates are high and enter into a long-term time charter if a market downturn is anticipated.

It is clear that due to the cyclicality and the external factors that affect the shipping business, even the most experienced operator is likely to misjudge. Therefore, the introduction of decision-making models in dry bulk chartering is increasingly attracting attention and interest in the maritime industry.

The first study in the area of optimal chartering decisions is carried out by Mossin (1968). He focuses on the lay-up decision and his model assumes that freight rates follow a random walk. The lay-up decision is taken on the basis of a fixed threshold, which is justified by assuming that the underlying process is stationary. Devanney (1971) develops a discrete-time finite-horizon model for chartering strategies. He considers the t/c rate and compares it with multiple spot rates.

In another study, Taylor (1981) uses simulation modeling for the determination of the optimal 'fleet mix'. A distinctive characteristic of his work is the introduction of a 'chartering preference function' that presents the proportion of long-term charters that operators are willing to take as a function of a freight index. One year later, Norman (1982) proposes two alternative approaches: a) the 'portfolio of charters', which focuses on the estimation of the operator's price of risk and risk preferences, as well as on the optimal mix of ships under spot and term charters. b) The 'chartering timing policies', where he uses historical data to establish a simple decision rule between the spot and term charter.

Strandenes (1984) measures the expected short- and long-term Time Charter Equivalent (TCE) in the spot market applying OLS and explores the operators' decision to commit their vessels on period charters below the spot rate. The PhD thesis of Goncalves (1992) employs stochastic optimal control and capital markets theory, aiming to develop a rational decision support system to optimize chartering policies.

Berg-Andreassen (1998) aims to establish optimal chartering strategies in the dry bulk market from a portfolio perspective. Given a combination of ships and routes he assumes that a fleet operator strives to maximize his profit through the most adequate allocation of chartering agreements. The effectiveness of this attempt is gauged by a risk-return model, which is adjusted to the dry freight market. The results suggest that when the ship operator hires in about 78% of his fleet, the expected return can be as high as 37%.

Alderton (2004) puts forth that the ideal chartering strategy is to pursue spot contracts when the market is surging and enter into period charters as soon as the market hits the bottom. Engelen, Meersman, and Voorde (2006) attempt to capture the dynamics involved in the decision making process of shipowning companies. This is done within a system dynamics framework, where an endogenous decision model is tailored to the dry cargo market and factors in the state of the market and the decision making process of individual owners. Finally, they perform a simulation which demonstrates the effectiveness of their approach.

Scarsi (2007) turns her attention to the decision making process of shipowners and tries to identify the main causes of wrong decisions. Her analysis refers both to investment and to chartering decisions, and she also uses the case of the Handysize vessel to illustrate that many investors missed out on a profitable market opportunity due their inability to read the market and make the decision in a timely manner. In a nutshell, she attributes the incorrect decisions a number of factors that include: lack of experience, reliance on intuition rather than on a combination of experience and modeling tools, imitation of competitors, over-enthusiasm, weak company culture, and inability to adapt to changing market conditions.

Ozer and Cetin (2012) conduct a survey to determine the most desired type of charter by Turkish owners of bulk carriers, as well as the key factors affecting their decision. It appears that the majority of shipowners prefer voyage charters, followed by consecutive voyages and short-period time charters. In conjunction with this, Factor Analysis indicates that the selection criteria include (in order of significance): risk, reliability of the charterer, condition of the vessel, sustainability of the trade income, profitability of trade, ship age, and experience of the shipowner in a particular charter. This study is quite insightful as it attempts to shed some light on the shipowner's decision among a variety of chartering options. However, on the downside, the results are largely dependent on the sample of shipowners and the prevailing market conditions at that particular point in time. Moreover, it does not provide any clue as to the connection of each individual charter type with the factors under consideration.

Wang, Huang, Liu, and Zheng (2013) concentrate on chartering decision making from the point of view of refineries. Practically acting as charterers, these entities aim to make chartering decision that will minimize the transport cost. In this setting, the authors devise geometric Brownian motion and Poisson processes for modeling the behavior of tanker freight rates and the number of ship offers respectively. It should be noted that these two factors are assumed independent, even though there are indications of (negative) correlation. Finally, the authors apply this methodology to the case of a Chinese refinery and find that it outperforms the company's strategy.

The thesis of Garnås (2014) is concerned with the implementation of Operations Research (OR) tools in the dry cargo market. In particular he attempts to utilize decision support software (DSS) in a number of chartering scenarios and then compare it to another optimization model (Turborouter). Though the idea of linking Operations Research with dry chartering seems interesting, the application has serious shortcomings as it ignores the dynamics of this market.

Gkochari (2015) introduces a novel approach into the shipping market, i.e. investment strategies based on option games, and applies it in the Capesize sector. His goal is to specify the most suitable timing of new investments and also explain the driving forces of shipping market cycles. Ultimately, he verifies the superiority of his approach by comparing it with a benchmark strategy which is based on the P/E ratio.

Kou and Luo (2015) use game theory to explain the problem of oversupply in shipping. According to their analysis, new orders constitute a rational decision at the extremes of the cycle and the return on investment is higher when the ordering activity is synchronized. However, the accumulation of many ship orders may result in overcapacity and drag down the freight rates.

4. MODELLING FRAMEWORK AND STATISTICAL TOOLS

4.1. Introduction

This chapter presents statistical tools and econometric methods which are relevant to the analysis that will follow in the ensuing chapters. It presents the general modelling framework of this thesis and sets the basis for the development of several more specific quantitative methods, which are described in the methodological section of each chapter. In addition, the statistical and diagnostic techniques discussed here are used for the robustness evaluation of the subsequent modelling approaches.

4.2. Descriptive Statistics

Every modelling attempt requires an investigation of the distributional characteristics of the data. This statistical analysis is referred as 'descriptive statistics' or 'moments of a variable' and includes measures of central tendency (e.g. mean), dispersion (e.g. range, variance, standard deviation) and distribution shape (e.g. skewness, kurtosis).

4.2.1. Mean

The arithmetic mean is calculated as the average of all observations in a given sample or population.

$$\text{Sample Mean:} \quad \bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{4.1}$$

$$\text{Population Mean:} \quad \mu = \frac{\sum_{i=1}^{N} x_i}{N} \tag{4.2}$$

where x_i denotes the values of observations, n the length of the sample and N the total number of observations in the population.

4.2.2. Standard Deviation

The standard deviation measures the dispersion of a variable, and unlike variance it is measured in the same unit as the data. It is defined as the square root of the variance. That is the square root of the average of the squared deviations from the arithmetic mean.

It is given by the following formulas for samples and populations respectively:

$$\text{Sample standard deviation: } s = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}} \tag{4.3}$$

$$\text{Population standard deviation: } \sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \mu)^2}{N}} \tag{4.4}$$

The fact that the sum of square deviations is divided by N in the case of population and by n-1 in the case of samples reflects that as the sample gets larger, the sample standard deviation becomes a more accurate estimator of the population standard deviation.

4.2.3. Skewness

Skewness (or third moment of the variable around its mean) is a measure of the degree of asymmetry of a distribution. The coefficient of skewness shows whether the variable is skewed left or right, or whether it is symmetric.

The skewness values are given by the following formulas:

$$\text{Sample skewness: } Sk_1 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^3 \Big/ (n-1)}{S^3} \tag{4.5}$$

$$\text{Population skewness: } Sk_2 = \frac{\sum_{i=1}^{N}(x_i - \mu)^3 \Big/ N}{\sigma^3} \tag{4.6}$$

A negative coefficient of skewness indicates that the data are skewed to the left. This means that the left tail is longer and fatter than the right tail. This type of distribution is characterized by a few extreme losses and numerous small gains. Conversely, a positively skewed distribution translates into a longer and fatter right tail. This type of skewness implies a large number of small losses and a few extreme gains. Zero skewness indicates a symmetric distribution around its mean (Figure 1). The latter is one of the main characteristics of the normal distribution.

The following figure presents the three different types of skewness:

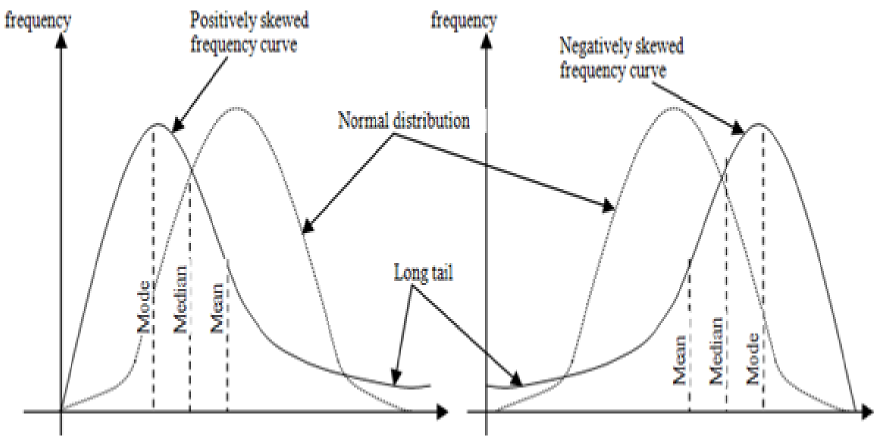


Figure 1: Types of Skewness

(Source: learnerator.com)

4.2.4. Kurtosis

Kurtosis (or fourth moment of the variable around its mean) is a measure of peakedness of a variable's distribution. The coefficient of kurtosis shows whether the data are flat of peaked in relation to the normal distribution.

The kurtosis values are given by the following formulas:

$$\text{Sample kurtosis: } Kurt_1 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^4 \Big/ (n-1)}{S^4} \tag{4.7}$$

$$\text{Population kurtosis: } Kurt_2 = \frac{\sum_{i=1}^{N}(x_i - \mu)^4 \Big/ N}{\sigma^4} \tag{4.8}$$

The symmetrical 'bell-shaped' (univariate) normal distribution has a kurtosis value of

3. Given that the estimated kurtosis is evaluated against the normal distribution, it turns out that the sample kurtosis has to be compared to 3. Hence, when the estimated kurtosis coefficient is higher than 3, the distribution of the variable is said to be leptokurtic and has heavy tails and a higher peakedness compared with the normal distribution (e.g. Laplace distribution). The heavy tails increase the likelihood of generating values that depart considerably from its mean. On the other hand, if the kurtosis is lower than 3, then the distribution is referred as platykurtic and is generally flatter that the normal distribution. Finally a sample kurtosis of 3, matches the peakedness of the normal distribution and the distribution is called mesokurtic (Figure 2).

The following figure depicts the above cases:

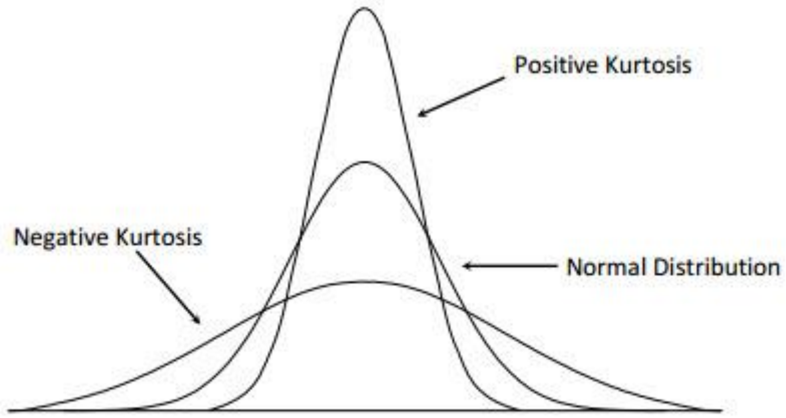


Figure 2: Types of Kurtosis

(Source: learnerator.com)

4.2.5. Jarque–Bera (JB) test

The Jarque-Bera test checks how the skewness and kurtosis of the sample data measure up against the skewness and kurtosis of the normal distribution. The related test statistic is given by the following formula:

$$JB = \frac{n-k+1}{6}\left[Sk_1^{\,2} + \frac{1}{4}\left(Kurt_1 - 3\right)^2 \right] \tag{4.9}$$

where Sk_1 and $Kurt_1$ are the skewness and kurtosis respectively and n the degrees of freedom.

Specifically, under the null hypothesis the skewness is zero and the kurtosis is three – the latter is equivalent to excess kurtosis of zero. This test becomes powerless in cases of very small samples, due to the high sensitivity of the chi-square approximation, which increases the likelihood of type I error.

4.3. Stationarity Tests

A time series is stationary if its mean, variance and auto-covariance are finite and time independent. In other words, stationary series are mean-reverting and do not follow any trends.

Non-stationary time series are not appropriate for classical linear regression modelling, as they violate the CLRM assumptions. Non-stationarity changes the distributional theory and consequently the F- and t- test statistics are not valid for non-stationary series. This implies that the hypothesis test results for the regressions parameters will not be reliable. In particular, the assumption for asymptotic analysis is violated, since the t-ratios do not follow a t-distribution.

The properties and behavior of time series are largely affected by stationarity. Non-stationary series may contain trends, cyclicality and persistent shocks.

The main problem is that non-stationary time series may lead to spurious results, as the model might mistakenly yield a high R^2 and identify relationships that do not exist in reality.

Therefore, it turns out that non-stationary time series can provide misleading results if they are not modeled properly. This issue is tackled in the current thesis by the utilizations of VAR and VECM models, which can adequately handle non-stationary variables.

The appropriate handling of non-stationary series is a very critical step in time series analysis, given that, as indicated by the relevant literature, most of the shipping and economic variables are not stationary.

A common way of transforming non-stationary time series into stationary is by differencing them till they becomes stationary (or alternatively fit an error correction model if the series are co-intergated). The number of differencing procedures it takes to achieve stationarity determines the order of integration, I(.). This reflects the number of unit roots that the series contains. For example, a non-stationary variable which is differenced once before it becomes stationary is denoted as I(1). Then it is called integrated of order one and is said to have one unit root. On the other hand, a stationary variable is denoted as I(0).

The stationarity is checked by means of unit root tests. The present analysis uses two different unit root tests, i.e. the Augmented Dickey-Fuller (1979) and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS, 1992) tests.

During the execution of unit root tests, the attention is drawn to the results for three different assumptions with regard to the exogenous regressors, i.e. none, constant and constant and linear trend (the KPSS test considers only the last two).

4.3.1. Augmented Dickey-Fuller test

Suppose the following typical AR(1) process:

$$y_t = r y_{t-1} + x'_t c + \varepsilon_t \tag{4.10}$$

where x´t are possible exogenous regressors, r and c are parameters and ε_t denotes white noise.

The ADF test, examines the following null and alternative hypotheses:

$$\begin{aligned} H_0&: r = 1 \\ H_1&: r < 1 \end{aligned} \tag{4.11}$$

After deducting y_{t-1} from both sides of (4.10), it becomes:

$$\Delta y_t = b y_{t-1} + x'_t c + \varepsilon_t \tag{4.12}$$

where b = r – 1. Thus the test hypothesis (4.11) is rewritten as:

$$\begin{aligned} H_0&: b = 0 \\ H_1&: b < 0 \end{aligned} \tag{4.13}$$

The evaluation is done through the t-ratio for b:

$$t_b = \frac{\hat{b}}{se(\hat{b})} \tag{4.14}$$

Where $\hat{b}$ is the estimator of b and $se(\hat{b})$ the coefficient standard error.

The ADF test entails some serious weaknesses when it comes to rejection of the null hypothesis of a unit root, especially under the presence of mean reversion which is long compared to the length of the sample (Harris, 1995; Maddala & Kim, 1998).

This is remedied by performing an alternative test, the KPSS test, which assumes that the variable is stationary and tests the alternative hypothesis of a unit root. The KPSS test is generally more suitable for relatively small samples (Caner & Kilian, 2001; Kuo and Tsong, 2005).

4.3.2. Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test

The residuals from the OLS between y_t and the exogenous x_t in equation 3.6 below, form the basis of the KPSS test.

$$y_t = x'_t c + e_t \tag{4.15}$$

The LM statistic is defined as:

$$LM = \sum_t \frac{S(t)^2}{T^2 f_0} \tag{4.16}$$

Where f_0 denotes an estimate of the residual spectrum under zero frequency and S(t) a cumulative residual function.

$$S(t) = \sum_{i=1}^{t} \hat{e}_i \tag{4.17}$$

where $\hat{e}_i = y_t - x'_t \hat{c}(0)$

4.4. Co-integration

A critical question in time series analysis is whether time series are stationary. This property is typically examined using a unit root test, such as the ADF and KPSS tests which are employed in this study. If the series are found non-stationary, their joint probability distribution as well as their mean and variance change over time. Thus they do not exhibit mean-reversion and their interaction cannot be captured by traditional econometric techniques.

However, if two (or more) non-stationary time series are integrated of the same order and at least one stationary linear combination between them exists, they are said to be co-integrated and have a common stochastic drift. This implies that their linear combination does not exhibit any spurious effects, while the error term of their regression is stationary. The distinctive feature of two co-integrated variables is the existence of a long-run equilibrium, characterized by short-run adjustments.

The two main methods of testing for co-integration are the Eagle and Granger (1987) two-step procedure and the Johansen test (1991, 1995). The present thesis study makes use of the latter method, as it is more powerful. In particular, the Johansen approach seeks the most stationary linear combination, unlike the OLS based Engle-Granger method that looks for the combination with the minimum variance. This leads to a more robust power function and less bias in the case of Johansen test. Furthermore, the Johansen test is able to detect more than one co-integrating relations, in contrast to Engle-Granger's method.

For a k-dimensional vector of I(1) time series, y_t , and a d-dimensional deterministic vector, x_t , (containing terms such as a constant and a linear trend), the VAR(n) model is:

$$y_t = A_1 y_{t-1} + ... + A_n y_{t-n} + Bx_t + \varepsilon_t \tag{4.18}$$

and becomes:

$$\Delta y_t = Ay_{t-1} + \sum_{i=1}^{n-1} C_i \Delta y_{t-i} + Bx_t + \varepsilon_t \tag{4.19}$$

where $A = \sum_{i=1}^{n} A_i - I$ and $C_i = -\sum_{j=i+1}^{n} A_j$

In essence, the Johansen test refers to the estimation of the coefficient matrix A.

According to Granger's representation theorem, if A has reduced rank r < k, then A = α b and b′ y(t) is I(0), where a and b are k x r matrices of full column rank r (which is the number of co-integrating relations). This ensures that there exist at least k – r unit roots and co-integration is generated when r ≥ 1.

Johansen co-integration test includes two types of tests; the trace and the maximum eigenvalue. The trace statistic is actually the trace of a diagonal matrix of generalized eigenvalues and is calculated by:

$$LR_{tr}(r \mid k) = -T\sum_{i=r+1}^{k}\log(1-\lambda_i) \text{, for r = 0,…, k-1} \tag{4.20}$$

where r is the number of co-integrating relations, k the number of endogenous variables λ_i are the eigenvalues of the A matrix and T is the sample size.

Lastly, the maximum eigenvalue statistic is computed by:

$$LR_{\max}(r \mid r+1) = -T\log(1-\lambda_{r+1}) \text{, for r = 0,…, k-1} \tag{4.21}$$

4.5. Vector Autoregression (VAR)

This study considers the VAR and VECM multivariate linear model classes, in order to overcome the issue of non-stationarity and capture the causal relationship between the dry bulk freight market and certain external factors. In addition, these models also serve as forecasting tools and generate freight rate predictions for different vessel sizes.

The VAR/VECM framework offers some additional advantages. First of all, it is a relatively simple method, considering that almost all variables can be treated as endogenous without a problem. However, in order to increase the robustness of the models under consideration, the present thesis is complemented by the adoption of the VARX modelling framework, which allows for the inclusion of some purely exogenous variables.

The estimation is straightforward, as it is carried out by applying Ordinary Least Squares (OLS) regression to each equation separately.

Lastly, VAR and VECM models are known for their satisfactory forecasting performance, especially compared with more complex models, such as the simultaneous equation methods.

In time series analysis the Vector Autoregression (VAR) model explains the evolution of an endogenous variable as a linear function of its own lags and potentially the lags of all others variables in the system. A n-th order VAR, VAR(n), for a time series y_t in the form of a m x 1 vector is described by the following formula:

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-n} + \varepsilon_t \tag{4.22}$$

where c is a m × 1 vector of intercepts, A_i is a time-invariant m × m matrix and ε_t is a m × 1 vector of error terms which are uncorrelated with their own lags, and have zero mean and no serial correlation across time (white-noise Gaussian residuals).

VAR is a non-structural modelling approach which can be employed as an appropriate econometric specification for investigating the relations between variables, such as Granger causality, as it describes the joint generation process of the variables involved. That is to say that VAR models can be used both as a framework for the examination of possible relationships between the time series of the system, as well as a tool for predicting inter-related variables. In this regard, VAR models can be used for forecasting purposes in lieu of the non-parsimonious structural models, whose specification is much more cumbersome.

4.6. VARX model

The VARX model is essentially an extension of the VAR model with the inclusion of one or more exogenous variables. This is mathematically represented as:

$$\mathrm{Y}_t = \lambda_0 + J_1 Y_{t-1} + \cdots + J_n Y_{t-n} + L_1 X_{t-1} + \cdots + L_m X_{t-m} + U_t \tag{4.23}$$

where Y_t stands for the endogenous variables, X_t is a vector of exogenous variables, L_i and J_i are coefficient matrices λ_0 is a vector of intercepts and the error U_t is i.i.d. normally distributed.

The endogenous and exogenous variables, y_i and x_i respectively, may be in levels or first differenced, depending on the properties of the data (i.e. the existence of stationarity).

An important requirement for the VARX model is the fulfillment of the following condition:

$$E[U_t \mid \{Y_{t-i}\}_{i=1}^{\infty}, \{X_{t-i}\}_{j=1}^{\infty}] = 0 \qquad (4.24)$$

with probability 1.

The absence of a contemporaneous X_t from eq. 4.23 does not compromise generality.

The proof is as follows:

Suppose a contemporaneous X_t is includes in the initial VARX model. Then it will take the form:

$$\begin{aligned} Y_t &= \lambda_0 + J_1 \mathrm{Y}_{t-1} + ... + J_n Y_{t-n} + \\ &+ L_0 \mathrm{X}_t + L_1 X_{t-1} + \cdots + L_m X_{t-m} + U_t \end{aligned} \qquad (4.25)$$

with $L_0 \neq 0$.

Assuming now a VAR model for X_t:

$$X_t = \lambda_1 + M_1 X_{t-1} + \cdots + M_q Y_{t-q} + V_t \qquad (4.26)$$

and $$E[V_t \mid \{Y_{t-i}\}_{i=1}^{\infty}, \{X_{t-i}\}_{j=1}^{\infty}] = 0 \qquad (4.27)$$

substituting eq. 4.26 in eq. 4.25, the latter becomes:

$$\begin{aligned} \mathrm{Y}_t &= \lambda_0 + B_0\lambda_1 + A_1 \mathrm{Y}_{t-1} + \cdots + A_n y_{t-n} + B_0(\mathrm{M}_1 \mathrm{X}_{t-1} + \cdots + \mathrm{M}_q \mathrm{Y}_{t-q}) + \\ &+ B_1 X_{t-1} + ... + B_m X_{t-m} + U_t + \mathrm{B}_0 V_t \end{aligned} \qquad (4.28)$$

This is of the (initial) form (4.23), therefore it confirms the maintenance of generality.

4.7. Vector Error Correction Model (VECM)

The Vector Error Correction Model (VECM) is actually a restricted version of VAR and incorporates an additional error correction component, which is obtained from co-integration. This term accounts for the gradual short-term adjustment to the long-run equilibrium after a change in an independent variable. In fact, VECM does not 'correct the error' of a VAR model. It calculates the speed of adjustment to a long-term equilibrium after a change in an independent variable. This speed is measured through the adjustment coefficients of the model.

An important precondition of the VECM is the co-integration of its variables. This implies that the VECM model is not valid if the variables are not co-integrated. In that case the appropriate modelling framework is the VAR. Thereby there exists a long-run equilibrium and the deviation from this is reflected into the short-term dynamics. Therefore, when the series are co-integrated one should use the VECM approach instead of the VAR. VECM is designed to capture the dynamic interrelationship between non-stationary but co-integrated variables. However, it is noteworthy that VECM models can also be developed with stationary data.

Symbolically, the general form of the VECM model is:

$$\Delta Y_t = \mu_t + \Pi Y_{t-1} + \sum_{i=1}^{n-1} \Gamma_i \Delta Y_{t-i} + \varepsilon_t \tag{4.29}$$

where μ_t is the deterministic term, Y_t is a vector of endogenous variables, Δ is the first difference operator, Γ_i and Π are coefficient matrices measuring the short- and long-term adjustments and ε_t is a vector of white noise error terms.

In the bivariate case, the VECM can be written in the form:

$$\begin{aligned} \Delta y_t &= b_{y0} + b_{y1}\Delta y_{t-1} + \ldots + b_{yn}\Delta y_{t-n} + \gamma_{y1}\Delta x_{t-1} + \ldots + \gamma_{yn}\Delta x_{t-n} - \lambda_y \left(y_{t-1} - a_0 - a_1 x_{t-1} \right) + \varepsilon_t^y \\ \Delta x_t &= b_{x0} + b_{x1}\Delta y_{t-1} + \ldots + b_{xn}\Delta y_{t-n} + \gamma_{x1}\Delta x_{t-1} + \ldots + \gamma_{xn}\Delta x_{t-n} - \lambda_x \left(y_{t-1} - a_0 - a_1 x_{t-1} \right) + \varepsilon_t^x \end{aligned} \tag{4.30}$$

where $y_t = \alpha_0 + \alpha_1 x_t$ is the long-run co-integrating relationship and λ_χ and λ_y are the error correction parameters.

4.8. VECMX model

The VECM model can be extended to embed exogenous variables, in addition to the endogenous. The form of the model can be mathematically represented as:

$$\Delta Y_t = \mu_t + \Pi Y_{t-1} + \sum_{i=1}^{n-1} \Gamma_i \Delta Y_{t-i} + \sum_{j=1}^{m-1} B_j \Delta X_{t-j} + \varepsilon_t \tag{4.31}$$

where X_t is a vector of exogenous variables and B_j are parameter matrices.

4.9. Granger causality

In general, correlation does not necessarily imply causality. Furthermore, although regression analysis establishes dependence among variables, it does not provide any information about the direction of the relationship or about the existence of causation (Gujarati, 2004). Therefore, a more robust tool is necessary, which can provide substantial statistical evidence with regard to causality. Thus, we make use of the Granger (1969) approach, which is a powerful and widely used method for the examination of causal relationships. This technique deals with the short run causality between a dependent and an independent variable.

In the case of two variables, y and z, Granger causality, is defined as follows:

"z is Granger-caused by y, if z can be better predicted using the lagged values of both variables, than by using only its own lagged values, or equivalently, if the coefficients of the lagged y's are statistically significant."

Mathematically, Granger causality is tested using the VAR model below:

$$\begin{aligned} z_t &= a_0 + a_1 z_{t-1} + \ldots + a_n z_{t-n} + b_1 y_{t-1} + \ldots + b_n y_{t-n} + u_t \\ y_t &= c_0 + c_1 y_{t-1} + \ldots + c_n y_{t-n} + d_1 z_{t-1} + \ldots + d_n z_{t-n} + v_t \end{aligned} \tag{4.32}$$

H_0: $b_1 = b_2 = \ldots = b_n = 0$ (*y does not* Granger-cause *z*), against H_1: 'Not H_0'

and

H_0: $d_1 = d_2 = \ldots = d_n = 0$ (*z does not* Granger-cause *y*), against H_1: 'Not H_0'

Therefore, Granger causality tests are equivalent to testing a set of linear hypotheses. According to Toda and Yamamoto (1995), Granger causality has to be checked by setting up a well specified VAR model in the level form of the data, regardless of the unit roots. Even if the data are non stationary the VAR model should be in levels (as if the data were stationary), adding one extra lag (which should not be included in the test formulation too) in order to fix up the distribution of the Wald test in such a way as to maintain the asymptotical chi-square distribution. Then the Granger causality tests can safely be performed. It is worth noting that the test statistics in the case of Granger causality analysis follow chi-square distribution and not F distribution.

It is crucial to note that the VAR model in the level form of I(1) data is appropriate only when testing for Granger causality. It should not be used for other purposes, such as Impulse Response (IR) analysis or forecasting. Thus, the IR analysis and forecast models that follow use VAR in first differences for non-stationary and non-co-integrated data, and VECM models for co-integrated variables.

Granger causality is a very useful descriptive technique and it plays a critical role in the specification of quantitative models. However, as Gujarati (2004) points out, Granger causality cannot be utilized to establish exogeneity. In other words, one cannot infer which variables are exogenous and which are endogenous, on the grounds of Granger causality tests alone. This decision can be made in light of an in-depth analysis of the fundamentals of each case, which may provide a sound theoretical justification.

4.10. Impulse Response (IR) Analysis

IR analysis complements Granger-causality providing further insights into the way that a pair of variables interacts with each other. This is very useful, given that the interpretation of the coefficients in the VAR models is not so straightforward.

In particular, the Impulse Response function identifies the reaction of one variable with regard to an impulse to another within a system that may involve a number of other variables as well.

The impulse enters the system through a positive shock of one standard deviation to the residual and then an impulse response function traces the effect on the endogenous variables in the VAR model.

IR analysis presumes that there is significant Granger causality between the endogenous variables under examination. However, as opposed to Granger Causality, the model specification of IR analysis cannot involve a VAR in levels if the data are found non stationary. It should involve either a VAR in first differences or a VECM if the variables are co-integrated.

4.11. Variance Decomposition

The variance decomposition or forecast error variance decomposition (FEVD) describes the percentage of the forecast variance that can be explained by random innovations to the endogenous variables in the VAR model. This implies that the FEVD reflects how much information is contributed by each endogenous variable within the system.

Therefore, the variance decomposition is particularly useful when fitting a VAR/VECM forecasting model. It can provide valuable insights as to the selection of appropriate explanatory variables.

4.12. Model Evaluation and Residual Diagnostics

The previous sections indicated that the VAR and VECM models are defined as systems of linear equations, with each individual equation describing an endogenous variable as a function of the sum of its own lags and the lags of every other variable in the system. The fact that those equations are linear and have the same number of explanatory variables enables the use of Ordinary Least Squares (OLS) for the estimate the coefficients of the overall system. This implies that the OLS estimators need to satisfy the assumptions of the Classical Linear Regression Model (CLRM) across the equations of the system. The CLRM requirements are discussed in 4.12.2.

4.12.1. The Coefficient of Determination R-Squared

The coefficient of determination (R^2) is a statistical measure that shows how well the data fits the model. It generally measures the goodness of fit of the regression line to the data.

Say that TSS stands for the Total Sum of Squares and is described as:

$$TSS = \sum y_i^2 = \sum \left(Y_i - \bar{Y}\right)^2 \tag{4.33}$$

while RSS is the Residual Sum of Squares (RSS) given by:

$$RSS = \sum \hat{u}_i^2 \tag{4.34}$$

Y denotes the independent variable, $\bar{Y}$ the sample mean and u_t the residual.

Then the value of R-squared is defined as:

$$R^2 = 1 - \frac{RSS}{TSS} \tag{4.35}$$

In view of the above definition, the R-squared provides an indication of how much variation in the dependent variable the independent(s) is/are able to explain.

The values of R^2 range from 0 to 1. A value of 1 indicates a perfect fit and implies that all movements of the dependent variable are completely explained, while an R-square of 0 means that the dependent variable is not related to the explanatory variable(s) at all.

A high R^2 (in excess of 0.8) suggests that a very high percentage of variation in the dependent variable is explained, which translates into a good fit.

However, a low R-squared is not sufficient evidence against the model (Goldberger, 1991). Therefore, the modeller should be more interested in the theoretical connection of the explanatory variables with the dependent one, as well as the statistical significance.

Moreover, an increase in the number of explanatory variables is likely to inflate the R-squared, due to a possible (associated) decrease in residuals. However, the inclusion of more variables does not necessarily enhance the robustness of the model; on the contrary it may well have the opposite effect.

4.12.2. The Assumptions of the Classical Linear Regression Model (CLRM)

The reliability of the detected relationship between variables is subject to the validity of the following assumptions about the data:

- The conditional mean of stochastic disturbances is zero, given the value of regressors.
- The variance of the errors is constant and finite. No heteroscedasticity.
- There is no autocorrelation between the error terms. Their covariance is zero.
- The errors are not correlated with the corresponding explanatory variables.
- No perfect multicolinearity exists between the explanatory variables.
- The error terms are normally distributed.
- The number of observations must exceed the number of explanatory variables.
- The explanatory variables are assumed non-stochastic.
- The model should be correctly specified. This requires the choice of correct variables and correct functional form, and the avoidance of specification error or specification bias.

Should the model fail to satisfy the assumptions of the CLRM, the estimators may lose their consistency and unbiasedness or they may no longer be Best Linear Unbiased Estimators (BLUE). In particular, the coefficient estimates and the standard errors may become biased rendering hypothesis testing invalid, and the assumed distribution for the test statistic will not be appropriate.

Furthermore the model should be properly specified. Common specification errors involve over-fitting, that is the inclusion of unnecessary variables and under-fitting which refers to the omission of critical variables.

The current analysis focuses on the examination of the properties of residuals in the estimated models. In this respect, it is checked if key assumptions, such as homoscedasticity and absence of autocorrelation, are fulfilled.

The following paragraphs of this chapter discuss the main problems associated with the violation of certain assumptions of the CLRM.

4.12.3. Heteroscedasticity

Heteroscedasticity is present when the conditional variance of the error terms, ε_i, is unequal across the observations. It is a highly undesirable feature in econometric modelling.

Given the value of the explanatory variables X_i, homoscedasticity -which is the opposite of heteroscedasticity- is expressed as:

$$\begin{aligned} var(\varepsilon_i \mid X_i) &= E[\varepsilon_i - E(\varepsilon_i \mid X_i)] \\ &= E(\varepsilon_i^2 \mid X_i) \\ &= \sigma^2 \text{ (constant)} \end{aligned} \tag{4.36}$$

The presence of heteroscedasticity has serious implications for the estimators, as it harms their efficiency (even in large samples) and their minimum variance status; overall they are no longer BLUE. Therefore, under such circumastances the t and F tests lose their reliability and may provide erroneous results.

Yet, heteroscedasticity does not affect the consistency and unbiasedness of estimators. In fact, many authors argue that heteroscedasticity does not merit a reason to reject an otherwise good model (Mankiw, 1990), while Fox (1997) claims that the exact impact of heteroscedasticity is vague and he goes on to say that it becomes a real problem only when the largest variance is ten time higher than the smallest.

Heteroscedasticity may be caused by various reasons. A usual source of heteroscedasticity is the presence of outliers in the sample. These outlying observations are very distant from the rest of the sample data and can create heteroscedasticity, especially in small samples. Another cause of heteroscedasticity can be the uneven distribution of an explanatory variable. If it is positively or negatively skewed, it may induce heteroscedasticity. Furthermore, heteroscedasticity might be owed to incorrect model specification, as a result of omission of important variables or inadequate functional forms. Lastly, heteroscedasticity may be due to inappropriate transformations of data.

There are a few diagnostic tests which are designed to detect variable variances. This study employs the White Heteroskedasticity test and the Auto Regressive Conditional Heteroscedasticity (ARCH) test.

4.12.3.1. White Heteroskedasticity test

These tests are based on White's (1980) general test for heteroscedasticity. The null hypothesis assumes homoscedasticity and the test checks if the non-constant explanatory variables are jointly significant.

The test is performed without Cross Terms, i.e. using only the levels and squares of the independent variables.

The test gives the LaGrange Multiplier (LM) chi-square statistic, which is distributed as a χ^2.

4.12.3.2. Auto Regressive Conditional Heteroscedasticity (ARCH) test

The Auto Regressive Conditional Heteroscedasticity (ARCH) test of Engle (1982) performs LaGrange Multiplier (LM) tests for ARCH effects in residuals. In general, ARCH models assume that the variance of errors terms is a function of error terms of past periods.

Although the White test is considered the best test for heteroscedasticity, when the dataset contains time series it is informative to check for ARCH errors.

4.12.4. Autocorrelation

Autocorrelation or serial correlation describes the correlation between the disturbance terms of different observations.

Symbolically,

$$E(\varepsilon_i \varepsilon_j) \neq 0, \quad i \neq j \tag{4.37}$$

where ε denotes the disturbances.

Even though some researchers make a distinction between the terms 'serial correlation' and 'autocorrelation', they are typically used interchangeably.

The most common sources of autocorrelation include model misspecification stemming from over-fitting or under-fitting, inertia or sluggishness of time series, data manipulation (resulting in smoothness and systematic patterns), extrapolation or interpolation of data, data transformation and non-stationary error terms.

The main consequence of autocorrelation is that the estimators are not efficient anymore, though they remain asymptotically normally distributed, unbiased and consistent. Therefore, the test statistics may not produce reliable estimates, while the R-squared may also provide misleading values.

There are several tests for autocorrelation, with the Durbin-Watson (DW) being the most commonly used. However, it is not a very powerful test, for it is based on certain conditions which cannot be fulfilled in the case of variables in first difference form. Those conditions call for the inclusion of a constant term, non-stochastic explanatory variables and no lags in the dependent variable. Moreover, the DW test is tailored to AR(1) errors, reducing the scope of this test. These weaknesses make an alternative test, the Breusch-Godfrey LM test, more suitable for the kind of this analysis.

4.12.4.1. Breusch-Godfrey LM test

The Breusch-Godfrey LM test can be used to test for ARMA errors of higher order than the DW test and can be applied irrespective of the existence of lagged dependent variables.

This test makes use of the estimated residuals in its formulation. It tests the null hypothesis of no serial correlation up to a specified lag and reports the F-statistics, which examine the lagged residuals in terms of their joint significance (as an omitted variable test).

4.12.5. Multicollinearity

Multicollinearity arises when there is a linear relationship among the explanatory variables. In that case, the estimators have large variances and the model coefficients contain large standard errors rendering their estimation imprecise. This may occur even if the R-squared values appear to be very large.

Nevertheless, despite the presence of multicollinearity, the estimators remain BLUE.

That is to say, that multicollinearity mainly affects the estimation of the model coefficients.

Another problem associated with the presence of multicollinearity is the sensitivity of the estimators to small changes in the data.

4.13. Forecasting - Criteria for a useful forecast

In the shipping market it is of paramount importance to develop forecasting models which are capable of providing the decision makers with relevant, practical, reasonable and thoroughly researched information. In this respect, the forecasts of this study should satisfy the following criteria:

- ***Relevance***

This refers to the particular area where the forecast focuses and to the extent to which it can be useful to practitioners.

The analysis of this thesis concentrates on the prediction of spot and period rates for different sizes of bulk carriers. The dilemma to enter the spot or the period market is faced by all ship operators, every time the previous employment of their vessels is terminated. Therefore, it would be very illuminating to obtain a hint as to the future levels of rates. Likewise, cargo owners weigh up if it is wiser to lock-into a long term contract at a fixed rate for the carriage of their cargoes or if it can be cheaper for them to continually seek tonnage in the spot market. Finally, numerous other related parties, such as shipbrokers, bankers, shipbuilders etc. can potentially use the forecasts of this analysis in order to complement their market assessment or consult their clients.

- ***Rationale***

As mentioned, predictions of spot and period rates are vital for a variety of shipping and shipping-related operations. Having a significant impact on the most crucial management decisions, forecasting has become an essential function of every business. Accurate forecasts can offer guidance and generally assist in decision making. Inability to make correct projections of the future state of the freight market may result in devastating financial losses.

This study adopts a multivariate modelling framework which factors in the most critical endogenous and exogenous variables. An integral part of this process is the selection between the VAR and VECM framework. This decision is contingent on the time series characteristics of each case. The rationale behind this approach is that the freight market is not isolated from its external environment. To the contrary, it is affected by global economic conditions, as well as by several other factors. This is apparent in all figures of Chapter 6, which illustrate the co-movement between freight rates and each of the exogenous variables. However, in order to ensure that this is not a matter of spurious correlation, a statistical justification of the explanatory power of the independent variables is provided. This is substantiated through Granger Causality tests and Variance Decomposition.

In addition, an alternative approach (i.e. the Box-Jenkins) is applied and serves as a benchmark for the assessment of the robustness of the previously described methodology. This technique is based on a different philosophy, as it adopts a univariate perspective and generates forecasts accordingly. The key idea of this framework is that the historical behaviour of rates is the sole determinant of their future evolution. In this context, a properly specified model tracks the historical fluctuations of the time series and identifies patterns that will be repeated in the future.

- ***Research***

The selection of explanatory variables is based on both theoretical and empirical analysis. In general, the specification and implementation of forecasting techniques, alongside the selection of the appropriate explanatory variables, requires a sound theoretical analysis, combined with econometrics. The present thesis is based on extensive analysis of every aspect of the dry bulk freight market and the factors affecting it. Furthermore, it contains a comprehensive literature review, which provides an account of the past research in this area. Thereafter, the focus is placed on quantitative methods and time series analysis, and this unfolds a detailed discussion of univariate and multivariate causal models. Eventually, these frameworks are adjusted to the novel approach of this thesis and the findings are evaluated.

4.14. Forecasting methods

Forecasting techniques can be divided into two broad categories: Quantitative and qualitative methods. The former comprises time series models and causal analysis models, while the latter is based on expert judgment.

The basic principle of time series models is that historical values can be used to predict future values. The ARIMA models which are used in the present thesis belong to this category.

Causal analysis forecasting models are determined by the relationship between a dependent variable and a number of independent ones, which are treated as either endogenous or exogenous. Some representative examples of this category include regression analysis models and the VAR-VECM framework (which is used in this study).

As opposed to the previously described quantitative methods, the qualitative forecasting approach relies on personal experience and expert knowledge in lieu of numerical data. It involves techniques such as surveys and the Delphi method.

4.15. The Box-Jenkins approach

4.15.1. Modelling Steps

Starting with the univariate case, the thesis adopts the most reliable and widespread method, the Box-Jenkins (1970) approach. The basis of this technique is the AutoRegressive Moving Average (ARMA) model. This model actually contains the **AR(p)** and **MA(q)** models. The mathematic representation of an **ARMA (p,q)** model is given by:

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{4.38}$$

where X_t is a time series c is a constant, the random variables ε_t, ε_{t-i} are white noise, p the order of autocorrelation, q the order of the moving average, and φ_i, θ_i are papameters.

The most important contribution of Box and Jenkins is that they respond to the stationarity limitation within the ARMA framework. In fact, ARMA models require stationary data and this largely restricts their applicability, since most series have unit roots. Box-Jenkins approach deals with this by differencing the successive observations of a series as many times as it is necessary until the (differenced) series becomes stationary.

Therefore, when the series is non-stationary, the most appropriate framework is referred to as AutoRegressive Integrated Moving Average **ARIMA (p,d,q)**. In essence ARIMA (p,d,q) has evolved from ARMA (p,q), with an extra parameter d representing the number of differencing to achieve stationarity.

The Seasonal ARIMA (SARIMA) model, is an extention of ARIMA (p,d,q) whereby a seasonal factor is added. The SARIMA model can be written as **SARIMA (p,d,q) (P,D,Q)**, where the capital letters P,D,Q refer to the counterparts of the parameters p,d,q for the seasonal model.

The ARIMA or 'Box-Jenkins approach involves the following modelling steps:

Step 1: **Identification**
This step includes stationarity testing - as a way to decide between ARMA and ARIMA-, and specification of the appropriate parameters (p,q) on the basis of correlograms.

Step 2: **Model Specification**
This step comprises the following two sub-steps:

- Examination of the autocorrelation (ACF) and partial autocorrelation (PACF) function. According to Yokum and Armstrong (1995), the forecasting model selection should be based on the precision of results. However, as there is no universally accepted measure of the accuracy of series' forecasting, the model is specified on the basis of the above examination.
- Determination of the optimum lags using the Akaike Information Criterion (AIC), and the Schwarz criterion. These criteria equip the model with a measure of goodness of fit and manage over fitting, by applying a penalty for excessive number of parameters. Thus, a new variable or lag will increase the penalty, despite reducing the error sum of square. The lower the criteria value the better the model specification.

Step 3: **Estimation**
Given the values (p, q), which have been specified in the previous steps, the method proceeds to the estimation of the ARMA terms using Least Squares.

Step 4: **Diagnostic checking**
This step examines the extent to which the models are valid and includes residual diagnostics, such as residual serial correlation and residual heteroscedasticity tests. In

addition, the R-squared of each model is calculated and reported.

Step 5: **Forecasting**
Generation of ex-post and ex-ante forecasts.

Step 6: **Evaluation of the forecasting accuracy**
The forecasting accuracy of the model is examined using the following criteria: Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE).

4.16. Causal Relationship Forecasting

The causal analysis models generally capture linear interdependencies among multiple variables. The concept of causal relationship forecasting is materialized by the construction of a proper model which predicts the future values of a dependent variable using independent variables other than time. The selection of the independent variables is a very critical step. The forecaster should ensure that they serve as leading indicators and at the same time they form a parsimonious model. What’s more, many seemingly causal relationships are in fact just correlated events. Therefore, a lot of care must be taken when selecting causal variables.

This study attempts to predict the future values of spot and period rates for Panamax and Capesize bulk carriers. To this end, the foregoing theoretical and empirical analysis determines the selection of appropriate independent variables. Hence, it is demonstrated that these should include: the fleet development of Panamax and Capesize vessels, the Chinese steel production, the Dry Bulk Economic Climate Index (DBECI), and the average bunker prices.

4.17. Dynamic Forecasting

Dynamic forecasting is a multistep process that predicts the values of the forecast sample using the previously forecasted values of the dependent variable. Initially, the first observation is estimated based on the lagged values of the dependent variable (one-step ahead forecast). This is followed by a number of consecutive predictions, which use the forecasted values of the previous steps. It is clear that the selection of the starting point is very crucial in this type of forecasting.

4.18. Static Forecasting

Static forecasts use the actual values of the lagged variables and generate one step ahead forecasts. Therefore, it is necessary to have actual data for every observation within the forecast sample, be it lagged endogenous or exogenous variable.

In this context, it is obvious that both static and dynamic forecasts will have a common starting point; i.e. the first observation in the sample.

4.19. Evaluation of Forecasting Accuracy

The evaluation of forecasts is not as straightforward as it may sound. Baranto (1977) argues that the correct examination of forecast errors and the forecast process itself can be equally challenging. For this reason, a proper assessment should be based on a combination of error statistics and not on a single criterion.

Forecast errors are indicative of the forecasting accuracy. The forecast error is the difference between the forecast value and what actually occurred. In fact, all forecasts contain some level of error. The main sources of error are: the bias which occur when a consistent mistake is made and the randomness that refers to errors that are not explained by the model being used. The predictive power of the proposed models will be examined using the following criteria:

- Mean Absolute Error (MAE)
- Root Mean Squared Error (RMSE)

4.19.1. Mean Absolute Error (MAE)

The mean absolute error is defined as:

$$\mathrm{MAE} = \frac{1}{N}\sum_{t=1}^{N}\left|F_t - A_t\right| \tag{4.39}$$

where F_t is the forecast value, A_t is the actual value and N is the sample size.

In time series analysis, it is a pretty widespread measure of forecasting accuracy. The

MAE is actually the average of absolute errors, providing an indication of the proximity of predictions to the actual values. The outcome is assessed according to the following rule of thumb: the larger the MAD the less accurate the model.

4.19.2. Root Mean Squared Error (RMSE)

In the same notation as above, the root mean squared error is defined by the formula:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(F_t - A_t\right)^2} \tag{4.40}$$

The MSE represents a measurement of the average of squared differences between the forecast and the actual values. This function corresponds to the variance and constitutes a measure of risk. Likewise, the RMSE corresponds to the deviation.

In general, when comparing two or more unbiased estimators, the one with the lowest variance is most desirable and the best predictor. Connecting this with the previously described convergence of MSE to the variance, it turns out that low values of MSE indicate a high degree of forecasting accuracy.

As opposed to the MAE, the MSE is more appropriate for forecasts that avoid great forecast errors. The main drawback of MSE is that it is highly vulnerable to outliers. Squaring magnifies their effect, weighing large errors more than small ones.

The root mean square error (RSME) is obtained by the square root of the MSE. This transformation does not affect the performance of this measure, but at the same time it does not correct the flaws of the MSE either.

4.20. Forecasting Methodology

In congruence with the above tools, this study employs three different forecasting techniques, which focus on the dry bulk freight market. These are based on the VAR/VECM, the VARX and the Box-Jenkins approach. The common objective of all these models is the generation of forecasts for the spot and period rates of the most representative categories of bulk carriers. It should be noted that all variables are modelled in logarithmic form.

Starting with the VAR/VECM, the first step is to test the time series for stationarity. If the data are found non-stationary, the next step is the investigation of the existence of co-integrating relations using the Johansen test (1991, 1995). The co-integrated variables are modelled within a VECM modelling environment, whilst the non-co-integrated within a VAR framework. Meanwhile, several lag length criteria are used, such as the sequential modified LR test statistic (LR), the Final prediction error (FPE), the Hannan-Quinn information criterion (HQ), the Schwarz information criterion (SC) and the Akaike information criterion (AIC) in order to come up with the most suitable number of lag intervals. In addition it is checked if the selected lag satisfies the no-residual-correlation criterion. If not, the selection is revised accordingly.

The next step is to fit the model and finally examine its specification in terms of serial correlation and heteroscedasticity. This purpose is served by several pertinent tests, such as the Residual Serial Correlation LM test and the Residual Heteroskedasticity test.

VARX models are built in a similar fashion and contain the same endogenous variables as their VAR/VECM counterparts, but they are enhanced by the addition of appropriate exogenous variables. The far-reaching goal of this study is to improve the forecasting accuracy of the previously described multivariate framework.

In addition to the aforementioned perspectives, the study adopts an additional approach, the ARIMA models, so as to obtain a complementary forecasting tool and eventually compare the predictive power of the proposed techniques.

The preceding steps lead to the development of appropriate modelling frameworks, which can potentially generate reliable forecasts. This allows the generation of comparable ex-post static and ex-ante dynamic forecasts by each model. Eventually, the predictive success of each approach is evaluated using the following criteria: Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE).

5. CONSTRUCTING A NEW COMPOSITE INDICATOR – THE DRY BULK ECONOMIC CLIMATE INDEX (DBECI)

5.1. Introduction

The economic environment constitutes an integral part of the context in which the freight market is developing. The profound connection of seaborne trade with the state of the economy has been reflected numerous times in the close relationship between business and freight cycles. It has also been documented ever since the early stages of the tramp market. For example, Isserlis (1938) points out the linkage between economic cycles and freight rate movements, noting that the demand for shipping is primarily triggered by the world economy. Platou (1970) pinpoints the influential role of the economic environment in the dry cargo market. For example, the sharp decline in the industrial production of 1958 reflected the sluggish world economy of that period which harmed the seaborne trade of raw materials and contributed to the falling freight rates.

The present study aims to capture those dynamics, by constructing a composite indicator which mirrors the macroeconomic environment of the dry bulk freight market. In particular, the Dry Bulk Economic Climate Index (DBECI) is composed of some carefully selected components and variables, which are consistent with its role as a leading indicator of the freight market. In fact each variable alone provides some stimulus to the future values of the freight rates (this is discussed in more detail in the following sections). Therefore, a new indicator can be formed by putting all those variables together and assigning the most appropriate weight to each of them. Such an indicator can gauge the relevant economic developments and provide advanced warnings of imminent changes in the freight market.

A major characteristic of the world economy is its cyclicality, which is compatible with the cyclical behaviour of the shipping market. On top of this, shipping cycles are frequently driven by economic cycles, reflecting the close ties of the demand for bulk carriers with the state of the economy. This cyclical process is occasionally precipitated by random economic shocks, which frequently have large-scale effects. These rare, but sudden disturbances cause substantial changes in the demand for shipping services, affecting the level of freight rates quite dramatically.

The high complexity of the world economy requires a painstaking process of analysing its fundamental factors. China and the US are at the core of this study, given the prominent role of their economies in the dry bulk market. In this regard, the variables making up the DBECI include several economic metrics of those two nations. This ensures that the underlying sample is not significantly influenced by the economic figures of countries that do not play an important part in the dry bulk seaborne trade.

The impact of the global economy on the dry bulk freight market has been quite evident over the course of shipping history.

The Wall Street Crash of 1929 and the subsequent great depression of 1930s set off a prolonged shipping recession which translated into a sharp drop of trade volume and a large number of lay-ups.

The global economic conditions deteriorated again in 1997, due to the crisis of the Asian economies. The falling industrial production dragged the freight market downwards. This lasted until 2000, when the 'Asian crisis' ended and the industrial production got back on track. The improved economic fundamentals led to a long anticipated rebound of the freight market, even though it proved short-lived.

The most notable surge of the freight market occurred between 2003 and 2007, when the rates reached all-time highs. The spurring growth of China and its massive imports of raw materials was the main driver behind this market rally. This ceased in the second half of 2007, when a deep financial crisis spread to the world economy and ultimately to the shipping market, causing an unprecedented plunge of freight rates in the second half of 2008.

5.2. Methodology

The aggregation of different individual indicators into a common composite indicator requires sound theoretical and quantitative analysis. Thus, the first step involves the development of the theoretical framework, which dictates the selection process of the underlying variables and explains their relevance to the dry bulk freight market. Furthermore, the DBECI is broken down into three sub-groups: power of consumers, liquidity, and industrial activity. This nested structure reflects the conceptual formation of the composite indicator by three distinct driving forces, each of which is described by a set of representative variables.

The data analysis begins with normalization of the selected indicators, so that they become comparable. Then multivariate analysis takes over in order to explore the overall structure of the indicators and ultimately apply an appropriate weighting method.

Most indicators rely on equal weights, but this study refrains from making use of this simplistic weighting scheme, so that it can reflect on the relative importance of each sub-indicator and also avoid other issues such as double counting. In fact, equal weights can be highly misleading and it is better to be avoided. Lovell, Pastor, and Turner (1995) state that the component parts of an indicator should not be restricted by equality.

This potential limitation is sidestepped by the adoption of a linear programming method which generates appropriate weights for the sub-indicators. In this respect, the weights are assigned using the ‘Benefit of the Doubt approach’ (BOD) (Melyn & Moesen, 1991; Cherchye, Moesen, Rogge, & Van Puyenbroeck, 2007), which derives from the Data Envelopment Analysis (DEA) (Charnes, Cooper and Rhodes, 1978). The core idea of BOD is that the assigned weights are estimated on the basis of the relative performance of each sub-indicator against a benchmarking frontier. In particular, the aggregation and weighting of the eight individual sub-indicators into a common indicator is based on an extension of the BOD approach, which includes an ideal time observation that acts as the absolute, unique benchmark for all time periods and thus makes the assessment scores constant over time. A detailed description of the mathematical background of this modified technique is beyond the scope of the current study, but it can be found in Tsioumas, Smirlis and Papadimitriou (2016).

5.3. Data and Descriptive Statistics

The data on each sub-indicator are gathered from various sources. Specifically, the New Residential Construction (or Housing Starts) is published monthly by the U.S. Department of Commerce's U.S. Census Bureau, the Euro/USD exchange rates are retrieved from Eurostat, the Yuan/USD and the World Industrial Production from the Global Economic Monitor (GEM) (World Bank Group), the Brent Crude Oil Price from Clarkson Shipping Intelligence Network, the Federal funds effective rate and the Consumer Credit Outstanding (Levels) (US) from the Board of Governors of the Federal Reserve System and finally the Manufacturing and Trade Inventories and

Sales (US) from the U.S. Department of Commerce's U.S. Census Bureau

Table 5 presents the Descriptive Statistics for each sub-indicator of the DBECI.

	Mean	Min	Max	Standard Deviation	Skewness	Kurtosis
Power of Consumers						
New Residential Construction	1355.04	513	2263	543.53	-0.11	-1.41
Euro/USD	1.22	0.85	1.58	0.18	-0.52	-0.68
Yuan/USD	7.48	6.05	8.28	0.84	-0.38	-1.58
Brent price	63.36	10.25	137.19	34.95	0.28	-1.32
Liquidity						
Fed rate	2.25	0.07	6.54	2.17	0.54	-1.24
Consumer Credit Outstanding	2336883.8	1431200	3233200	467178.3	-0.22	-0.88
Industrial Activity						
Industrial Production	1337.01	1020	1710	170.68	0.06	-1.16
Inventories	1028734.9	674466	1400400	184228.8	0.19	-1.14

Table 5: Descriptive Statistics (Index components)

5.4. Normalisation of data

Normalization is an essential step towards the construction of the composite index, considering that the sub-indicators are expressed in different units of measurement. This adjustment makes data handling possible, as they are converted in a common scale.

In the context of the BOD approach, the values of each sub-indicator are normalized using max-min rescaling. Say x_{ij} is a sub-indicator then the normalized values $\overline{x}_{ij}$ will be given by the following formula:

$$\overline{x}_{ij} = \frac{x_{ij} - x_{i\min}}{x_{i\max} - x_{i\min}} \tag{5.1}$$

where $x_{i\min}$, $x_{i\max}$ are the lowest and highest bounds respectively.

5.5. Conceptual Framework

The DBECI is divided into three major components (i.e. Power of Consumers, Liquidity and Industrial Activity). Each of them describes a separate dimension of the DBECI and their combination shapes the final composite indicator. This division gives rise to a nested structure and reflects the conceptual formation of the composite indicator by the aggregation of three distinct driving forces. The underlying sub-indicators are the New Residential Construction (US), the Euro/USD and Yuan/USD Exchange rates, the Brent Crude Oil Price, the Federal funds rate, the Consumer Credit Outstanding (US), the World Industrial Production and the Manufacturing and Trade Inventories (US). Specifically, the precise allocation of sub-indicators with respect to the corresponding component parts is presented below.

Index Components:

1) Power of Consumers

- *New Residential Construction (US)*
- *Exchange Rate Euro/USD*
- *Exchange Rate Yuan/USD*
- *Brent Crude Oil Price*

2) Liquidity

- *Federal funds rate*
- *Consumer Credit Outstanding (Levels) (US)*

3) Industrial Activity

- *World Industrial Production*
- *Manufacturing and Trade Inventories (US)*

In what follows the chapter provides a description of each individual sub-indicator, as well as explanations of its linkage with the dry bulk freight market.

5.5.1. New Residential Construction (US)

New residential construction (or Housing Starts) captures the newly issued building permits, the new construction projects and the housing that were brought to completion. Its significance lies in the fact that the housing sector is one of the major investment options and accounts for a considerable part of consumer spending. In particular this indicator tracks the constructors' behavior and reflects their market expectations.

The construction industry uses several dry bulk commodities such as steel, cement, clinker etc. Therefore, an increase in construction activity pushes the demand for such commodities upwards, favoring the bulk carriers.

5.5.2. Consumer Credit Outstanding (Levels)_US

The Federal Reserve releases monthly the Consumer Credit report which monitors the consumer credit conditions, tracking the changes in the consumer outstanding debt, as this is measured by the combination of revolving and non-revolving credit. Specifically, revolving credit mainly involves credit card loans and prearranged overdraft plans, while non-revolving comprises education, vehicle and personal loans.

This variable actually expresses the availability of credit for consumers. To that extent, it is a major determinant of consumer spending and needs to be taken into careful consideration. Especially since a large variety of products and services are bought on credit.

5.5.3. Exchange Rates: Euro/USD and Yuan/USD

In the aftermath of the breakdown of the Bretton Woods system in 1971, the global economy has switched to floating exchange rates, which are highly volatile. This has largely impacted the world trade, re-establishing the trading relationships and activities, and rendering them reliant on the exchange rates fluctuations.

The exchange rate of EUR against USD has a significant impact on the Trans-Atlantic trade and this extends to the entire dry cargo market. In particular, a strong USD is seen as very expensive by European importers and this affects negatively the US exports of dry commodities, such as grain and coal, to Europe. Likewise, the Chinese imports from the US are significantly affected by the prevailing exchange rate.

5.5.4. Brent Crude Oil Price

Brent crude price tracks the prices of crude oil in the Atlantic and serves as a leading benchmark for the global oil trade. The Brent crude oil price is a major driver of the world economy. As oil prices fluctuate, inflation follows suit and ultimately determines the buying power of consumers. Crude oil is a prime source of energy and its products have various uses that range from heating and electricity generation to their utilization as fuel in every mode of transport. Importantly, a possible rise in oil prices increases the production and transport costs, and eventually it is passed on the end user through higher product prices. Consequently, higher oil prices may translate into lower consumer spending and in turn into sluggish trading activity and diminished demand for raw materials.

Yet, this is not always the case. Despite the two oil crises of 1973 and 1979 and the collapse of the tanker market, the dry bulk market withstood this challenging economic environment and boomed on the back of dry commodities stockpiling and port congestion. As a matter of fact, the rising oil prices favoured the dry cargo market, as they increased the revenues and the liquidity of oil producing countries, providing a boost to their trading activity. Furthermore, the high oil prices of that period proved to be very beneficial for the coal trade, which was used as a substitute for oil. Consequently, this also contributed to the booming dry bulk market. Before long, the outset of an economic recession, combined with falling oil prices and some other factors, led the dry bulk market to a slump. (Stopford, 2009)

5.5.5. Federal funds rate

The US federal funds rate represents a target interest rate that is set by the Federal Open Market Committee and effectively determines the interbank borrowing. When Fed decides to raise the rate, banks are discouraged from borrowing money and subsequently the loan interest rates rise, disincentivizing investments and generally reducing consumption. In this context, consumers typically prefer to deposit money into their bank accounts, exploiting the higher rates, rather than borrowing debt to buy goods or assets.

Moreover, a possible Fed rate hike could enhance the attractiveness of the USD relative to foreign market currencies. This may be harmful for the US exports, as the devaluation of other currencies against the USD, will make the US exported goods more expensive.

5.5.6. World Industrial Production

World industrial production measures the industrial output in the global economy. This includes mining, manufacturing, electricity power, and utilities.

Stopford (1999) illustrates that world industrial production is strongly related to seaborne trade. He also provides historical evidence that falling industrial production played a central role in harming the demand for ships. Focusing on the dry cargo market, the level of industrial production is closely linked to the volume of seaborne trade of the underlying raw materials. Therefore, a sudden drop in industrial production can spiral the freight market downwards.

5.5.7. Manufacturing and Trade Inventories and Sales (US)

The Manufacturing and Trade Inventories and Sales (US) provide insights on the economic conditions. This metric corresponds to the aggregated value of inventories and sales across the manufacturing, retail and wholesale sectors.

High inventory levels indicate slowing sales and the economy is contracting too. In this sense, this variable is tied to the state of the economy and the trading activity alike, providing useful clues about the demand for the underlying raw materials. A large chunk of the latter is imported by bulkers, marking the key role of inventory levels for the dry bulk market.

Figure 3 presents the evolution of DBECI from January 1999 to July 2014. This composite indicator, as explained, is constructed by the aggregation of the previously described variables. It is noteworthy that the movements of DBECI prior to 2007 demonstrate that this leading indicator would have been able to predict the market crash of 2007 and the subsequent shipping market recession.

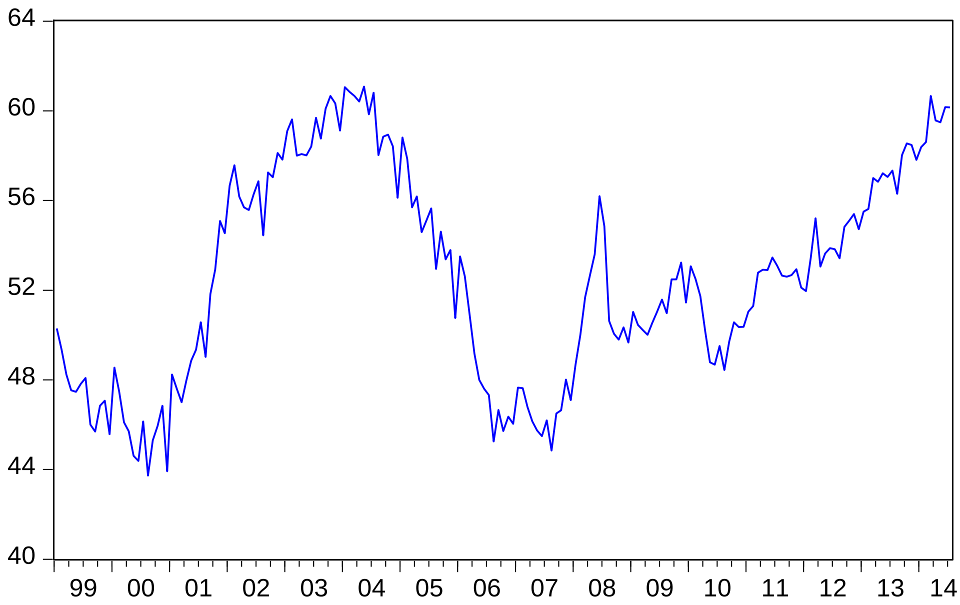


Figure 3: DBECI

The next chapters will explore the relationship of this indicator with the dry bulk freight market and ultimately its utilization in forecasting models.

6. IMPACT OF EXTERNAL FACTORS ON THE FREIGHT MARKET

6.1. Introduction

The dry bulk freight market is essentially an open system and as such it is in constant interaction with its external environment. Therefore, it will be utterly useful to specify the most critical variables in terms of their impact on rates. This will reinforce the in-depth analysis of freight rate fluctuations, laying the foundation for the modeling work that will follow.

As discussed in the literature review of Chapter 3, many authors have attempted to identify the key factors that affect the freight market. However, the complex nature of this market suggests that there might be more outside factors that have a significant effect on freight rates.

In this reading, the current analysis undertakes to detect additional factors that play an influential role in the transportation of dry cargo. This is accomplished using causality and Impulse Response analyses. In particular, certain variables which can theoretically be viewed as leading indicators of future freight rates are shortlisted and then their dynamic relationship with the Baltic Exchange indices for different vessels sizes is empirically investigated. This set of variable comprises the Dry Bulk Economic Climate Index (DBECI), the average IFO price, the Chinese steel production, the port congestion and the commodity prices of the major bulks.

6.2. Data

The analysis is performed using the EViews software and the dataset consists of monthly time series for the period starting from January 1999 to July 2014. The Baltic exchange indices are published by the Baltic Exchange. Monthly historical data for BCI, BPI, BSI (available from July 2005 onwards) and Chinese crude steel production were obtained from the Clarkson's Research Services Ltd (CRLS) database. The same source also provides data for IFO (380 cst) bunker prices, as well as for Capesize Port Congestion (as a percentage of the Capesize fleet) (from January 2010 onwards), Panamax Port Congestion (as a percentage of the Panamax fleet) (from January 2010 onwards) and Handymax Port Congestion (as a percentage of the Handymax fleet (from January 2010 onwards). The latter was used due to the unavailability of port congestion data for Supramax. Therefore data was found for the most closely related vessel category.

The commodity prices data were taken from World Bank. All commodity prices are expressed on a Free On Board (FOB) basis. Also, it is important to mention that there are no data for FOB iron ore prices after the December of 2010, due to the introduction of Cost and Freight (CFR) China's spot pricing. In a future study, the analysis can be enriched with more recent data which could be obtained by subtracting the Australia – China Capesize freight rates from the CFR price. The prices of the Australian thermal coal refer to 6,300 kcal/kg of less than 0.8% and sulfur 13% ash, from 2002 onwards, whilst the grade under consideration prior to this was: 6,667 kcal/kg of less than 1.0% sulfur and 14% ash content. The iron ore of this analysis has a 64.5% Fe content and the wheat type is no. 2 Hard Red Winter (ordinary).

Finally, the data sources of the underlying sub-indicators of the DBECI are stated in Chapter 5.

It should be noted that the data analysis and the relevant tests are performed in log-transformed data.

6.3. Descriptive Statistics

Table 1: Descriptive Statistics

	Mean	Min	Max	Standard Deviation	Skewness	Kurtosis	J-B
Supramax							
BSI	7.456384	6.056784	8.784468	0.631458	0.29388	2.483711	2.779578 [0.249128]
Panamax							
BPI	7.621196	6.244167	9.27153	0.699573	0.405845	2.412986	7.818366 [0.020057]
Capesize							
BCI	7.976203	6.767343	9.729610	0.710936	0.433155	2.412623	8.444516 [0.014665]
AVG_IFO	5.665112	4.114164	6.606637	0.650939	-0.195059	1.803429	12.34179 [0.002089]
Steel_Prd_Ch	10.293280	9.108972	11.162400	0.652012	-0.405058	1.705315	18.174040 [0.000113]
DBECI	3.959326	3.778041	4.112170	0.089844	-0.067338	1.886095	9.809107 [0.007413]
Commodity Prices							
Coal_Aus	4.055929	3.178054	5.261965	0.58744	-0.074772	1.703569	13.26995 [0.001314]
Iron _Aus	3.853521	3.282038	4.974386	0.575082	0.601563	1.910924	14.4848 [0.000716]
wheat_USG	5.317629	4.67367	6.118097	0.399924	0.099622	1.666786	14.15869 [0.000842]

Notes:

Figures in [.] are p-values

The Jarque-Bera (J-B) test is used to check for normality. The J-B statistic is asymptotically $\chi^2(2)$-distributed.

Table 6: Descriptive Statistics

First of all, the values of Baltic indices presented in Table 6 suggest that the larger the vessel size the higher the standard deviation. This corresponds to the higher volatility that characterizes the larger bulk carriers as a result of their reliance on certain trades.

As far as the shape of the sample distribution is concerned, it is illustrated that all three Baltic Exchange indices are positively skewed and the same holds for iron ore and wheat prices. All other variables are skewed to the left. According to Table 6 the sample kurtosis is less than 3 in all cases, therefore the distribution of each variable is flatter than the normal distribution. Lastly, the Jarque-Bera tests indicate that the sample data do not match a normal distribution, with the exception of BSI. However, the available data for BSI begin from July 2005. This means that the dataset for this particular index is very short, and this renders the Jarque-Bera test unreliable.

6.4. Theoretical Framework – Methodology

The lead-lag relationship refers to the situation where the values of a leading variable are linked to the values of a lagged variable at later times.

The analysis, first of all, tests for unit roots performing the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test and the Augmented Dickey–Fuller (ADF) test. Both tests are carried out in the log-levels and log-differences of the series of this analysis. The KPSS test examines the null hypothesis of stationarity under two different assumptions: First the series have an intercept, and second, a constant and linear trend. On the other hand, the ADF test is performed on the log- levels and log-differences of the same variables and tests the null hypothesis of non-stationarity under three different assumptions: An intercept, a constant and linear trend, and neither.

If the series are found non-stationary it is necessary to examine the existence of co-integration, using the Johansen test. Then, a VAR model is set up in the levels of the data, and the appropriate lags are determined using various lag length criteria, such as the sequential modified LR test statistic (LR), the Final prediction error (FPE), the Hannan-Quinn information criterion (HQ), the Schwarz information criterion (SC) and the Akaike information criterion (AIC) (See Appendix B). Thereafter, it is checked if the model is well specified by looking at its R-squared, and by applying the VAR Residual Serial Correlation LM test and the VAR Residual Heteroskedasticity Test.

Based on that model, the study employs Granger causality tests, as a way to investigate the existence of causal relationships. When the results are significant, it is sensible to proceed to Impulse Response (IR) analysis in order to explore the manner in which the variables affect each other. In particular, IR analysis will indicate if changes in one variable have a positive or negative effect on the other and how long this effect will last. It should be noted that if two variables are co-integrated, the IR analysis should be based on a VECM model and if not, on an unrestricted VAR.

6.5. Dry Bulk Economic Climate Index (DBECI) and Freight Market

The construction of the DBECI was described in Chapter 5. This section investigates the linkage of this composite indicator to the dry bulk freight market.

6.5.1. Empirical Results

6.5.1.1. Stationarity Tests

The ADF and KPSS unit root tests are carried out in the log-levels and log-differences of DBECI and Baltic indices. The KPSS tests the null hypothesis of stationarity under two different assumptions: First the series have an intercept, and second, a constant and linear trend. Alongside, the ADF test is performed on the log- levels and log-differences of the same variables and tests the null hypothesis of non-stationarity under three different assumptions: An intercept, a constant and linear trend, and neither.

	Log-Levels			**Log-first differences**		
	Intercept	Const. & trend	None	Intercept	Const. & trend	None
DBECI	-2.338886	-2.395470	-0.836106	-2.710362*	-2.704792	-2.658569***
BCI	-2.620608*	-2.517031	-0.113657	-10.15873***	-10.19775***	-10.18645***
BPI	-2.525228	-2.497892	-0.304766	-10.84987***	-10.89695***	-10.87895***
BSI	-2.142959	-3.442606*	-0.467363	-7.410905***	-7.415576***	-7.437151***

Notes:

*** indicates rejection of the null at 1% level, **at 5% and * at 10%

H_0: the series is non stationary, H_1: the series is stationary

Table 7: ADF test (DBECI)

	Log-Levels		Log-first differences	
	Intercept	Const. & trend	Intercept	Const. & trend
DBECI	0.228546	0.167210**	0.113229	0.094181
BCI	0.354190*	0.328912***	0.152610	0.035532
BPI	0.331683	0.331278***	0.167447	0.023463
BSI	0.770942***	0.094768	0.073853	0.041639

Notes:

*** denotes rejection of H_0 at 1% level, **at 5% and * at 10%

H_0: the series is stationary, H_1: the series is non stationary

The bandwidth for each test is chosen on the basis of the Newey-West selection using Berlett kernel

Table 8: KPSS test (DBECI)

The results of the ADF and KPSS tests are presented in Tables 7 and 8. The combination of those two tests provides sufficient evidence that all series are non-stationary in level forms, but stationary in first differences.

6.5.1.2. Co-integration Analysis

Given that the series are integrated of order 1, Johansen Co-integration test investigates the existence of co-integrating relations. The results are presented in Table 9:

Pair of variables	Lags	Hypothesized No. of CE(s)	Trace	0.05 CV (trace)	Max Eigenvalue	0.05 CV (Max Eigen.)
BCI - DBECI	8	None	10.16576	20.26184	6.904804	15.8921
BPI - DBECI	8	None	11.94067	20.26184	9.306167	15.8921
BSI - DBECI	5	None*	17.73629	20.26184	16.53512	15.8921
		At most 1	1.201178	9.164546	1.201178	9.164546

Notes:

* denotes rejection of the hypothesis at the 0.05 level.

The tests assume a restricted intercept in the co-integrating equation and no deterministic trends in the series.
The trace statistic tests H_0: r cointegrating relations against H_1: k cointegrating relations.
The max eigenvalue statistic tests H_0: r cointegrating relations against H_1: r+1 cointegrating relations.

Table 9: Johansen Co-integration test (DBECI)

The results demonstrate that there are no co-integrating relations. Therefore each pair of variables will be modelled using an unrestricted VAR.

6.5.1.3. Causality Analysis

Dependent variable	Excluded variable	Model	Lags	Chi-sq. (p-value)	Outcome	Residual Serial Corr. LM test	Residual Heteroskedasticity	R-sq.
BCI	DBECI	VAR	8	0.0074	causality at 1%	0.0755*	0.0084***	0.298954
DBECI	BCI		8	0.5710	No causality			
BPI	DBECI	VAR	8	0.0002	causality at 1%	0.4741	0.0001***	0.219027
DBECI	BPI		8	0.6256	No causality			
BSI	DBECI	VECM	5	0.0014	causality at 1%	0.7917	0.0000***	0.343648
DBECI	BSI		5	0.2633	No causality			

Notes:

*** indicates rejection of H_0 at 1% level, **at 5% and * at 10%

H_0: All lagged terms of excluded variable insignificant

The test statistic follows the chi-square distribution under H_0

VAR/VEC Residual Heteroskedasticity Tests: No Cross Terms / H_0: homoscedasticity in residuals

VAR/VEC Residual Serial Correlation LM test / H_0: no serial correlation at lag order h

Table 10: Granger Causality Test (DBECI)

Table 10 reports the outcome of several Granger causality tests between the BDECI and the respective Baltic Exchange indices. It turns out that there is significant unidirectional causality between the BDECI and each of the representative indices. Specifically, BDECI causes BCI, BPI and BSI at a 1% level. On the flip side, there is no causality running from any of those indices to BDECI. Therefore, this is an indication that BDECI could be used as an exogenous variable in a freight forecasting model.

The R^2 values show that the underlying models are satisfactory in terms of goodness of fit, relatively speaking. In addition the LM tests demonstrate that the models are free from serial correlation, with the exception of the BCI – DBECI VAR model, which appears auto-correlated at a high level though (10%).

Finally, even though the variables were converted into logarithmic forms, residual heteroscedasticity is still present as shown by the relevant White heteroscedasticity tests (no-cross terms). This may be due to the uneven distribution of the variables of this analysis, as indicated by the skewness that the descriptive statistics of Table 1 detect. Another possible source of heteroscedasticity is the existence of outliers, combined with the small sample size.

In any case, although the presence of heteroscedasticity harms the efficiency of estimators, it does not affect their consistency and unbiasedness. Hence, it normally does not merit a reason to reject an otherwise satisfactory model.

6.5.1.4. Impulse Response Analysis

The next step involves IR analysis. The figures below depict the responsiveness of the freight market to a positive shock to DBECI. Specifically, IR analysis detects the precise reaction of each Baltic index, given a sudden spike in the DBECI.

The vertical axis measures the magnitude of the effect of the shock on each variable and the horizontal axis the number of months after the shock.

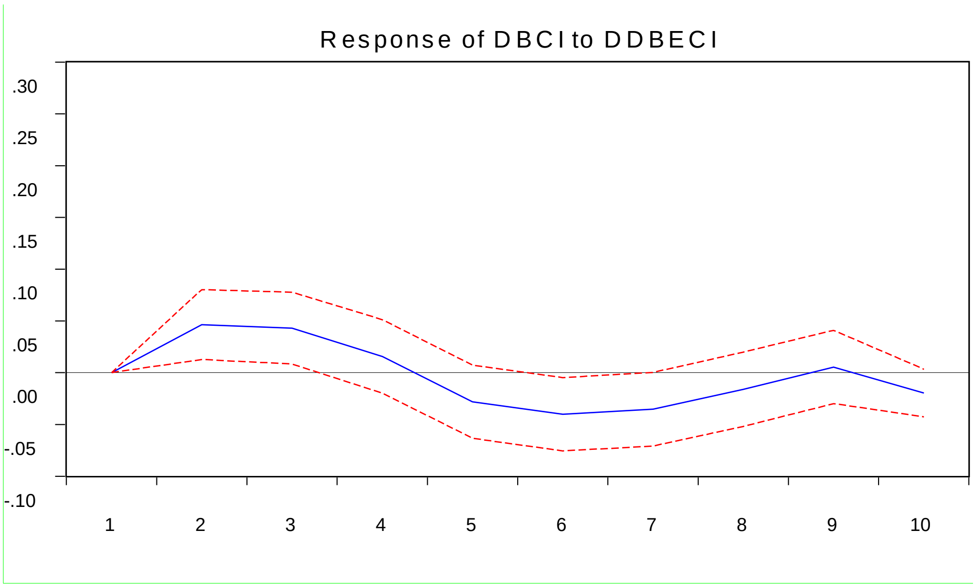


Figure 4: BCI and DBECI

According to Figure 4 the BCI is expected to head upwards over the short and medium term, suggesting that a booming economic environment has a long lasting positive impact on Capesize rates. Eventually, after some fluctuations the effect of the shock dies out.

This behaviour is consistent with the theoretical expectations of the relationship under consideration. Therefore, IR analysis provides empirical evidence of the direction of the relationship between DBECI and BCI and effectively validates the utilization of the DBECI as a leading indicator of the freight rates.

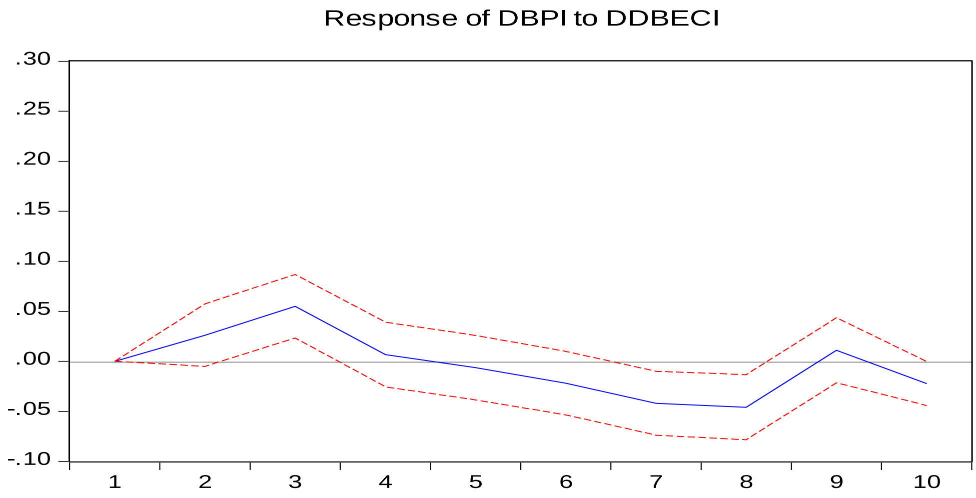


Figure 5: BPI and DBECI

Figure 5 shows the reaction of BPI to a positive shock to DBECI. The exhibit demonstrates that the response of the BPI is quite similar to BCI. The main difference is that in the case of Panamax vessels the full effect of the shock comes up slower, while it dies out a little sooner and slightly more steeply. Therefore, Capesize ships are more susceptible to changes in economic conditions, than the smaller and relatively more versatile Panamaxes.

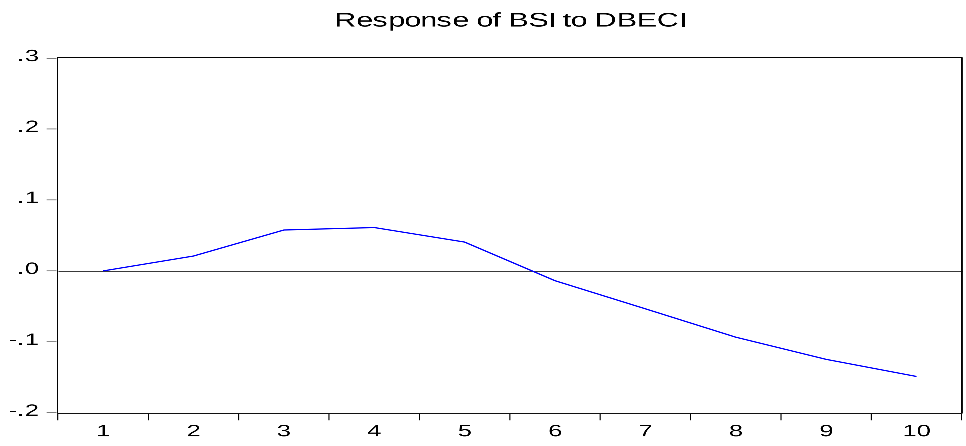


Figure 6: BSI and DBECI

Finally, Figure 6 shows that BSI responds in a similar manner as the other two types of bulk carriers. However, given that the BSI has been found co-integrated with the DBECI, the effect of the shock does not die out. On the contrary, the two variables reach a long-term equilibrium emanating from their co-integrating relation.

6.6. Steel Production and Freight Market

This analysis provides statistical evidence in support of the view, widely held in the dry industry, that there is a lead-lag relationship between Chinese steel production and dry bulk freight rates. Furthermore, this raises an important question about the direction of their relationship. Despite the plethora of studies on micro and macro economic determinants of freight rates, there have been no studies addressing these issues. Hence, this study undertakes such an investigation at an empirical level. The results are generally in line with industry expectations and contribute to the understanding of the interplay between commodity demand and freight market movements.

Given that this analysis is tailored to the dry bulk market, it uses the Chinese steel production as a proxy of the total steel which is produced using raw materials carried by sea. In this sense, the world steel output would not be an equally accurate measure, considering that many steel producing countries buy raw materials from domestic mines or mines in their proximity and transport them overland. To the contrary, China has developed into the major iron ore importer, while its steel industry accounts for over 50% of world steel production (Figure 7). At the same time, the dry bulk freight market is largely driven by Chinese iron ore (primarily) and coking coal imports. Considering that those two commodities are the basic components of steel, it is interesting to investigate how China's steel output interacts with the entire dry cargo market.

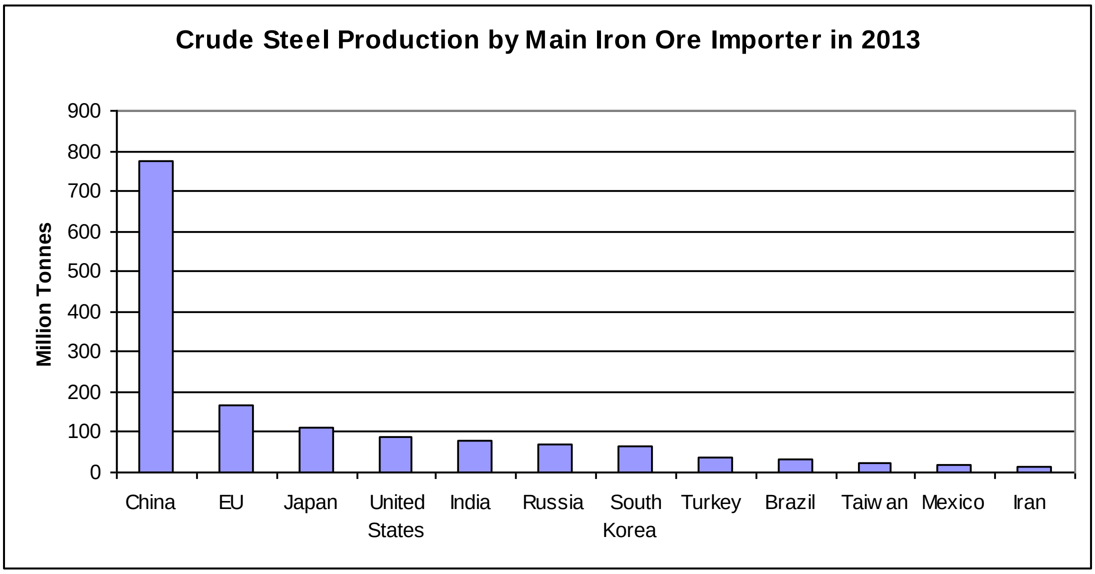


Figure 7: Steel output by iron ore importer

Chapter 3 provides a detailed account of the related research activities. However, it appears that there is a gap in the literature, as there has been no thorough empirical examination of the underlying relationship between those variable. The general consensus is that the level of steel production is a bellwether of demand for raw materials and in turn of freight rate fluctuations; though, so far this only has theoretical grounding. Hence, the current study intends not only to cover this gap, but also shed some light on this interaction.

6.6.1. Empirical Results

6.6.1.1. Stationarity Tests

The results, which are presented in Tables 11 and 12, reject the null hypothesis in almost all cases of level forms suggesting that the series are non-stationary.

	Log-Levels			Log-first differences		
	Intercept	Const. & trend	None	Intercept	Const. & trend	None
Stl_Prd_Ch	-1.873946	-0.797431	2.473431	-3.248202**	-3.655370**	-1.824531*
BCI	-2.620608*	-2.517031	-0.113657	-10.15873***	-10.19775***	-10.18645***
BPI	-2.525228	-2.497892	-0.304766	-10.84987***	-10.89695***	-10.87895***
BSI	-2.142959	-3.442606*	-0.467363	-7.410905***	-7.415576***	-7.437151***

Notes:

*** indicates rejection of the null at 1% level, **at 5% and * at 10%

H_0: the series is non stationary, H_1: the series is stationary

Table 11: ADF test (Chinese Steel Production)

	Log-Levels		Log-first differences	
	Intercept	Const. & trend	Intercept	Const. & trend
Stl_Prd_Ch	1.611345***	0.389544***	0.25282	0.10718
BCI	0.354190*	0.328912***	0.152610	0.035532
BPI	0.331683	0.331278***	0.167447	0.023463
BSI	0.770942***	0.094768	0.073853	0.041639

Notes:

*** denotes rejection of H_0 at 1% level, **at 5% and * at 10%

H_0: the series is stationary, H_1: the series is non stationary

The bandwidth for each test is chosen on the basis of the Newey-West selection using Berlett kernel

Table 12: KPSS test (Chinese Steel Production)

Since the variables are non stationary, Johansen Co-integration tests investigate the existence of co-integrating relations. The results are discussed in the next paragraph.

6.6.1.2. Co-integration Analysis

The results of the Johansen Co-integration test are presented in Table 13:

Pair of variables	Lags	Hypothesized No. of CE(s)	Trace	0.05 CV (trace)	Max Eigenvalue	0.05 CV (Max Eigen.)
BCI - Stl_Prd_Ch	3	None	18.60982	20.26184	11.31229	15.89210
BPI - Stl_Prd_Ch	2	None*	21.11337	20.26184	15.42237	15.89210
		At most 1	5.690995	9.164546	5.690995	9.164546
BSI - Stl_Prd_Ch	3	None	18.93434	20.26184	12.15577	15.89210

Notes:

* denotes rejection of the hypothesis at the 0.05 level.

The tests assume a restricted intercept in the co-integrating equation and no deterministic trends in the series.
The trace statistic tests H_0: r cointegrating relations against H_1: k cointegrating relations.
The max eigenvalue statistic tests H_0: r cointegrating relations against H_1: r+1 cointegrating relations.

Table 13: Johansen Co-integration test (Chinese Steel Production)

According to the results, there is only one co-integrating relation; that is between BPI and Chinese steel production. This implies that only this pair of variables will be modelled using a VECM model, whereas all the rest will require an unrestricted VAR.

6.6.1.3. Causality Analysis

On the basis of the VAR framework, Granger Causality tests examine the lead-lag relationship between Baltic indices and crude steel production. Table 14 summarizes the test results, together with the results of the tests examining the model specification.

Dependent variable	Excluded variable	Model	Lags	Chi-sq. (p-value)	Outcome	Residual Serial Corr. LM test	Residual Heteroskedasticity	R-sq.
BCI	Stl_Prd_Ch	VAR	3	0.0439**	causality at 5%	0.9587	0.0000***	0.155048
Stl_Prd_Ch	BCI		3	0.0743*	causality at 10%			
BPI	Stl_Prd_Ch	VECM	2	0.0002***	causality at 1%	0.0494**	0.0006***	0.132597
Stl_Prd_Ch	BPI		2	0.1005	No causality			
BSI	Stl_Prd_Ch	VAR	3	0.0015***	causality at 1%	0.5235	0.0000***	0.354126
Stl_Prd_Ch	BSI		3	0.0012***	causality at 1%			

Notes:

*** indicates rejection of H_0 at 1% level, **at 5% and * at 10%

H_0: All lagged terms of excluded variable insignificant

The test statistic follows the chi-square distribution under H_0

VAR/VEC Residual Heteroskedasticity Tests: No Cross Terms / H_0: homoscedasticity in residuals

VAR/VEC Residual Serial Correlation LM test / H_0: no serial correlation at lag order h

Table 14: Granger Causality Test (Chinese Steel Production)

The above results suggest that for the Capesize, there is significant causality from Chinese steel production to BCI (5%). In fact, a bi-directional relationship exists between China's steel production and Capesize rates. A similar two-way lead-lag relationship is generated in the Supramax sector as well. However, in Panamax vessels, the Chinese steel production leads the BPI, but the opposite is not true.

Finally, the results reported in Table 14 show that the variables under consideration are not serially correlated (except BPI-Steel Production) but heteroscedastic. However, the latter is a matter of small samples which are prone to noise that ultimately affects the variances of the disturbance terms. All in all, the current models can be considered acceptable in terms of goodness of fit and residual diagnostics.

6.6.1.4. Impulse Response Analysis

The last step of the methodology involves Impulse Response analysis. The results are provided in figures 8 - 10 respectively. The horizontal axis represents the number of months after the shock, while the vertical axis measures the magnitude of the effect on the variables.

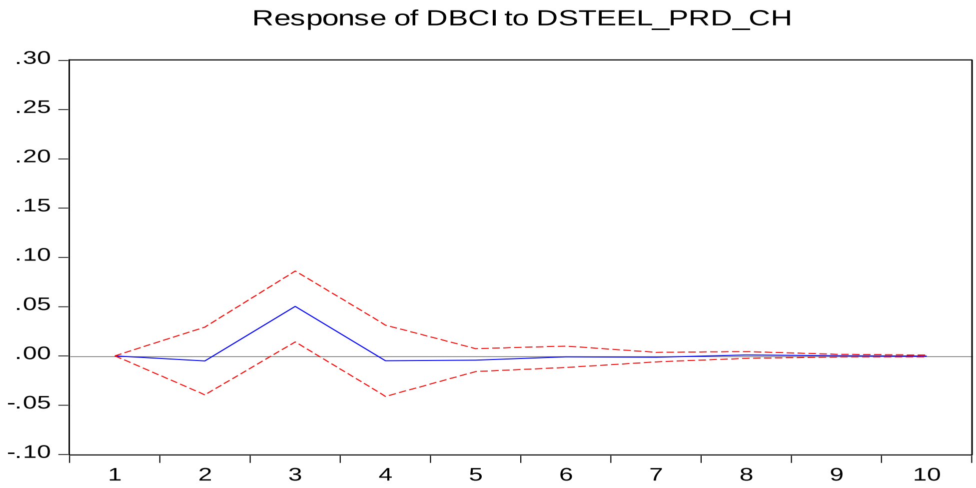


Figure 8: BCI and Chinese Steel Production

In Figure 8 it is observed that a positive shock to steel output, initially triggers a small-scale and marginally negative reaction of BCI, which can be attributed to market nervousness, as the Capesize market is highly dependent on Chinese iron ore imports and a high output may give rise to worries of overcapacity. However, the high level of steel production creates the need to restock the raw materials utilized in the steel mills, and usually this process starts taking place about one month later. This explains the positive response of BCI after approximately 1.5 month, as the graph shows. At some point the restocking phase ends, leading to a decline in the demand for transport of raw materials by Capesize vessels. Eventually, the effects of the shock die out, as no co-integration relationship exists.

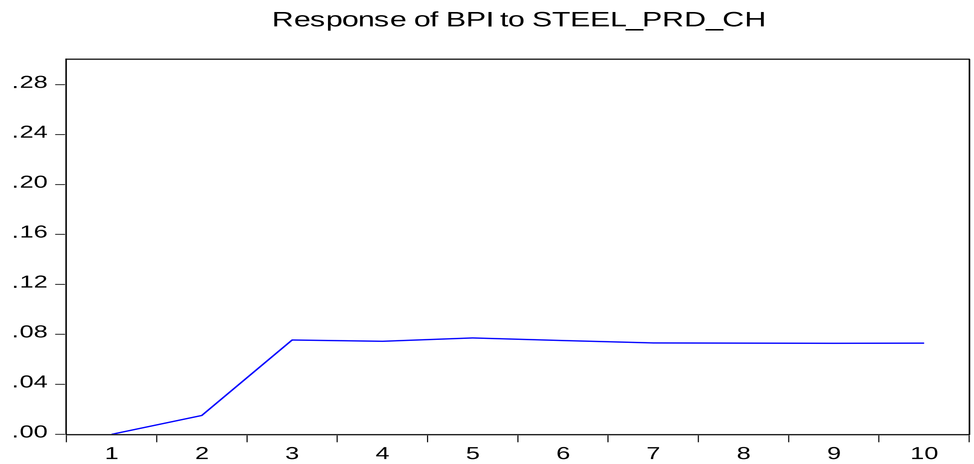


Figure 9: BPI and Chinese Steel Production

Looking at the BPI, in Figure 9, it is noticeable that Panamax ships, unlike Capesizes, are not negatively affected over the first 1-1.5 month, but their rates exhibit a modest upward trend. Given that Panamax vessels are not as much reliant on iron ore trade as Capesizes, the BPI is less volatile than the BCI and less affected by market sentiment in the short term. Thereafter, Panamax rates start to increase. This corresponds to the expectation of a new seasonal increase in production and imports of raw materials. Thus, after some overshooting, the BPI and the steel production reach a long term equilibrium emanating from their co-integration.

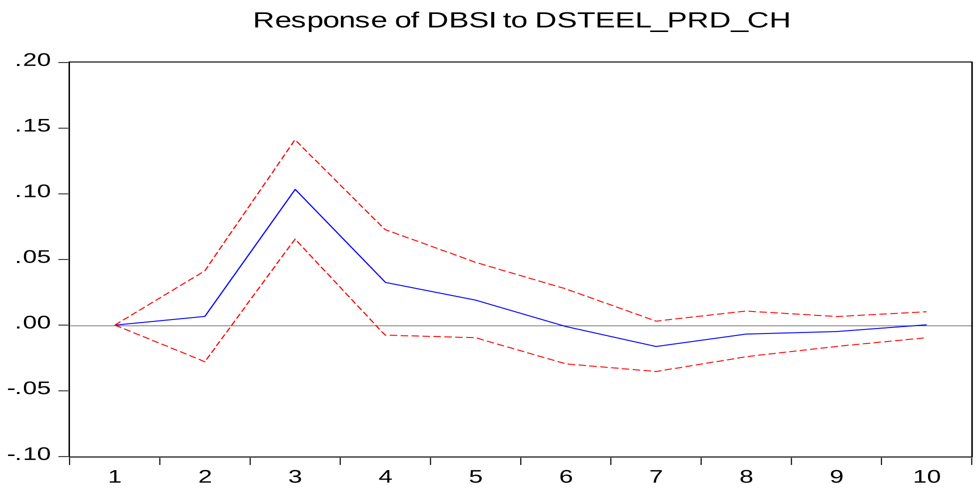


Figure 10: BSI and Chinese Steel Production

Figure 10 shows that the response of Supramax resembles the one of Panamax in the short-term. This was anticipated considering that this smaller vessel size targets a greater variety of cargoes, including minor bulks, and this makes them even less dependent on iron ore trade. Nevertheless, they overly engage in iron ore and coking coal trades, especially on short-haul routes within the Pacific. This explains their causal relationship with China’s steel production, as well as their positive response to a sudden increase in steel output.

6.7. Average Bunker Prices and Freight Market

The bunker prices vary from station to station and as a result a ship operator needs to check the offered prices of each refuel station separately and then plan the optimal route. However, this study intends to factor in the effect of the marine fuel oil prices on the freight market. This purpose is better served through an indicator that describes the average monthly price of the most widely used fuel in shipping, i.e. the Intermediate Fuel Oil (IFO) with a maximum viscosity of 380 Centistokes (cst).

Thus, the first step is to identify the most representative bunkering stations worldwide and thereafter to calculate the average IFO 380 price. These include: Rotterdam, Singapore, Japan, Houston, Los Angeles, Philadelphia, Genoa, Panama, Fujairah and Fos.

The relationship between dry freight rates and bunker prices has been investigated quite extensively in the literature. Chapter 3 provides an extensive literature review of this subject matter. In general, fuel cost usually accounts for over 50% of the vessel's voyage expenses. This means that when bunker prices rise, ship operators press for higher freight rates, in order to break-even. In this regard, high bunker prices trigger a considerable increase in the total transport cost, which translates into higher freight rates. Nevertheless, occasionally, high fuel prices might impede seaborne trade, due to the expensive fuel bill that fosters the total transport costs, acting as a disincentive for traders.

6.7.1. Empirical Results

6.7.1.1. Stationarity Tests

The results of the two unit root tests are reported in Tables 15 and 16 and reject the null hypothesis in almost all cases of level forms. Therefore all variables are non-stationary.

	Log-Levels			Log-first differences		
	Intercept	Const. & trend	None	Intercept	Const. & trend	None
AVG_IFO	-1.962037	-4.611779***	1.332059	-9.490358***	-9.532666***	-9.324351***
BCI	-2.620608*	-2.517031	-0.113657	-10.15873***	-10.19775***	-10.18645***
BPI	-2.525228	-2.497892	-0.304766	-10.84987***	-10.89695***	-10.87895***
BSI	-2.142959	-3.442606*	-0.467363	-7.410905***	-7.415576***	-7.437151***

Notes:

*** indicates rejection of the null at 1% level, **at 5% and * at 10%

H_0: the series is non stationary, H_1: the series is stationary

Table 15: ADF test (Average Bunker Prices)

	Log-Levels		Log-first differences	
	Intercept	Const. & trend	Intercept	Const. & trend
AVG_IFO	1.736481***	0.108420	0.096349	0.031577
BCI	0.354190*	0.328912***	0.152610	0.035532
BPI	0.331683	0.331278***	0.167447	0.023463
BSI	0.770942***	0.094768	0.073853	0.041639

Notes:

*** denotes rejection of H_0 at 1% level, **at 5% and * at 10%

H_0: the series is stationary, H_1: the series is non stationary

The bandwidth for each test is chosen on the basis of the Newey-West selection using Berlett kernel

Table 16: KPSS test (Average Bunker Prices)

6.7.1.2. Co-integration Analysis

Since the variables are non stationary, Johansen Co-integration analysis checks the existence of co-integrating relations. The results are presented in Table 17:

Pair of variables	Lags	Hypothesized No. of CE(s)	Trace	0.05 CV (trace)	Max Eigenvalue	0.05 CV (Max Eigen.)
BCI - AVG_IFO	3	None	12.43565	20.26184	9.000719	15.8921
BPI - AVG_IFO	4	None	10.83456	20.26184	6.893213	15.89210
BSI - AVG_IFO	2	None*	24.68866	20.26184	22.56969	15.89210
		At most 1	2.118967	9.164546	2.118967	9.164546

Notes:

* denotes rejection of the hypothesis at the 0.05 level.

The tests assume a restricted intercept in the co-integrating equation and no deterministic trends in the series.

The trace statistic tests H_0: r cointegrating relations against H_1: k cointegrating relations.

The max eigenvalue statistic tests H_0: r cointegrating relations against H_1: r+1 cointegrating relations.

Table 17: Johansen Co-integration test (Average Bunker Prices)

According to the results, there is only one co-integrating relation; that is between BSI and the average IFO price.

6.7.1.3. Causality Analysis

The results of the Granger causality test are presented in Table 18 below.

Dependent variable	Excluded variable	Model	Lags	Chi-sq. (p-value)	Outcome	Residual Serial Corr. LM test	Residual Heteroskedasticity	R-sq.
BCI	AVG_IFO	VAR	3	0.0298**	causality at 5%	0.2459	0.0000***	0.147165
AVG_IFO	BCI		3	0.2772	No causality			
BPI	AVG_IFO	VAR	4	0.0060***	causality at 1%	0.9502	0.0000***	0.132809
AVG_IFO	BPI		4	0.0633*	causality at 10%			
BSI	AVG_IFO	VECM	2	0.0000***	causality at 1%	0.0843*	0.0000***	0.331345
AVG_IFO	BSI		2	0.0724*	causality at 10%			

Notes:

*** indicates rejection of H_0 at 1% level, **at 5% and * at 10%

H_0: All lagged terms of excluded variable insignificant

The test statistic follows the chi-square distribution under H_0

VAR/VEC Residual Heteroskedasticity Tests: No Cross Terms / H_0: homoscedasticity in residuals

VAR/VEC Residual Serial Correlation LM test / H_0: no serial correlation at lag order h

Table 18: Granger Causality Test (Average Bunker Prices)

To that end, there is significant unidirectional causality from Average IFO to BCI, at a 5% level, while BCI does not cause the Average IFO price. In the case of BPI and BSI, it appears that they are both caused by Average IFO prices at a 1% level of significance. According to the tests there is two-way causality, as both the BPI and the BSI cause the Average IFO price at a 10% level.

The residual diagnostic tests and the R-squared values suggest that the models can be accepted, despite the presence of heteroscedasticity.

6.7.1.4. Impulse Response Analysis

The final step is to run Impulse Response analysis. The results are provided in figures 11 - 13 respectively. The vertical axis measures the magnitude of the effect of the shock on the variables, while the horizontal axis stands for the number of months after the shock

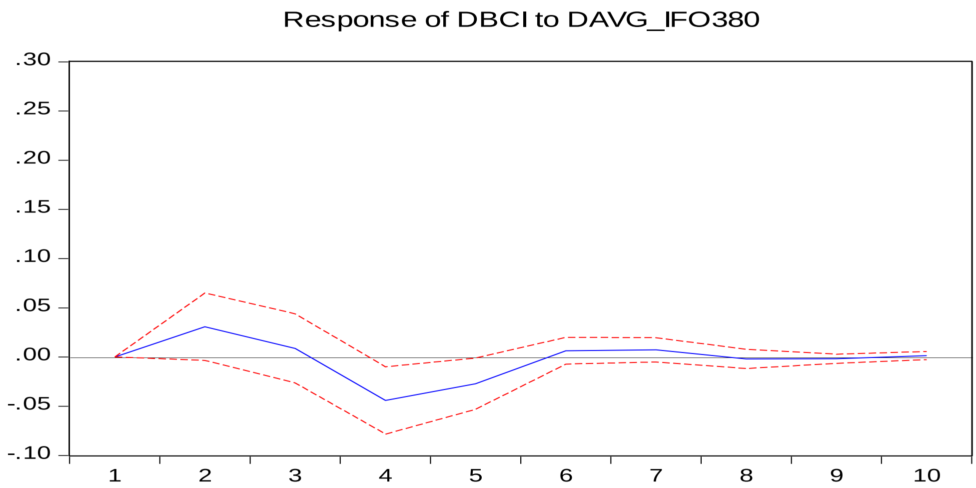


Figure 11: BCI and Average Bunker Prices

Figure 11 shows that a positive shock to the average IFO price will trigger a positive response of the BCI in the short run. After about three months, the effect of this shock will ease off and eventually dissipate.

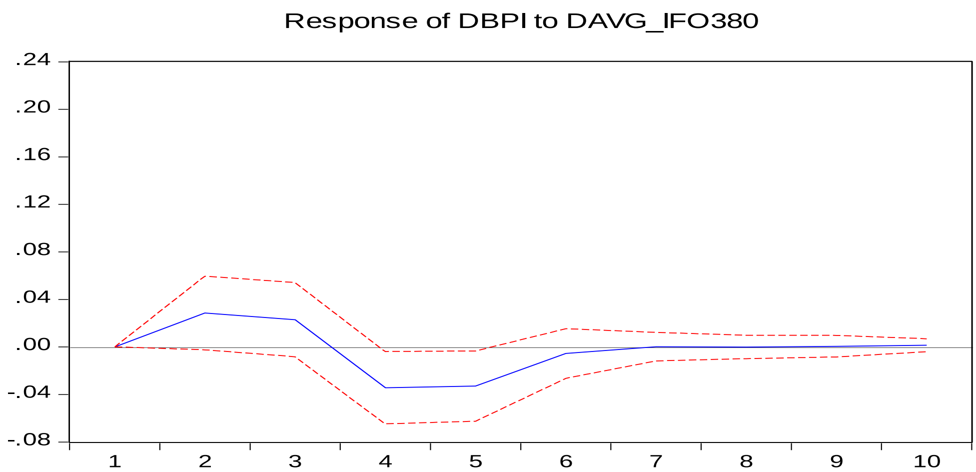


Figure 12: BPI and Average Bunker Prices

Likewise, the Panamax rates are also sensitive to a sharp increase in bunker prices. As Figure 12 illustrates, they surge during the first three months and then they start to abate till the effect completely vanishes.

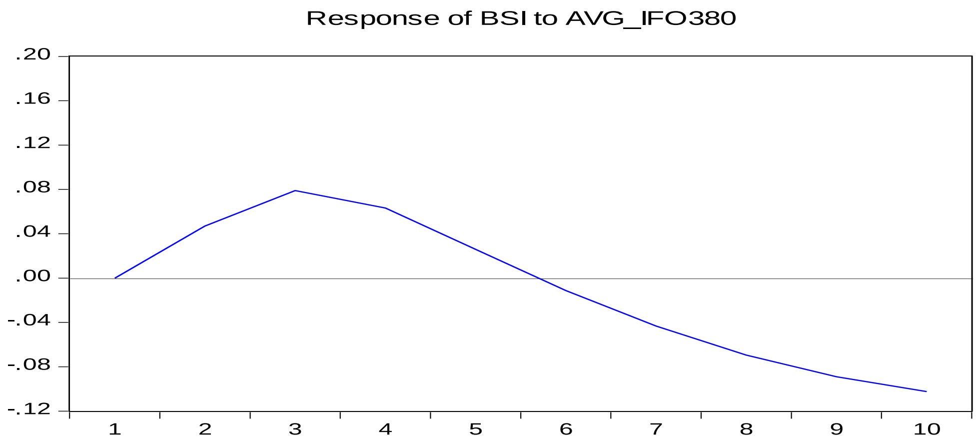


Figure 13: BSI and Average Bunker Prices

Finally, the impact of skyrocketed bunker prices on BSI is quite similar to the other two peer vessels. What differentiates this ship category is that BSI appears to have a co-integrating relation with average IFO prices. Therefore, the effect reaches a long-term equilibrium, instead of vanishing over time.

6.8. Commodity Prices and Freight Market

The aim of this analysis is to investigate empirically the relationship between the dry bulk freight market and the prices of 'major bulks'. The interacton between dry commodity prices and freight rates has not attracted so much attention in the maritime literature so far. However, changing commodity prices can influence the timing and quantity of imports and exports and, by extension, the volume of seaborne trade. In this context, many maritime practitioners tend to monitor the levels of commodity prices in order to obtain insights into the anticipated demand for bulk carries. Therefore the empirical examination of this relationship deserves further attention.

Hence, this section examines the underlying relationship between commodity prices and freight rates at an empirical level and then provides a theoretical interpretation. The elements of this analysis consist of representative prices of coal, iron ore and wheat, and Baltic Exchange indices that correspond to the most widely used vessel size for each commodity.

The dry cargo market is mainly driven by the trade of the 'so-called' major bulk cargoes, i.e. iron ore, coal and grain. In fact, the trade dynamics of those commodities actually shape the level of freight rates for the entire dry cargo market. The price of those commodities seems to interact with the respective freight rates. The present study investigates the existence of such a causal relationship and subsequently focuses on the way they are related.

In general, commodity prices reflect the level of economic activity. Changes in demand cannot be accommodated instantaneously by supply adjustments and as a consequence prices fluctuate accordingly. High commodity prices, as long as they are not driven by supply shocks, indicate robust economic activity and more vessels are employed to carry raw materials such as iron ore and coal, as well as commodities like grain to cover the increasing food consumption. Grains encompass a variety of products, but the most traded of them include wheat, coarse grains, and soyabeans. In particular, wheat is primarily used for human consumption (unlike coarse grains which are mainly used in livestock feed). This implies that high consumer demand for food products containing wheat, assuming a steady supply, is expected to inflate the prices of this commodity. According to Trostle (2008), the rapid growth in average income since the late 1990s was one of the prime contributors to higher food commodity prices, like grain prices. However, low commodity prices do not necessarily drag freight rates lower, unless they result from weak demand. In periods of excessive production, the low commodity prices act as an incentive for more imports, benefiting the freight market. On top of this, some trading practices are related to commodity prices. For example, sometimes China tends to accumulate huge stockpiles of iron ore and coal, and withhold imports until the prices get down to a critical level which triggers an upsurge in imports.

Conversely, transport costs are a significant portion of the total import costs and they may ultimately affect the selling price.

This analysis provides a quantitative assessment of the dynamics described above. In this context, it examines the interactive relationship between the price of the major dry bulk commodities and some selected dry cargo indices. It should be noted that only the pairs of variables with significant causation are reported.

6.8.1. Empirical Results

The BCI is modelled with respect to Australian coal and iron ore prices because both of these commodities are primarily shipped in Capesize vessels from Australia to China and Japan (mainly). Likewise, the BPI is analyzed in relation to the wheat exports from USG, since this ship type is generally preferred for this trade. Finally, given that Supramax is used at times for the carriage of Australian coal, the study examines if there is any linkage between BSI and coal price.

6.8.1.1. Stationarity tests

The ADF and KPSS unit root tests are performed in the log-levels and log-differences of the commodity prices and Baltic indices. The results, which are reported in Tables 19 and 20 respectively, reject the null hypothesis in almost all cases of level forms. Therefore all variables are non-stationary.

	Log-Levels			**Log-first differences**		
	Intercept	Const. & trend	None	Intercept	Const. & trend	None
Coal_Aus	-1.543081	-1.871604	0.504107	-9.278440***	-9.296026***	-9.261264***
Iron _Aus	-0.518144	-2.513173	1.163481	-11.45257***	-11.42865***	-11.35782***
wheat_USG						
BCI	-2.620608*	-2.517031	-0.113657	-10.15873***	-10.19775***	-10.18645***
BPI	-2.525228	-2.497892	-0.304766	-10.84987***	-10.89695***	-10.87895***
BSI	-2.142959	-3.442606*	-0.467363	-7.410905***	-7.415576***	-7.437151***

Notes:

*** indicates rejection of the null at 1% level, **at 5% and * at 10%

H_0: the series is non stationary, H_1: the series is stationary

Table 19: ADF test (Commodity Prices)

	Log-Levels		Log-first differences	
	Intercept	Const. & trend	Intercept	Const. & trend
Coal_Aus	1.409133***	0.181499**	0.101358	0.057427
Iron _Aus	1.26978***	0.248529***	0.121429	0.085554
wheat_USG	1.571722***	0.0886	0.048387	0.044197
BCI	0.354190*	0.328912***	0.152610	0.035532
BPI	0.331683	0.331278***	0.167447	0.023463
BSI	0.770942***	0.094768	0.073853	0.041639

Notes:

*** denotes rejection of H_0 at 1% level, **at 5% and * at 10%

H_0: the series is stationary, H_1: the series is non stationary

The bandwidth for each test is chosen on the basis of the Newey-West selection using Berlett kernel

Table 20: KPSS test (Commodity Prices)

6.8.1.2. Co-integration Analysis

The next step is the investigation of the existence of co-integrating relations using the Johansen Co-integration test. The results are presented in Table 21:

Commodity	Pair of variables	Lags	Hypothesized No. of CE(s)	Trace	0.05 CV (trace)	Max Eigenvalue	0.05 CV (Max Eigen.)
Coal	BCI - Coal_Aus	2	None	19.37321	20.26184	13.75200	15.89210
	BSI - Coal_Aus	2	None*	21.25867	20.26184	14.49940	15.89210
			At most 1	6.759270	9.164546	6.759270	9.164546
Iron Ore	BCI - Iron_Aus	3	None	18.37316	20.26184	12.68811	15.89210
Wheat	BPI - Wheat_USG	2	None	11.46379	20.26184	7.74861	15.89210

Notes:

* denotes rejection of the hypothesis at the 0.05 level.

The tests assume a restricted intercept in the co-integrating equation and no deterministic trends in the series.
The trace statistic tests H_0: r cointegrating relations against H_1: k cointegrating relations.

The max eigenvalue statistic tests H_0: r cointegrating relations against H_1: r+1 cointegrating relations.

Table 21: Johansen Co-integration test (Commodity Prices)

According to the results, there are two co-integrating relations; one between BCI and iron ore price and another one between BSI and coal price.

6.8.1.3. Causality Analysis

Table 22 summarizes the results of Granger Causality tests, as well as the results of the tests examining model specification.

Commodity	Model	Dependent variable	Excluded variable	Lags	Chi-sq. (p-value)	Outcome	Residual Serial Corr. LM test	Residual Heteroskedasticity	R-sq.
Coal	VAR	BCI	Coal_Aus	2	0.0867*	causality at 10%	0.0187**	0.0177**	0.129555
		Coal_Aus	BCI	2	0.0896*	causality at 10%			
	VECM	BSI	Coal_Aus	2	0.0005***	causality at 1%	0.1665	0.0005***	0.274252
		Coal_Aus	BSI	2	0.2580	No causality			
Iron Ore	VAR	BCI	Iron_Aus	3	0.0181**	causality at 5%	0.1264	0.0001***	0.329797
		Iron_Aus	BCI	3	0.0372**	causality at 5%			
Wheat	VAR	BPI	Wheat_USG	2	0.0506	causality at 5%	0.9935	0.6623	0.077409
		Wheat_USG	BPI	2	0.4191	No causality			

Notes:

*** indicates rejection of H_0 at 1% level, **at 5% and * at 10%

H_0: All lagged terms of excluded variable insignificant

The test statistic follows the chi-square distribution under H_0

VAR/VEC White Heteroskedasticity Test: No Cross Terms / H_0: homoscedasticity in residuals

VAR/VEC Residual Serial Correlation LM test / H_0: no serial correlation at lag order h

Table 22: Granger Causality Test (Commodity Prices)

The results reveal the existence of a bi-directional relationship in the cases of iron ore and coal, while they indicate that wheat price leads the BPI but the opposite is not true. Those findings can support decision making in both dry bulk chartering and commodity trading.

6.8.1.4. Impulse Response Analysis

The final step is to proceed to IR analysis. The focus is on the effect of commodity prices on the freight market. Therefore, the IR graphs under analysis depict the response of Baltic Indices to positive shocks to commodity prices.

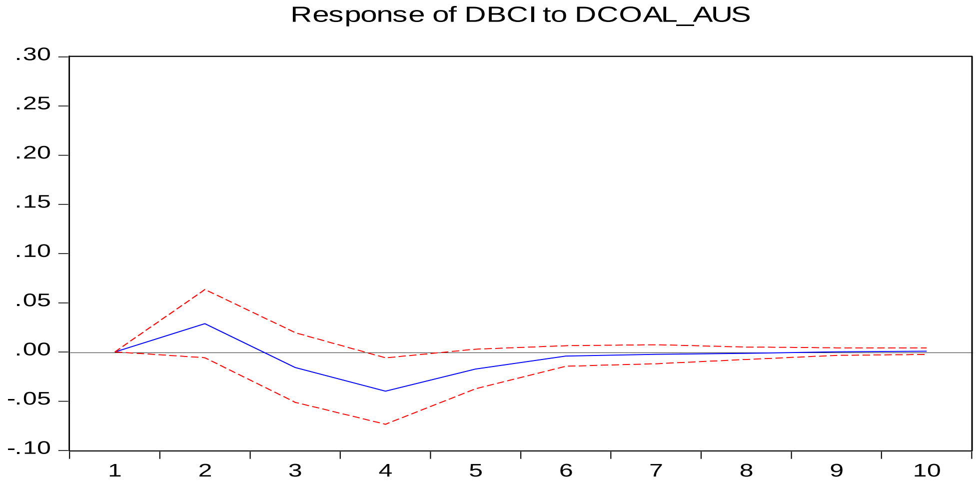


Figure 14: BCI and Coal Price

Figure 14 illustrates the response of BCI to a positive shock to the price of Australian coal. The exhibit actually implies that Capesize freight rates are drifting upwards for a certain period after a sudden increase in coal prices. Apparently this reflects an upswing in coal demand, which will be strong enough to boost coal exports. This is in turn beneficial for Capesize rates as coal shipments from Australia are mainly carried by Capesize vessels. However, this is not expected to last long; as the graph shows, at some point the high coal price hampers the coal trade, pushing the freight rates downwards.

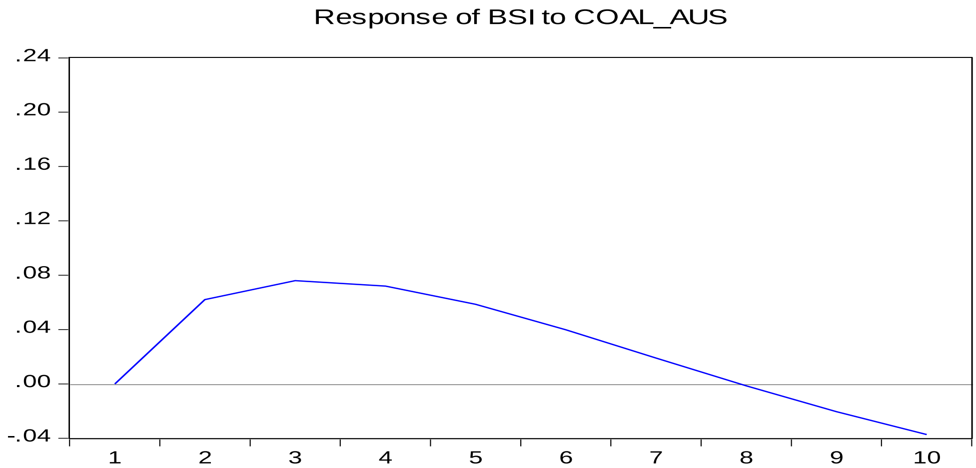


Figure 15: BSI and Coal Price

Figure 15 shows that BSI behaves in a similar fashion as the BCI over the short term. However, its drop is not as steep as in the case of Capesizes. This insensitiveness can be attributed to the low degree of volatility that characterizes the smaller vessels sizes.

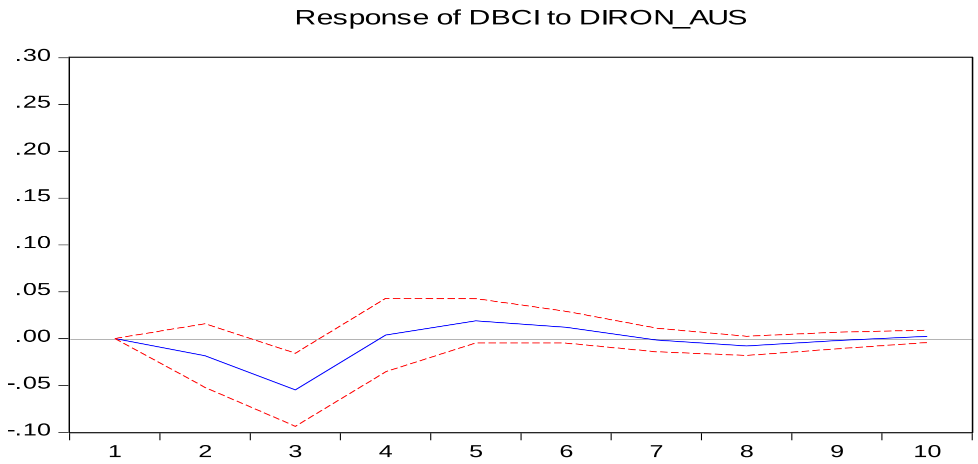


Figure 16: BCI and Iron Ore Price

Figure 16 suggests that a positive shock to the iron ore price pushes rates below the equilibrium level for some time until they recover and head upwards, towards a long-term equilibrium stemming from their co-integration. The iron ore trade is particularly sensitive to ore price fluctuation and as a result the initial response is negative. A price hike in this commodity seems to have an adverse effect on its trade in the short run. However, a few months later this effect subsides, as the graphs illustrates.

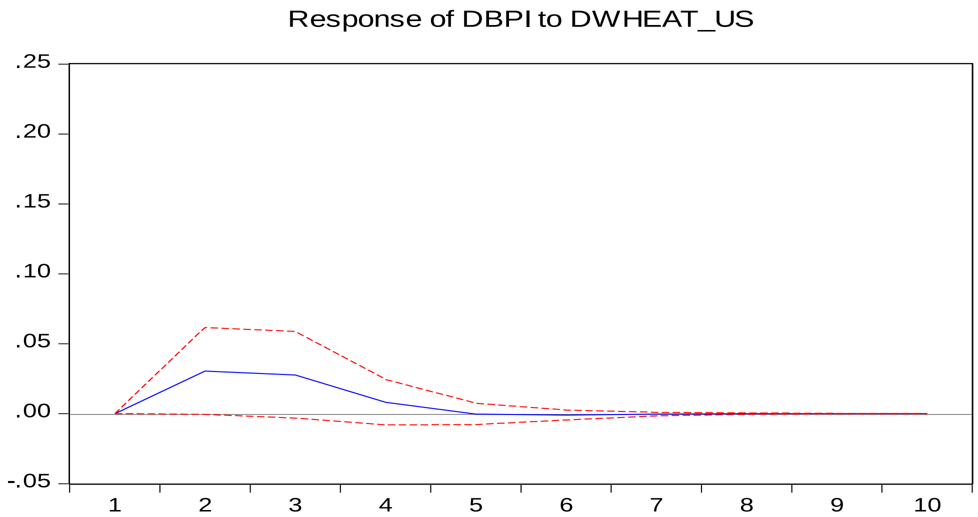


Figure 17: BPI and Wheat Price

Figure 17 depicts how BPI reacts to a positive shock to the US wheat price. The soaring wheat price is indicative of robust consumption and traders rush to fix tonnage to move cargoes and make a profit from the high wheat price. In this regard, charterers are ready to pay higher freight rates as long as a shipowner presents a vessel promptly.

6.9. Port Congestion and Freight Market

Port congestion can potentially influence freight rates. In general, time spent in port, relative to time spent at sea can have a significant effect on ship supply. When the port turnaround times increase, ships travel less frequently in a given time period and the (short-term) supply falls. Given that the freight rates are determined by the balance between supply and demand, it turns out that longer time in port is expected to have a knock-on effect on freight rates, pushing them upwards. That is to say that congestion may ultimately reinforce the dry bulk freight market. Effectively, port congestion absorbs much of the excess tonnage, providing a market relief.

Many times in the history of the dry bulk market, congestion has played an influential role in the development of shipping cycles. For instance, in 1980, congestion was one of the key drivers of the dry cargo market recovery. The booming US coal exports led to congestion in the domestic ports and raised the waiting time of ships to more than three months towards the end of the year. Similar congestion issues came up in West African and Middle Eastern ports, due to their poor infrastructure. Overall, this increased the need for available ships and drove the rates upwards, triggering a 50% year-on-year rise. The opposite happened 3-4 years later, when the elimination of port congestion, coupled with an economic downturn resulted in depressed freight rates Stopford (2009). Between 2003 and 2007 many ports were heavily congested as a result of severe weather conditions and poor infrastructure. This largely contributed to the market boom of that period.

6.9.1. Empirical Results

6.9.1.1. Stationarity Tests

The results of the two unit root tests are reported in Tables 23 and 24. They reject the null hypothesis in almost all cases of level forms. Therefore all variables are non-stationary.

	Log-Levels			Log-first differences		
	Intercept	Const. & trend	None	Intercept	Const. & trend	None
Cong_Cape	-3.524470**	-4.059646**	-0.887461	-8.326591***	-8.246193***	-8.369764***
Cong_Pmx	-3.159872**	-3.767521**	-1.228787	-9.745167***	-9.839376***	-9.774455***
Cong_Hmx	-3.162065**	-4.252115***	-2.434370**	-7.503366***	-7.469655***	-7.484993***
BCI	-2.620608*	-2.517031	-0.113657	-10.15873***	-10.19775***	-10.18645***
BPI	-2.525228	-2.497892	-0.304766	-10.84987***	-10.89695***	-10.87895***
BSI	-2.142959	-3.442606*	-0.467363	-7.410905***	-7.415576***	-7.437151***

Notes:

*** indicates rejection of the null at 1% level, **at 5% and * at 10%

H_0: the series is non stationary, H_1: the series is stationary

Table 23: ADF test (Port Congestion)

	Log-Levels		Log-first differences	
	Intercept	Const. & trend	Intercept	Const. & trend
Cong_Cape	0.645304**	0.171148**	0.172505	0.114037
Cong_Pmx	0.738893**	0.183900**	0.369572*	0.339336
Cong_Hmx	0.781518***	0.097543	0.134762	0.077703
BCI	0.354190*	0.328912***	0.152610	0.035532
BPI	0.331683	0.331278***	0.167447	0.023463
BSI	0.770942***	0.094768	0.073853	0.041639

Notes:

*** denotes rejection of H_0 at 1% level, **at 5% and * at 10%

H_0: the series is stationary, H_1: the series is non stationary

The bandwidth for each test is chosen on the basis of the Newey-West selection using Berlett kernel

Table 24: KPSS test (Port Congestion)

6.9.1.2. Co-integration Analysis

As a next step, the Johansen Co-integration test investigates the existence of a long-term equilibrium.

Pair of variables	Lags	Hypothesized No. of CE(s)	Trace	0.05 CV (trace)	Max Eigenvalue	0.05 CV (Max Eigen.)
BCI - Cong_Cape	1	None*	22.10549	20.26184	16.52982	15.89210
		At most 1	5.575674	9.164546	5.575674	9.164546
BPI - Cong_Pmx	1	None*	21.10717	20.26184	15.27828	15.89210
		At most 1	5.828895	9.164546	5.828895	9.164546
BSI - Cong_Smx	1	None*	19.86777	20.26184	16.33397	15.89210
		At most 1	3.533800	9.164546	3.533800	9.164546

Notes:

* denotes rejection of the hypothesis at the 0.05 level.

The tests assume a restricted intercept in the co-integrating equation and no deterministic trends in the series.
The trace statistic tests H_0: r cointegrating relations against H_1: k cointegrating relations.

The max eigenvalue statistic tests H_0: r cointegrating relations against H_1: r+1 cointegrating relations.

Table 25: Johansen Co-integration test (Port Congestion)

Table 25 demonstrates that the three pairs of variables of this analysis are co-integrated.

6.9.1.3. Causality Analysis

The next step is to investigate each pair in terms of causation. Table 26 reports the relevant results.

Dependent variable	Excluded variable	Model	Lags	Chi-sq. (p-value)	Outcome	Residual Serial Corr. LM test	Residual Heteroskedasticity	R-sq.
BCI	Cong_Cape	VECM	1	0.0034***	causality at 1%	0.8486	0.8670	0.149849
Cong_Cape	BCI		1	0.9613	No causality			
BPI	Cong_Pmx	VECM	1	0.7980	No causality	0.4250	0.7274	0.116397
Cong_Pmx	BPI		1	0.0707	causality at 10%			
BSI	Cong_Hmx	VECM	1	0.5180	No causality	0.5543	0.0001***	0.060568
Cong_Hmx	BSI		1	0.1455	No causality			

Notes:

*** indicates rejection of H_0 at 1% level, **at 5% and * at 10%

H_0: All lagged terms of excluded variable insignificant

The test statistic follows the chi-square distribution under H_0

VAR/VEC Residual Heteroskedasticity Tests: No Cross Terms / H_0: homoscedasticity in residuals

VAR/VEC Residual Serial Correlation LM test / H_0: no serial correlation at lag order h

Table 26: Granger Causality Test (Port Congestion)

The Granger causality tests reveal that the only index caused by port congestion is the BCI, at a 1% level. Therefore Impulse Response analysis is only conducted for this particular pair of variables. However, the small number of observations for the port congestion series (data starts from January 2010) harms the reliability of this causality analysis, and this is reflected in the low values of R-squared. Especially for Panamax and Supramax the R^2 values stand at 0.12 and 0.06 respectively. Therefore, it is hardly surprising that the theoretical relationship between port congestion and the rates of those two vessel types cannot be confirmed at an empirical level.

6.9.1.4. Impulse Response Analysis

The final step involves Impulse response analysis. Given that the only Baltic index caused by port congestion is the BCI (Table 26), it is reasonable to apply IR analysis solely to this case.

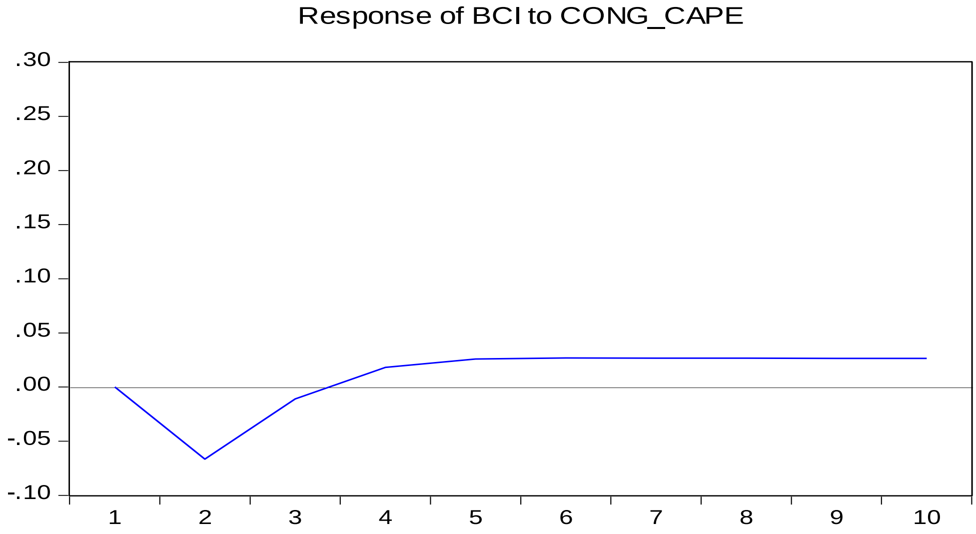


Figure 18: BCI and Port Congestion

Figure 18 demonstrates that the expected positive reaction of BCI to a sharp increase in Capesize congestion occurs with a noticeable delay, while it is ultimately aligned to a long-term equilibrium for the months ahead. This delayed response can be explained by the fact that the implications of congestions for the short term supply of ships are not realized instantly by the freight market. On the contrary, the market needs an adjustment period till it practically reflects on the new supply conditions.

6.10. Concluding Remarks

This chapter investigates the interactive relationship between the Baltic Exchange indices and a set of carefully selected external variables. The empirical results suggest that all of the variables lead the BCI, while there is a bi-directional lead-lag relationship in the case of Chinese steel production, coal price and iron ore price. The BPI is caused by Chinese steel production, DBECI, average bunker prices and wheat prices. On the other hand, only iron ore prices and Panamax congestion cause the BPI. As for the BSI, there is a one-way relationship running from Chinese steel production, average bunker prices and coal price, while the opposite holds only in the case of Chinese steel production and bunker prices.

Finally it should be noted that the DBECI and the average bunker prices exhibit the most significant causality with each of the Baltic indices (1%). This constitutes evidence in favour of their utilization as explanatory variables in a forecasting model. This is attempted in Chapter 8, where both of these variables are embedded in a VARX model.

7. FORECASTING DRY BULK FREIGHT RATES

7.1. Introduction

Freight rate forecasting, as an instrument of decision making, is particularly crucial for a variety of practitioners and stakeholders in the shipping business. Shipowners need forecasts in order to make the most profitable chartering decision for their vessels, charterers usually adjust their commercial decisions according to the expected transport costs and bankers are interested in the future inflows of borrowers during the loan evaluation process.

This chapter focuses on the generation of forecasts for the spot and period rates of Panamax and Capesize bulk carriers, using ARIMA, VAR/VECM and VARX/VECMX models. Based on the detailed description of each of those three modelling approaches (Chapter 4), they are now put into practice and their relative performance is assessed. To this end, the chapter presents the necessary test statistics and then describes the formulation of the most appropriate models.

7.2. Methodology

Initially ARIMA models are set up and produce pertinent forecasts. This method will mainly serve as a benchmark for comparison with the more sophisticated approaches that will be developed afterwards. The ARIMA models are built for the spot and period rates of Panamax and Capesize vessels. First it is shown that the time series of this analysis are first-differenced stationary. Therefore the predictions need to be based on an ARIMA, rather than on an ARMA framework. The structure of ARIMA models is determined using several model specification tools, such as correlograms and Inverse Roots of AR/MA Polynomials. Thereafter, those models are used in order to make forecasts and to compare their accuracy with the alternative approaches.

In the case of VAR and VARX models, the series are first checked in terms of Stationarity and Co-integration and then undergo Granger causality tests in order to validate the variable selection. The underlying models are set up in the levels of the data and the appropriate lags are determined using various lag length criteria, such as the sequential modified LR test statistic (LR), the Final prediction error (FPE), the Hannan-Quinn information criterion (HQ), the Schwarz information criterion (SC) and the Akaike information criterion (AIC) (See Appendix C).

At the same time, the residual diagnostics and the goodness of fit of the models are examined, so that the reliability of the results can be verified. Eventually, ex-post and ex-ante forecasts are produced and relevant criteria are employed in order to decide upon the most robust technique.

The in-depth analysis of the factors impacting the freight market (Chapter 6), combined with the extensive theoretical discussion of the supply-demand dynamics and the related factors (Chapter 2), enables the selection of appropriate independent variables for the proposed models. Specifically, the VAR/VECM models are formulated using as endogenous variables the fleet development (of the corresponding vessel size) and the Chinese steel production. The former reflects the ship supply, while the latter is a leading indicator of the demand for bulk carriers. The choice of those variables and their treatment as endogenous is justified by the preceding analysis. In particular, it has been demonstrated that freight rates are largely determined by the available tonnage, assuming a constant demand. On the flip side, the state of the freight market plays a major part in scrapping and in newbuilding ordering activity, and as a result it affects fleet development. As far as the Chinese steel production is concerned, the causality analysis of Chapter 6 provides evidence that there is a reciprocal relationship between China's steel production and the dry bulk freight market. Interestingly, the impulse response analysis demonstrates that a spike of Chinese steel output triggers an increase in the Baltic Exchange indices. Conversely, Tsioumas and Papadimitriou (2015) show that a positive shock to freight rates may lead the steel plants to cut back on steel output until the transport cost is adjusted downwards.

Within this perspective, it turns out that both the fleet development and the Chinese steel production are influenced by the dependent variable of the system, that is, the freight rates. Therefore, they can be classified as endogenous. Of course, the utilization of such variables in the proposed modelling approach will also be validated through a series of econometric tests that constitute an integral part of the following analysis.

The VARX models of this analysis contain the same endogenous variables as the VAR/VECM specification and the target is to enhance the forecasting ability of the latter models, by incorporating two carefully selected exogenous variables. These are the DBECI and the Average IFO price. The construction of the DBECI has been described in detail in Chapter 5, while the calculation of the Average IFO price is discussed in Chapter 6. Both variables have been found to significantly affect the dry cargo freight market and this justifies their utilization in the first place. Furthermore, the DBECI and the average bunker prices are principally determined by world economic and political factors and therefore they are independent of the dry bulk rates. This implies that both of these variables have to be treated as exogenous.

Hence, the analysis produces ex-post and ex-ante forecasts for the Panamax and Capesize spot and period rates using each of those three approaches. Ultimately, the forecasting accuracy of the respective models is evaluated using the Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). This enables the determination of the most robust modelling framework for the prediction of bulk carrier rates in both the spot and the period freight market.

7.3. Data

The analysis of this chapter is based on monthly data for the period January 1999 to July 2014. Forecasts are generated for the spot and period rates of representative Panamax and Capesize vessels. Data was retrieve from Clarkson's Research Services Ltd (CRLS). This database provides historical average spot and period rates for each vessel category. Specifically, the study considers the following variables: 6-month time-charter rate for a standard 75,000 dwt Panamax (available from March 2001 onwards), Panamax average spot earnings, 6-month time-charter rate for a standard 170,000 dwt Capesize (available from December 2001 onwards) and Capesize average spot earnings.

According to Clarksons Research Services Limited (2014), the quoted average spot rates express the average voyage earnings of the most representative routes, while the period rates are calculated as the average of quotations for delivery in Atlantic and Pacific and redelivery worldwide (Sources & Methods for the Shipping Intelligence Weekly, 2013, pp. 3-4).

In addition, the same database provides data for the Capesize and Panamax fleet development, the Chinese steel production and the bunker prices (as discussed in Chapter 6).

It should be noted that the data analysis and the following tests are performed in log-transformed data.

7.4. Descriptive Statistics

	Mean	Min	Max	Standard Deviation	Skewness	Kurtosis	J-B
Capesize							
Avg spot	10.1499	7.299797	12.14761	0.951129	-0.11551	2.457137	2.712053 [0.257683]
6-m tc 170k	10.44399	9.076809	12.10349	0.794059	0.288493	2.190916	6.254357 [0.043841]
Panamax							
Avg spot	9.510897	7.734559	11.21316	0.77262	0.293751	2.341401	6.069005 [0.048099]
6-m tc 75k	9.912624	8.779557	11.39639	0.663752	0.371453	2.329400	6.719158 [0.034750]
Endogenous Variables							
Ch_steel production	10.293280	9.108972	11.162400	0.652012	-0.405058	1.705315	18.174040 [0.000113]
Cape fleet developmet	4.894069	4.352733	5.708873	0.445268	0.567334	1.915983	19.18747 [0.000068]
Pmx fleet development	4.627833	4.142279	5.251735	0.320771	0.356991	2.013045	11.56167 [0.003086]
Exogenous Variables							
DBECI	3.959326	3.778041	4.112170	0.089844	-0.067338	1.886095	9.809107 [0.007413]
IFO_avg	5.665112	4.114164	6.606637	0.650939	-0.19506	1.803429	12.34179 [0.002089]

Notes:
Figures in [.] are p-values

The Jarque-Bera (J-B) test is used to check for normality. The J-B statistic is asymptotically $\chi^2(2)$-distributed.

Table 27: Descriptive Statistics

As reported in Table 27, the unconditional volatility (standard deviation) of Capesize vessels is higher than that of Panamax. This is in line with theoretical expectations, as the freight rates of larger bulk carriers are generally more volatile due to their reliance on a smaller number of trades and routes. Furthermore, the standard deviation of spot rates is greater than period rates' for both sectors. This implies that the spot market is more volatile than the period market.

Table 27 also shows that Capesize spot rates, Chinese steel production, DBECI and average bunker prices are negatively skewed, whilst Capesize period rates, Panamax spot and period rates, Capesize fleet development and Panamax fleet development are right-tailed. Those asymmetric distribution shapes are likely to create heteroscedasticity in residuals. The coefficients of kurtosis are less than 3 for all variables. Thus, the sample distribution is platykurtic and as such it is flatter than the normal distribution. Finally, the Jarque-Bera tests reveal that all variables under consideration deviate from normality, except Capesize spot rates.

7.5.1.1. Stationarity tests

First of all, the ADF and the KPSS unit root tests are applied so as to examine the stationarity of the series. The tests are performed in the log-levels and log-differences of the variables. The results, which are presented in Tables 28 and 29, reject non-stationarity in most cases of level forms, while the combination of the outcomes of those two unit root tests suggests that all series of this analysis can be treated as integrated of order 1, i.e. I(1).

	Log-Levels			Log-first differences		
	Intercept	Const. & trend	None	Intercept	Const. & trend	None
Capesize						
Avg spot	-2.726120*	-3.241553*	-0.266505	-10.03327***	-10.05386***	-10.06686***
6-m tc 170k	-2.715559*	-3.072885	-0.071153	-9.216683***	-9.235168***	-9.246937***
Panamax						
Avg spot	-1.816000	-2.451533	-0.322688	-11.40529***	-11.47329***	-11.44123***
6-m tc 75k	-2.798544*	-2.948510	-0.080346	-7.796749***	-7.864675***	-7.821839***
Endogenous Variables						
Ch_steel production	-1.873946	-0.797431	2.473431	-3.248202**	-3.655370**	-1.824531*
Cape fleet developmet	-0.155199	-2.537684	1.741868	-2.123648***	-2.045969***	-1.139691***
Pmx fleet development	2.062845	-1.920478	3.990434	-4.202614***	-4.909135***	-1.112253
Exogenous Variables						
DBECI	-2.33889	-2.395470	-0.836106	-2.710362*	-2.704792	-2.658569***
IFO_Average	-1.962037	-4.611779***	1.332059	-9.490358***	-9.532666***	-9.324351***

Notes:

*** indicates rejection of the null at 1% level, **at 5% and * at 10%

H_0: the series is non stationary, H_1: the series is stationary

Table 28: ADF test

	Log-Levels		Log-first differences	
	Intercept	Const. & trend	Intercept	Const. & trend
Capesize				
Avg spot	0.354555*	0.329984***	0.143769	0.043076
6-m tc 170k	0.419046*	0.262273***	0.154757	0.062233
Panamax				
Avg spot	0.343910	0.332426***	0.154909	0.025768
6-m tc 75k	0.276823	0.273947***	0.115373	0.037239
Endogenous Variables				
Ch_steel production	1.611345***	0.389544***	0.25282	0.10718
Cape fleet developmet	1.444268***	0.317433***	0.532207**	0.213227*
Pmx fleet development	1.455519***	0.302044***	0.738906**	0.090258
Exogenous Variables				
DBECI	0.228546	0.167210**	0.113229	0.094181
IFO_Average	1.736481***	0.108420	0.096349	0.031577

Notes:

*** denotes rejection of H_0 at 1% level, **at 5% and * at 10%

H_0: the series is stationary, H_1: the series is non stationary
The bandwidth for each test is chosen on the basis of the Newey-West selection using Berlett kernel.

Table 29: KPSS test

7.5. Forecasting spot and period rates – Empirical Results

7.5.1. ARIMA Modeling

Below are the results of the various steps pertaining to the Box-Jenkins' approach.

7.5.1.1. Identification – Correlograms

Starting with the identification phase of the ARIMA models, it is important to examine the correlation between the current values of residuals and their past values. In essence, the modeller needs to ensure that the models have accounted for any possible autocorrelation.

In this respect, the correlograms below are generated and are used to investigate the autocorrelation and the partial correlation of each variable. The former measures the degree of correlation between the current and the lagged values of each series. The latter also stands for the correlation coefficient between the current and the lagged series, but it additionally accounts for the predictive power of the values of the series with smaller lags.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.943	0.943	137.84	0.000
		2	0.863	-0.238	253.99	0.000
		3	0.790	0.070	352.05	0.000
		4	0.728	0.027	435.98	0.000
		5	0.679	0.055	509.48	0.000
		6	0.619	-0.168	570.96	0.000
		7	0.566	0.103	622.60	0.000
		8	0.531	0.102	668.41	0.000
		9	0.512	0.069	711.29	0.000
		10	0.484	-0.159	749.89	0.000
		11	0.444	-0.020	782.56	0.000
		12	0.393	-0.095	808.32	0.000

Figure 19: Capesize 6m t/c (levels)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.267	0.267	10.974	0.001
		2	-0.066	-0.148	11.647	0.003
		3	-0.101	-0.045	13.229	0.004
		4	-0.121	-0.097	15.528	0.004
		5	0.067	0.125	16.230	0.006
		6	-0.052	-0.149	16.662	0.011
		7	-0.178	-0.132	21.718	0.003
		8	-0.197	-0.147	28.000	0.000
		9	0.136	0.259	31.006	0.000
		10	0.157	-0.045	35.067	0.000
		11	0.095	0.066	36.568	0.000
		12	-0.074	-0.156	37.471	0.000

Figure 20: Capesize 6m t/c (1st differences)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.905	0.905	155.63	0.000
		2	0.792	-0.147	275.61	0.000
		3	0.711	0.122	372.78	0.000
		4	0.647	0.012	453.59	0.000
		5	0.606	0.107	524.90	0.000
		6	0.557	-0.084	585.39	0.000
		7	0.500	-0.016	634.43	0.000
		8	0.468	0.113	677.73	0.000
		9	0.484	0.227	724.15	0.000
		10	0.492	-0.060	772.47	0.000
		11	0.484	0.008	819.55	0.000
		12	0.458	-0.057	861.96	0.000

Figure 21: Capesize spot (levels)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.105	0.105	2.0972	0.148
		2	-0.181	-0.194	8.3354	0.015
		3	-0.088	-0.047	9.8093	0.020
		4	-0.103	-0.128	11.843	0.019
		5	0.005	0.006	11.849	0.037
		6	0.064	0.016	12.642	0.049
		7	-0.102	-0.132	14.681	0.040
		8	-0.277	-0.270	29.774	0.000
		9	0.062	0.084	30.530	0.000
		10	0.095	-0.033	32.338	0.000
		11	0.076	0.040	33.481	0.000
		12	0.042	-0.023	33.832	0.001

Figure 22: Capesize spot (1st differences)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.943	0.943	137.84	0.000
		2	0.863	-0.238	253.99	0.000
		3	0.790	0.070	352.05	0.000
		4	0.728	0.027	435.98	0.000
		5	0.679	0.055	509.48	0.000
		6	0.619	-0.168	570.96	0.000
		7	0.566	0.103	622.60	0.000
		8	0.531	0.102	668.41	0.000
		9	0.512	0.069	711.29	0.000
		10	0.484	-0.159	749.89	0.000
		11	0.444	-0.020	782.56	0.000
		12	0.393	-0.095	808.32	0.000

Figure 23: Panamax 6m t/c (levels)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.267	0.267	10.974	0.001
		2	-0.066	-0.148	11.647	0.003
		3	-0.101	-0.045	13.229	0.004
		4	-0.121	-0.097	15.528	0.004
		5	0.067	0.125	16.230	0.006
		6	-0.052	-0.149	16.662	0.011
		7	-0.178	-0.132	21.718	0.003
		8	-0.197	-0.147	28.000	0.000
		9	0.136	0.259	31.006	0.000
		10	0.157	-0.045	35.067	0.000
		11	0.095	0.066	36.568	0.000
		12	-0.074	-0.156	37.471	0.000

Figure 24: Panamax 6m t/c (1st differences)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.930	0.930	134.04	0.000
		2	0.851	-0.099	247.11	0.000
		3	0.793	0.110	345.78	0.000
		4	0.722	-0.139	428.33	0.000
		5	0.664	0.089	498.63	0.000
		6	0.615	-0.015	559.37	0.000
		7	0.560	-0.049	609.94	0.000
		8	0.513	0.033	652.71	0.000
		9	0.477	0.029	689.94	0.000
		10	0.450	0.067	723.31	0.000
		11	0.413	-0.109	751.68	0.000
		12	0.361	-0.118	773.42	0.000

Figure 25: Panamax spot (levels)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.071	0.071	0.7719	0.380
		2	-0.112	-0.118	2.7377	0.254
		3	0.102	0.122	4.3876	0.223
		4	-0.066	-0.102	5.0791	0.279
		5	-0.073	-0.031	5.9247	0.314
		6	0.068	0.046	6.6570	0.354
		7	-0.049	-0.058	7.0437	0.424
		8	-0.118	-0.091	9.2981	0.318
		9	-0.036	-0.053	9.5103	0.392
		10	0.045	0.048	9.8391	0.455
		11	0.083	0.089	10.979	0.445
		12	0.066	0.048	11.710	0.469

Figure 26: Panamax spot (1st differences)

The above correlograms, aid the identification of the type of the most suitable ARIMA models. According to Figures 19 - 26, the correlograms confirm the results of the Stationarity tests which show that all series are non-stationary in levels, but stationary in first differences. In addition, the observed behaviour of the autocorrelation and partial-correlation functions for twelve different lags provides another indication of the optimum order of ARIMA models. Furthermore, for the safest determination of the most appropriate lag order, it is essential to also take into consideration some pertinent information criteria, such as the Akaike information criterion and Schwarz criterion. Their values are reported in Appendix C.

The selected lag order for each ARIMA model is presented in the second column of

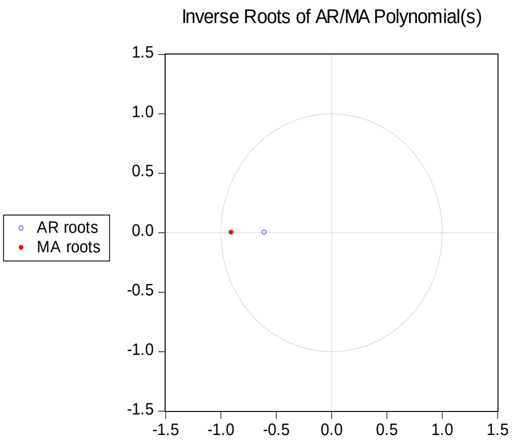
Table 30 under ‘Model type’.

7.5.1.2. ARIMA Equation Diagnostics

The next step is to examine the structure of the ARMA portion of the estimated equation.

7.5.1.2.1. Inverse Roots of AR/MA Polynomials

The first method, the Inverse Roots of AR/MA Polynomials, displays the inverse roots of the AR and MA characteristic polynomial. The ARMA process is stationary and invertible, if and only if the AR and MA roots respectively fall inside the unit circle. The generated graphs reveal that this condition is satisfied by all variables under examination.



Inverse Roots of AR/MA Polynomial(s)
Specification: D(C_6M_170K) C AR(1) MA(1)
Sample: 1999M01 2014M07
Included observations: 150

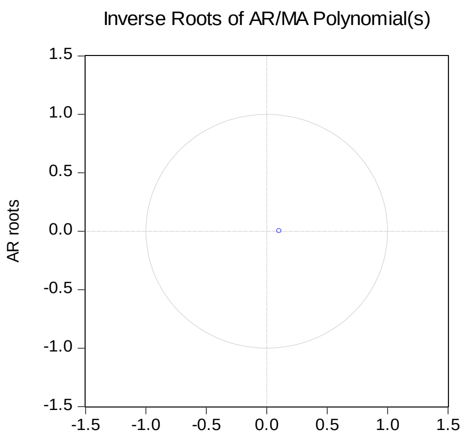
AR Root(s)	Modulus	Cycle
-0.604204	0.604204	

No root lies outside the unit circle.
ARMA model is stationary.

MA Root(s)	Modulus	Cycle
-0.904643	0.904643	

No root lies outside the unit circle.
ARMA model is invertible.

Figure 27: Capesize 6m t/c inverse roots

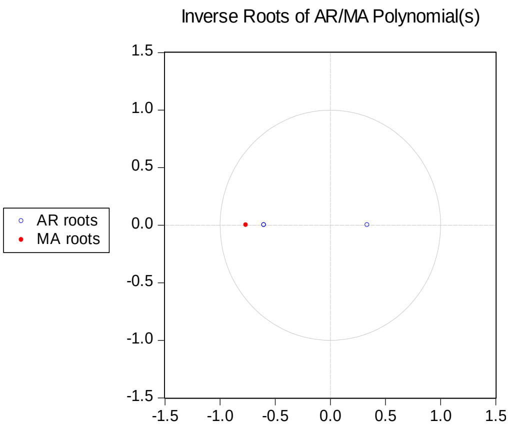


Inverse Roots of AR/MA Polynomial(s)
Specification: D(CP_AVG_SPOT) C AR(1)
Sample: 1999M01 2014M07
Included observations: 185

AR Root(s)	Modulus	Cycle
0.105426	0.105426	

No root lies outside the unit circle.
ARMA model is stationary.

Figure 28: Capesize average spot inverse roots



Inverse Roots of AR/MA Polynomial(s)
Specification: D(PMX_6M_75K) C AR(1) AR(2) MA(1)
Sample: 2001M03 2014M07
Included observations: 158

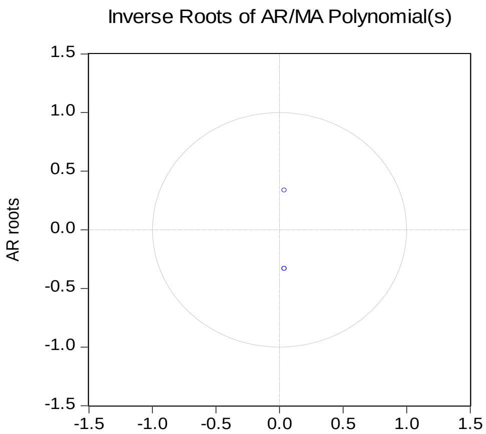
AR Root(s)	Modulus	Cycle
-0.600123	0.600123	
0.335685	0.335685	

No root lies outside the unit circle.
ARMA model is stationary.

MA Root(s)	Modulus	Cycle
-0.763274	0.763274	

No root lies outside the unit circle.
ARMA model is invertible.

Figure 29: Panamax 6m t/c inverse roots



Inverse Roots of AR/MA Polynomial(s)
Specification: D(PMX_AVG_SPOT) C AR(1) AR(2)
Sample: 1999M01 2014M07
Included observations: 184

AR Root(s)	Modulus	Cycle
0.040200 ± 0.334514i	0.336920	4.329665

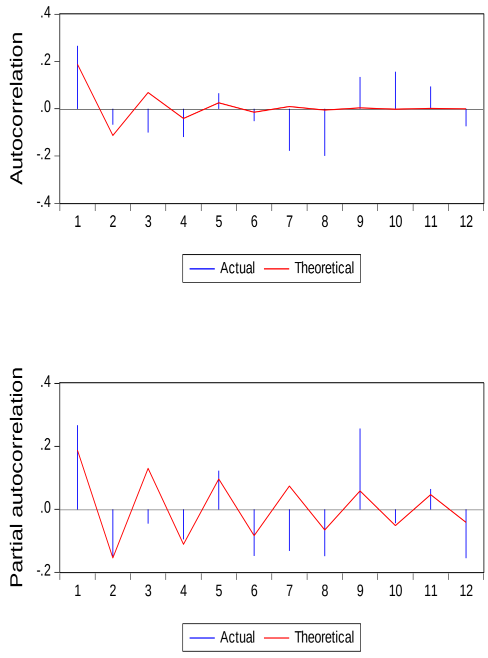
No root lies outside the unit circle.
ARMA model is stationary.

Figure 30: Panamax average spot inverse roots

7.5.1.2.2. Correlogram Diagnostic (Actual and ARMA Model Correlogram)

The second method compares the autocorrelation and partial autocorrelation pattern of the structural residuals with the estimated model, for a given number of periods. It should be noted that the structural residuals are the residuals that occur after removing the impact of the fitted exogenous regressors but not the ARMA terms.

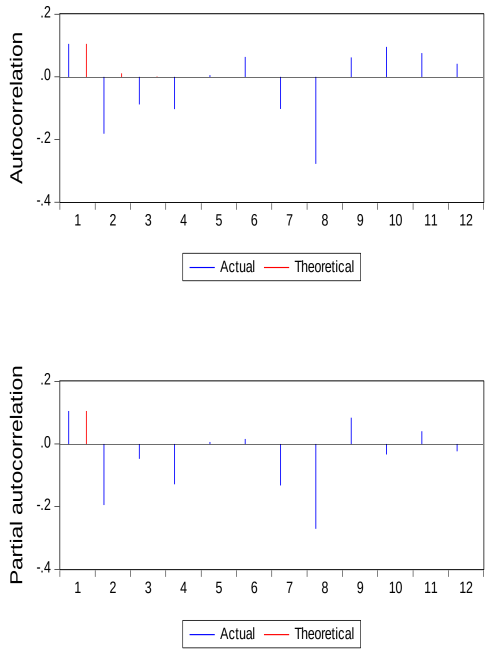
The model is seen as well specified if the estimated autocorrelations and partial autocorrelations are close to the residual.



Actual and ARMA Model Correlogram
Specification: D(C_6M_170K) C AR(1) MA(1)
Sample: 1999M01
2014M07
Included observations: 150

	Autocorrelation				Partial Autocorrelation		
	Actual	Model	Difference		Actual	Model	Difference
0	1.000	1.000	0.000	0	1.000	1.000	0.000
1	0.266	0.188	0.079	1	0.266	0.188	0.079
2	-0.067	-0.113	0.047	2	-0.149	-0.154	0.006
3	-0.101	0.069	-0.169	3	-0.045	0.130	-0.175
4	-0.119	-0.041	-0.078	4	-0.095	-0.111	0.016
5	0.066	0.025	0.041	5	0.123	0.096	0.027
6	-0.052	-0.015	-0.037	6	-0.148	-0.084	-0.064
7	-0.177	0.009	-0.187	7	-0.132	0.074	-0.206
8	-0.199	-0.006	-0.193	8	-0.148	-0.065	-0.083
9	0.135	0.003	0.131	9	0.256	0.058	0.198
10	0.157	-0.002	0.159	10	-0.044	-0.052	0.008
11	0.094	0.001	0.093	11	0.064	0.046	0.018
12	-0.074	-0.001	-0.074	12	-0.155	-0.042	-0.113

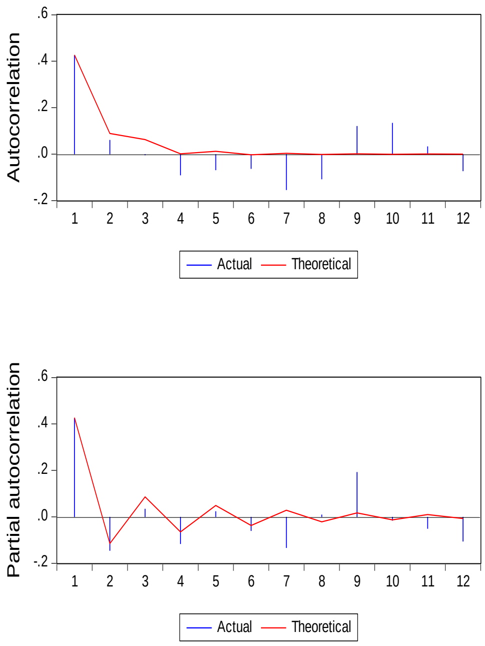
Figure 31: Capesize 6m t/c (correlogram)



Actual and ARMA Model Correlogram
Specification: D(CP_AVG_SPOT) C AR(1)
Sample: 1999M01
2014M07
Included observations: 185

	Autocorrelation				Partial Autocorrelation		
	Actual	Model	Difference		Actual	Model	Difference
0	1.000	1.000	0.000	0	1.000	1.000	0.000
1	0.105	0.105	-0.000	1	0.105	0.105	-0.000
2	-0.181	0.011	-0.192	2	-0.194	0.000	-0.194
3	-0.088	0.001	-0.089	3	-0.047	0.000	-0.047
4	-0.103	0.000	-0.103	4	-0.128	-0.000	-0.128
5	0.005	0.000	0.005	5	0.006	0.000	0.006
6	0.064	0.000	0.064	6	0.016	-0.000	0.016
7	-0.102	0.000	-0.102	7	-0.132	0.000	-0.132
8	-0.277	0.000	-0.277	8	-0.270	-0.000	-0.270
9	0.062	0.000	0.062	9	0.084	-0.000	0.084
10	0.095	0.000	0.095	10	-0.033	0.000	-0.033
11	0.076	0.000	0.076	11	0.040	0.000	0.040
12	0.042	0.000	0.042	12	-0.023	-0.000	-0.023

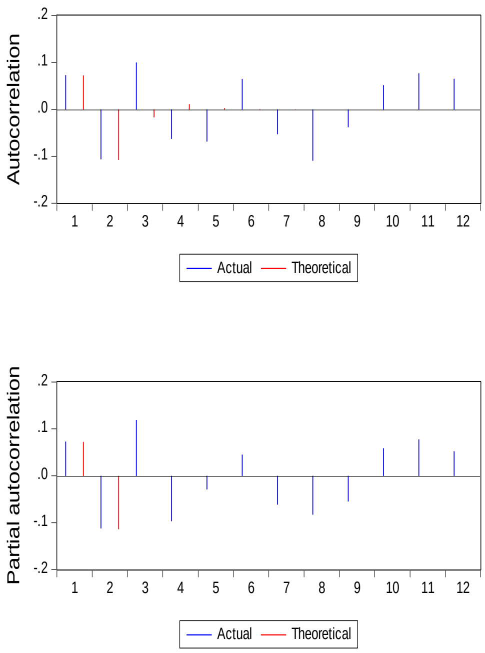
Figure 32: Capesize average spot (correlogram)



Actual and ARMA Model Correlogram
Specification: D(PMX_6M_75K) C AR(1) AR(2) MA(1)
Sample: 2001M03
2014M07
Included observations: 158

	Autocorrelation				Partial Autocorrelation		
	Actual	Model	Difference		Actual	Model	Difference
0	1.000	1.000	0.000	0	1.000	1.000	0.000
1	0.425	0.427	-0.002	1	0.425	0.427	-0.002
2	0.061	0.089	-0.027	2	-0.146	-0.115	-0.031
3	-0.004	0.063	-0.067	3	0.035	0.086	-0.051
4	-0.090	0.001	-0.092	4	-0.116	-0.065	-0.051
5	-0.069	0.012	-0.081	5	0.024	0.049	-0.025
6	-0.063	-0.003	-0.060	6	-0.060	-0.037	-0.023
7	-0.154	0.003	-0.157	7	-0.133	0.029	-0.162
8	-0.107	-0.001	-0.106	8	0.010	-0.022	0.032
9	0.121	0.001	0.120	9	0.193	0.017	0.176
10	0.134	-0.001	0.135	10	-0.016	-0.013	-0.003
11	0.033	0.000	0.033	11	-0.051	0.010	-0.061
12	-0.073	-0.000	-0.073	12	-0.106	-0.007	-0.099

Figure 33: Panamax 6m t/c (correlogram)



Actual and ARMA Model Correlogram
Specification: D(PMX_AVG_SPOT) C AR(1) AR(2)
Sample: 1999M01
2014M07
Included observations: 184

	Autocorrelation				Partial Autocorrelation		
	Actual	Model	Difference		Actual	Model	Difference
0	1.000	1.000	0.000	0	1.000	1.000	0.000
1	0.073	0.072	0.001	1	0.073	0.072	0.001
2	-0.106	-0.108	0.002	2	-0.112	-0.114	0.002
3	0.100	-0.017	0.117	3	0.119	-0.000	0.119
4	-0.063	0.011	-0.073	4	-0.097	-0.000	-0.097
5	-0.068	0.003	-0.071	5	-0.029	-0.000	-0.029
6	0.065	-0.001	0.066	6	0.045	-0.000	0.045
7	-0.053	-0.000	-0.052	7	-0.061	-0.000	-0.061
8	-0.109	0.000	-0.110	8	-0.083	0.000	-0.083
9	-0.038	0.000	-0.038	9	-0.055	-0.000	-0.055
10	0.052	-0.000	0.052	10	0.059	0.000	0.059
11	0.077	-0.000	0.077	11	0.078	-0.000	0.078
12	0.065	0.000	0.065	12	0.053	0.000	0.053

Figure 34: Panamax average spot (correlogram)

Overall, the results of the equation diagnostics show that the graphs of this analysis trace the theoretical patterns with satisfactory accuracy. Therefore the fitted ARIMA models can be considered parsimonious.

7.5.1.3. Residual Diagnostics

Variable	Model type	Residual Serial Corr. LM test	Residual Heteroskedasticity	R-sq.
Capesize				
avg spot	ARIMA(1,1,0)	0.0083***	0.0000***	0.0111
6-m tc 170k	ARIMA(1,1,1)	0.3133	0.0601*	0.1255
Panamax				
avg spot	ARIMA(2,1,0)	0.0670*	0.6272	0.0176
6-m tc 75k	ARIMA(2,1,1)	0.7832	0.6659	0.2087

Notes:
*** indicates rejection of H_0 at 1% level, **at 5% and * at 10%
Breusch-Godfrey Serial Correlation LM test / H_0: no serial correlation
ARCH Heteroskedasticity Test / H_0: homoscedasticity in residuals

Table 30: Residual Diagnostics (ARIMA)

Table 30 provides evidence that the specification of the ARIMA models of this analysis can be deemed acceptable. Specifically, the Breusch-Godfrey LM tests reveal the absence of serial correlation in all cases.

At the same time, the majority of the series do not exhibit heteroscedasticity, according to ARCH Heteroskedasticity test. The only exceptions are the Capesize average spot rates, which are found heteroscedastic and the Capesize 6-m t/c rates. However, in the latter case the homoscedasticity hypothesis is rejected at a 10% level, which is not a grave problem, considering that the chi-square probability is more meaningful at the 1% and 5% levels.

The values of R-squared are relatively low and this may have a negative effect on the precision of predictions. The low R-squared may be attributed to the size of the sample, since ARIMA models typically require a larger number of observations to operate effectively.

Overall, despite the addressed weaknesses, the ARIMA models appear to be satisfactorily specified.

7.5.2. VAR / VECM Models

7.5.2.1. Johansen Co-integration tests

Given that the series are non-stationary (see 7.5.1.1.) Johansen co-integration tests are performed so as to search for potential long-term equilibriums. The results are presented below.

Variables	Lags	Hypothesized No. of CE(s)	Trace	0.05 CV (trace)	Max Eigenvalue	0.05 CV (Max Eigen.)
Capesize Avg spot ***vs*** {Cp fleet devel Ch_steel prod}	7	None	34.18947	35.19275	21.80002	22.29962
6-m tc 170k ***vs*** {Cp fleet devel Ch_steel prod}	5	None	6.571528	35.19275	6.563918	22.29962
Panamax Avg spot ***vs*** {Pmx fleet devel Ch_steel prod}	5	None	30.94755	35.19275	19.44932	22.29962
6-m tc 75k ***vs*** {Cp fleet devel Ch_steel prod}	2	None*	42.93139	35.19275	25.81752	22.29962
		At most 1	17.11387	20.26184	9.344156	15.8921

Notes:

* denotes rejection of the hypothesis at the 0.05 level.

The tests assume a restricted intercept in the co-integrating equation and no deterministic trends in the series

The trace statistic tests H_0: r cointegrating relations against H_1: k cointegrating relations.

The max eigenvalue statistic tests H_0: r cointegrating relations against H_1: r+1 cointegrating relations.

Table 31: Johansen Co-integration test (VAR/VECM)

As Table 31 illustrates, there is only one co-integrating relation, and that is between Panamax period rates and the selected set of endogenous variables. Therefore, the forecasts have to be based on VECM modelling for Panamax period rates and on VAR for all other cases.

7.5.2.2. Causality Analysis

Granger causality tests check the validity of the explanatory variables. It should be noted that this study follows the Toda and Yamamoto (1995) approach, by which the Granger causality tests are conducted on the basis of a well specified VAR model in the levels of the data, even though they are I(1). This is vital so as to maintain the asymptotical chi-square distribution of the Wald test. Therefore, we construct a VAR model in levels adding one extra lag. Yet this additional lag is not included in the test formulation.

Table 32 summarizes the results.

	Model	Dependent variable	Excluded variables	Lags	Chi-sq. (p-value)	Outcome
Capesize	VAR	Avg spot	Cp fleet devel	7	0.0566*	causality at 10%
			Ch_steel prod		0.0245**	causality at 5%
			All		0.0121**	causality at 5%
	VAR	6-m tc	Cp fleet devel	5	0.0978*	causality at 10%
			Ch_steel prod		0.0281**	causality at 5%
			All		0.0359**	causality at 5%
Panamax	VECM	Avg spot	Pmx fleet devel	5	0.0477**	causality at 5%
			Ch_steel prod		0.0017***	causality at 1%
			All		0.0002***	causality at 1%
		6-m tc	Pmx fleet devel	2	0.0001***	causality at 1%
			Ch_steel prod		0.0855*	causality at 10%
			All		0.0000***	causality at 1%

Notes:
*** indicates rejection of H_0 at 1% level, **at 5% and * at 10%
H_0: All lagged terms of excluded variable insignificant
The test statistic follows the chi-square distribution under H_0

Table 32: Granger Causality (VAR/VECM)

It is evident that all variables exhibit significant causality with the respective rates. This implies that they can be safely treated as explanatory variables in the ensuing VAR/VECM models.

7.5.2.3. Variance Decomposition

The next step is to further scrutinize the selected explanatory variables by means of Forecast Error Variance Decomposition (FEVD). This will determine the proportion of the variance of the forecast error which is attributable to the respective endogenous variables for each period.

Tables 33 – 36 present the outcome of this analysis for each individual dependent variable.

Period	S.E.	DC_6M_170K	DCP_DEVEL	DCH_STEEL_PR
1	0.234287	100.0000	0.000000	0.000000
2	0.244111	98.87041	0.479180	0.650411
3	0.250285	94.82607	1.318075	3.855860
4	0.253072	93.91638	2.295857	3.787759
5	0.257022	93.44870	2.393935	4.157366
6	0.257968	92.87159	2.393070	4.735343
7	0.259402	92.10234	2.665986	5.231670
8	0.259486	92.06821	2.687289	5.244503
9	0.260415	91.48199	2.983102	5.534911
10	0.261051	91.20041	3.064577	5.735016

Table 33: Capesize 6m t/c

Period	S.E.	DCP_AVG_SPOT	DCP_DEVEL	DCH_STEEL_PR
1	0.422201	100.0000	0.000000	0.000000
2	0.428837	97.97422	1.227030	0.798745
3	0.451073	94.43394	1.482124	4.083938
4	0.460927	92.25602	3.828787	3.915197
5	0.463302	92.09726	3.844418	4.058326
6	0.465622	91.30731	4.006322	4.686366
7	0.469341	90.72438	4.492760	4.782855
8	0.475368	89.40445	5.886806	4.708739
9	0.478148	89.28422	5.829239	4.886543
10	0.480228	88.68566	5.986277	5.328066

Table 34: Capesize spot

Period	S.E.	PMX_6M_75K	PMX_DEVEL	CH_STEEL_PR
1	0.144949	100.0000	0.000000	0.000000
2	0.251200	99.01218	0.507279	0.480542
3	0.334414	93.12696	3.974288	2.898753
4	0.399281	87.55384	7.630662	4.815493
5	0.453011	81.96164	11.89630	6.142065
6	0.498693	77.55551	15.45009	6.994396
7	0.539717	73.97875	18.50994	7.511308
8	0.577218	71.21857	20.91358	7.867855
9	0.612337	68.99762	22.87592	8.126456
10	0.645418	67.20679	24.45359	8.339623

Table 35: Panamax 6m t/c

Period	S.E.	DPMX_AVG_SPOT	DPMX_DEVEL	DCH_STEEL_PR
1	0.255825	100.0000	0.000000	0.000000
2	0.258822	98.39645	1.142369	0.461185
3	0.280596	87.94859	4.980959	7.070447
4	0.281803	87.73660	4.938402	7.324994
5	0.283301	87.48392	4.887078	7.629000
6	0.285525	87.20156	5.149411	7.649029
7	0.289013	85.18802	6.146508	8.665473
8	0.289085	85.16410	6.166050	8.669847
9	0.289557	84.97907	6.147284	8.873646
10	0.289852	84.81471	6.316638	8.868654

Table 36: Panamax spot

Table 33 illustrates that about 5% of Capesize period rates forecast error is due to steel price shocks and another 2 - 3% due to changes in the supply of Capesize vessels. Alongside, it appears that more than 90% of the prediction error is self-generated.

In this context, Tables 33 – 36 present a similar picture. The self-generated variation accounts for proportions that vary between 85 – 95%, while the contribution of the Chinese steel production ranges between 5 – 9% and that of the fleet development between 3 – 6% (except for the Panamax period rates where it contributes up to 25.5%).

All in all, as expected, the largest portion of the forecast error is generated by the dependent variables themselves over time. The notable characteristic of the foregoing analyses is that all endogenous variables of this study explain a significant part of the variation in the respective forecast errors.

7.5.2.4. Residual Diagnostics

	Model Type	Dependent	Independent (Endogenous)	Lags	Residual Serial Corr. LM test	Residual Heteroskedasticity	R-sq.
Capesize	VAR	Avg spot	Ch_steel prod Coal cons	7	0.6482	0.0001***	0.242989
	VAR	6-m tc	Cp fleet devel Ch_steel prod	5	0.1722	0.0001***	0.205895
Panamax	VAR	Avg spot	Pmx fleet devel Ch_steel prod	5	0.9270	0.0005***	0.236271
	VECM	6-m tc	Pmx fleet devel Ch_steel prod	2	0.0024***	0.0059***	0.322904

Notes:
*** indicates rejection of H_0 at 1% level, **at 5% and * at 10%
VAR Residual Serial Correlation LM test / H_0: no serial correlation at lag order h
VAR/VEC White Heteroskedasticity Tests: No Cross Terms / H_0: homoscedasticity in residuals

Table 37: Residual Diagnostics (VAR/VECM)

The above residual diagnostics suggest that all of the VAR models are well specified, as their residuals do not exhibit serial correlation. In contrast, the VECM for the 6-month Panamax rates appears affected by serial correlation. This points to data misspecification and may be the reason for the large forecast errors that arise in this case (see 7.8). Along these lines, the R-squared of this VECM model is greater than any other VAR of this analysis. However, this may be misleading due to questionable estimates of the related test statistics in the presence of serial correlation.

The main pitfall of all VAR/VECM models developed in this study is the detection of heteroscedasticity, as shown in Table 37. This can be attributed to the asymmetric shape of the distribution of each variable, as indicated by the non-zero coefficients of skewness reported in Table 37. In fact, positive or negative skewness can be the major cause of heteroscedasticity. Nevertheless, as discusses in Chapter 4, this is not a reason to reject an otherwise satisfactory model.

Table 37 also illustrates that the values of R-squared are higher than the respective values for the ARIMA models (see Table 30). Therefore it can be inferred that the VAR/VECM models formulated provide a better fit for the data than the ARIMA framework.

7.5.3. VARX Models

7.5.3.1. Johansen Co-integration tests

As discussed in 7.5.1.1., all variables of this analysis have unit roots. Thus, Johansen co-integration tests should be performed to investigate the existence of long-term equilibriums.

Series	Exogenous series	Lags	Hypothesized No. of CE(s)	Trace	0.05 CV (trace)	Max Eigenvalue	0.05 CV (Max Eigen.)
Capesize							
Avg spot ***vs*** {Cp fleet devel Ch_steel prod}	DBECI IFO_avg	5	None	32.88359	35.19275	21.94628	22.29962
6-m tc 170k ***vs*** {Cp fleet devel Ch_steel prod}	DBECI IFO_avg	7	None	33.70651	35.19275	21.19163	22.29962
Panamax							
Avg spot ***vs*** {Pmx fleet devel Ch_steel prod}	DBECI IFO_avg	3	None	29.98012	35.19275	19.90082	22.29962
6-m tc 75k ***vs*** {Cp fleet devel Ch_steel prod}	DBECI IFO_avg	3	None	27.75045	35.19275	18.68955	22.29962

Notes:

* denotes rejection of the hypothesis at the 0.05 level.

The tests assume a restricted intercept in the co-integrating equation and no deterministic trends in the series
The trace statistic tests H_0: r cointegrating relations against H_1: k cointegrating relations.

The max eigenvalue statistic tests H_0: r cointegrating relations against H_1: r+1 cointegrating relations.

Table 38: Johansen Co-integration test (VARX)

Table 38 shows that there is no co-integration whatsoever. Therefore, the forecasting models have to be built on the basis of a VARX rather than a VECMX framework.

7.5.3.2. Causality Analysis

The development of parsimonious VARX models requires the careful and statistically sound selection of explanatory variables. For this purpose Granger causality tests are carried out and investigate the explanatory power of each independent series. As in the case of VAR/VECM models, the study uses the Toda and Yamamoto (1995) approach.

	Dependent variable	Excluded variables	Lags	Chi-sq. (p-value)	Outcome
Capesize	Avg spot	Cp fleet devel	5	0.0544*	causality at 10%
		Ch_steel prod		0.0152**	causality at 5%
		All		0.0100***	causality at 1%
	6-m tc	Cp fleet devel	7	0.0788*	causality at 10%
		Ch_steel prod		0.0767*	causality at 10%
		All		0.0542*	causality at 10%
Panamax	Avg spot	Pmx fleet devel	3	0.0146**	causality at 5%
		Ch_steel prod		0.0005***	causality at 1%
		All		0.0000***	causality at 1%
	6-m tc	Pmx fleet devel	3	0.0136***	causality at 1%
		Ch_steel prod		0.0507*	causality at 10%
		All		0.0037***	causality at 1%

Notes:
*** indicates rejection of H_0 at 1% level, **at 5% and * at 10%
H_0: All lagged terms of excluded variable insignificant
The test statistic follows the chi-square distribution under H_0

Table 39: Granger Causality (VARX)

Table 39 provides evidence that each and every independent variable causes the respective rates. This confirms that they can serve as explanatory variables and form appropriate VARX models.

7.5.3.4. Residual Diagnostics

	Model Type	Dependent	Independent (Endogenous)	Independent (Exogenous)	Lags	Residual Serial Corr. LM test	Residual Heteroskedasticity	R-sq.
Capesize	VARX	Avg spot	Ch_fleet devel Ch_steel prod	DBECI IFO_avg	5	0.2272	0.0077***	0.266838
	VARX	6-m tc	Cp fleet devel Ch_steel prod	DBECI IFO_avg	7	0.8366	0.0021***	0.334145
Panamax	VARX	Avg spot	Pmx fleet devel Ch_steel prod	DBECI IFO_avg	3	0.2600	0.0000***	0.207289
	VARX	6-m tc	Pmx fleet devel Ch_steel prod	DBECI IFO_avg	3	0.2549	0.0002***	0.335293

Notes:
*** indicates rejection of H_0 at 1% level, **at 5% and * at 10%
VAR Residual Serial Correlation LM test / H_0: no serial correlation at lag order h
VAR/VEC White Heteroskedasticity Tests: No Cross Terms / H_0: homoscedasticity in residuals

Table 40: Residual Diagnostics (VARX)

The residual diagnostics presented in Table 40 suggest that all VARX models are well specified, relatively speaking. According to the LM tests, the residuals are free from autocorrelation, but they are heteroscedastic. As discussed earlier, heteroscedasticity affects the efficiency and the minimum variance status of estimators. However, given that it has no repercussions for their consistency and unbiasedness, the models are not rejected on the grounds of heteroscedasticity. After all, its presence was anticipated, in light of the results of Descriptive Satistics (Table 27) which indicated that all variables are unevenly distributed (skewed left or right).

In the scope of the present study, the most serious problem arising out of heteroscedasticity would be the unreliability of F-tests, since they rely on homoscedasticity. This obstacle is overcome by using the Wald test statistics when testing for Granger causality.

As far as the goodness of fit is concerned, Table 40 shows that the VARX models have higher R-squared values in all cases, except the Panamax spot rates. This is indicative of the substantial improvement that the addition of two exogenous variables brings about. The VARX models are able to explain a larger portion of the variation in the dependent variables, compared to the respective VAR/VECM and ARIMA models.

7.6. Forecasts

The final step of this analysis involves the generation of point ex-post and ex-ante forecasts.

First, ex-post forecasting is performed and the forecasted values are compared with the true values of the data for the selected period. This provides a first indication of the performance and the goodness-of-fit of the proposed models.

Subsequently, ex-ante forecasts are produced for seven periods ahead, using as starting values the last known values of the resized samples. It is worth noting that each model generates ex-post and ex-ante forecasts for the same sample size and over the same horizon. This ensures consistency across the different modelling approaches.

7.6.1. Ex-post forecasts

In ex-post forecasts, the values of the series are known throughout the selected period. Hence, the forecasted values can be checked against existing data so that the historical fit and the predictive ability of the model can be evaluated. Specifically, the models produce one step-ahead static in-sample forecasts and the relevant error is calculated for each step, so that the forecasting performance of the model can be evaluated.

The following figures (35 – 46) depict the ex-post forecasts for ARIMA, VAR/VECM and VARX approaches. It should be noted that the vertical axis of both ex-post and ex-ante forecasts of VAR/VECM and ARIMA models measure logarithms. Furthermore, the ARIMA forecast results have been transformed from first differences into levels, and so they are presented. The precise time interval for each case is as follows: [10/2002 – 07/2014] for Capesize spot rates, [12/2002 – 07/2014] for Capesize period rates, [10/2002 – 07/2014] for Panamax spot rates and [03/2002 – 07/2014] for Panamax period rates.

7.6.1.1. ARIMA models

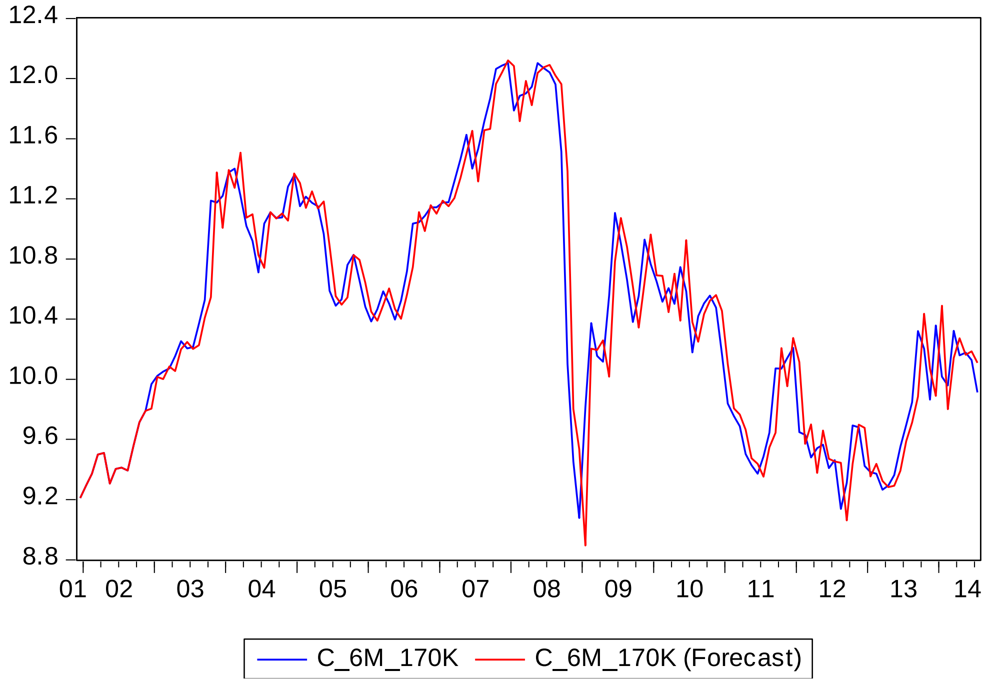


Figure 35: Capesize 6m t/c ex-post (ARIMA)

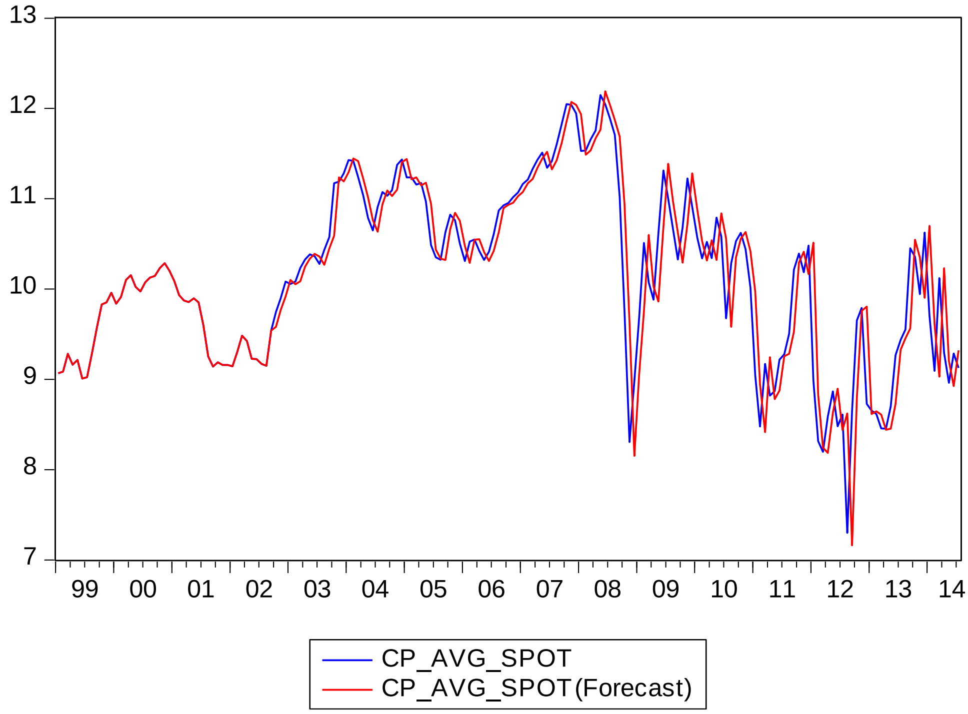


Figure 36: Capesize spot ex-post (ARIMA)

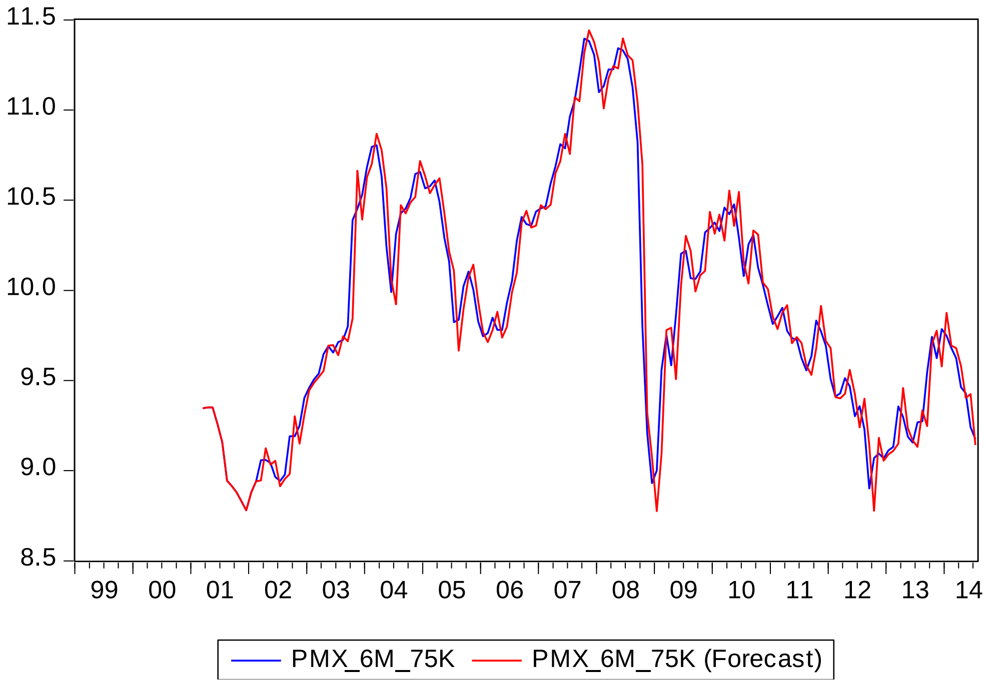


Figure 37: Panamax 6m t/c ex-post (ARIMA)

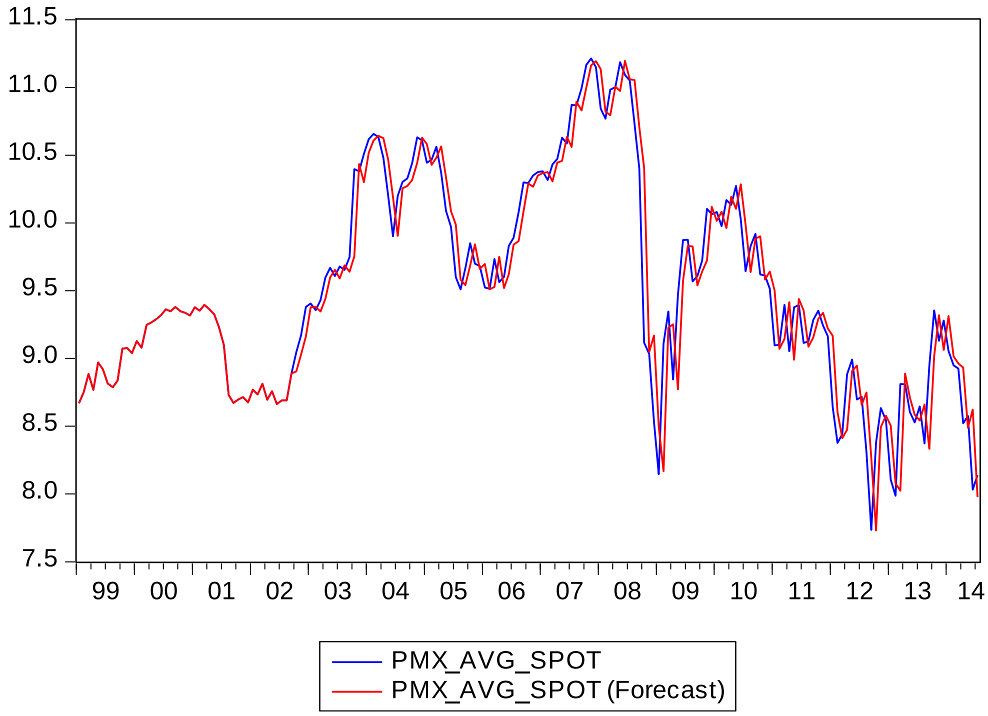


Figure 38: Panamax spot ex-post (ARIMA)

7.6.1.2. VAR / VECM Models

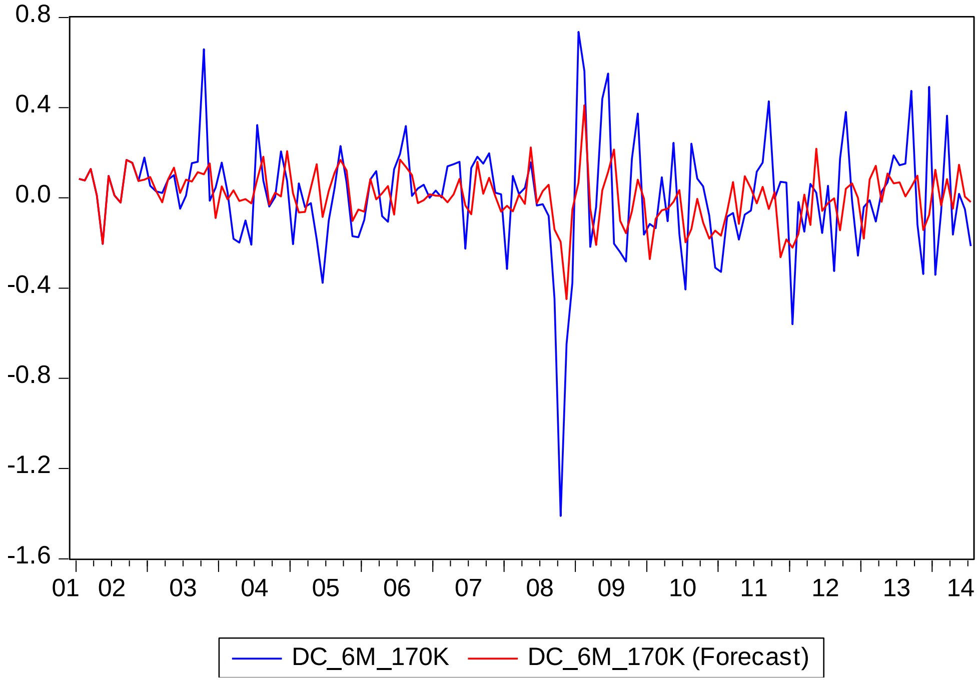


Figure 39: Capesize 6m t/c ex-post (VAR)

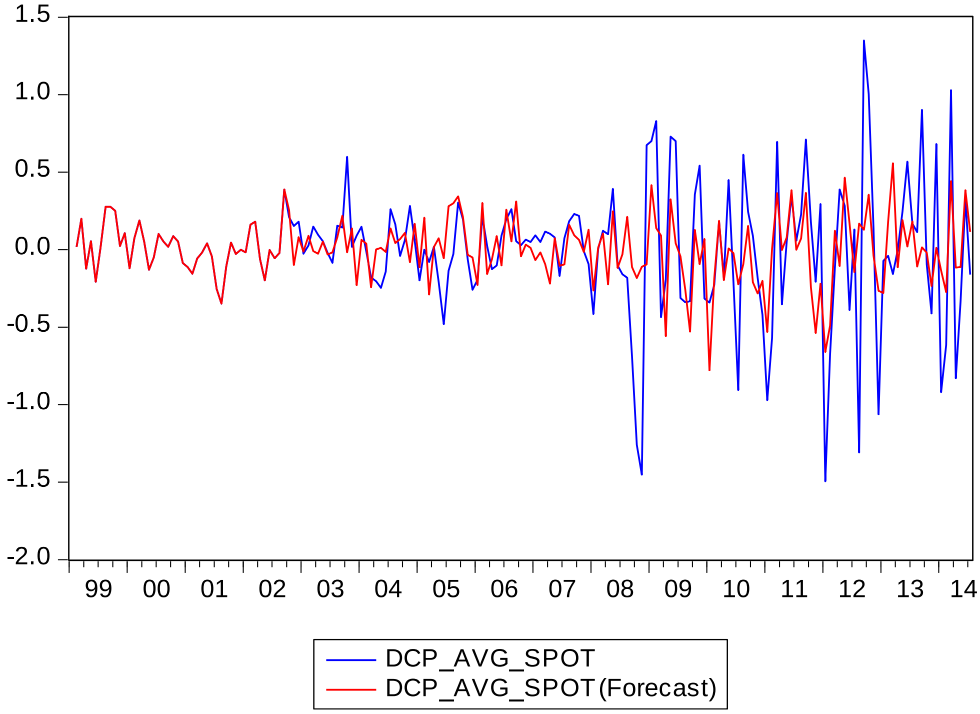


Figure 40: Capesize spot ex-post (VAR)

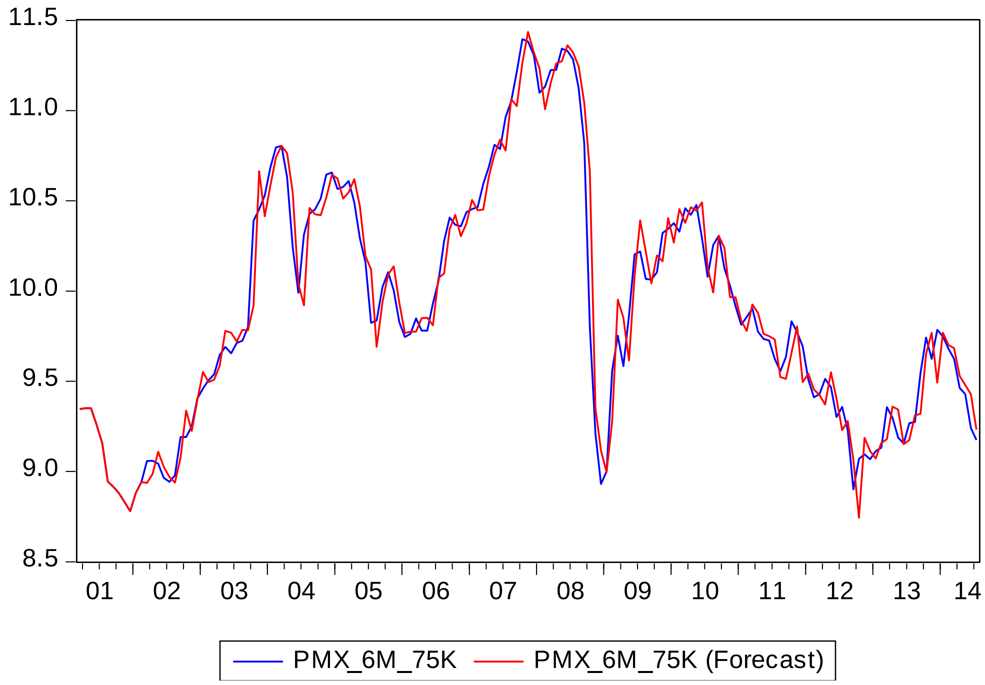


Figure 41: Panamax 6m t/c ex-post (VECM)

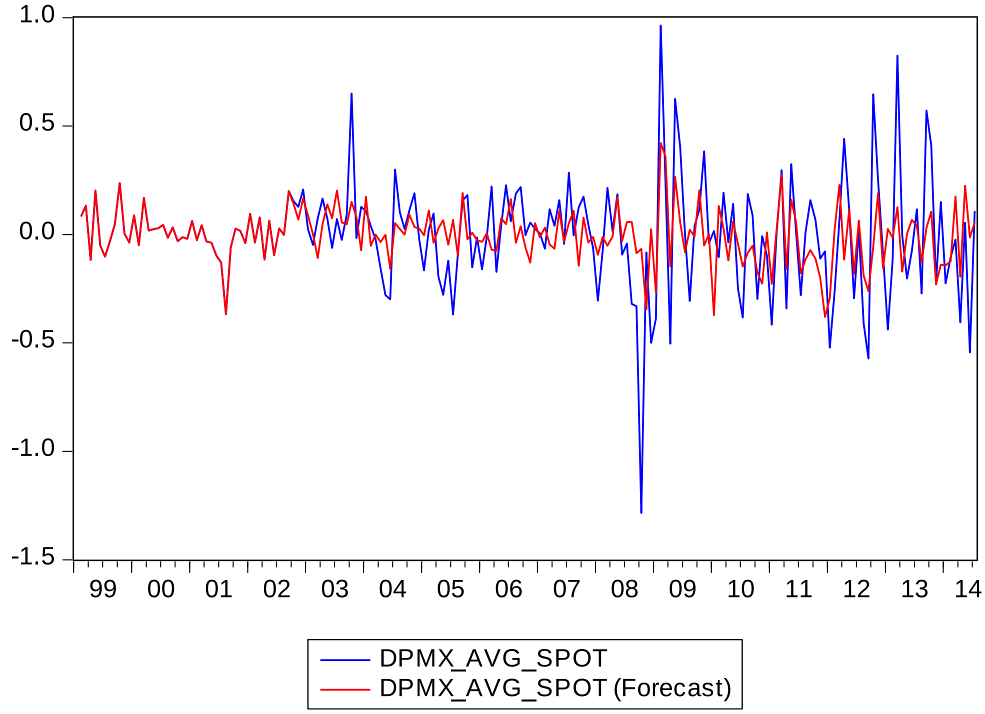


Figure 42: Panamax spot ex-post (VAR)

7.6.1.3. VARX Models

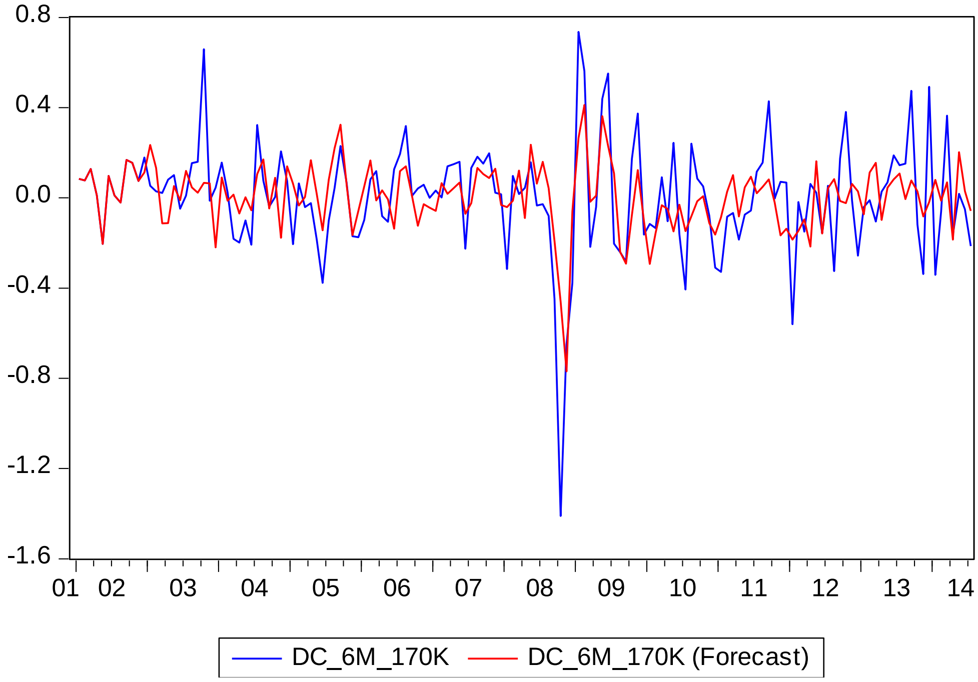


Figure 43: Capesize 6m t/c ex-post (VARX)

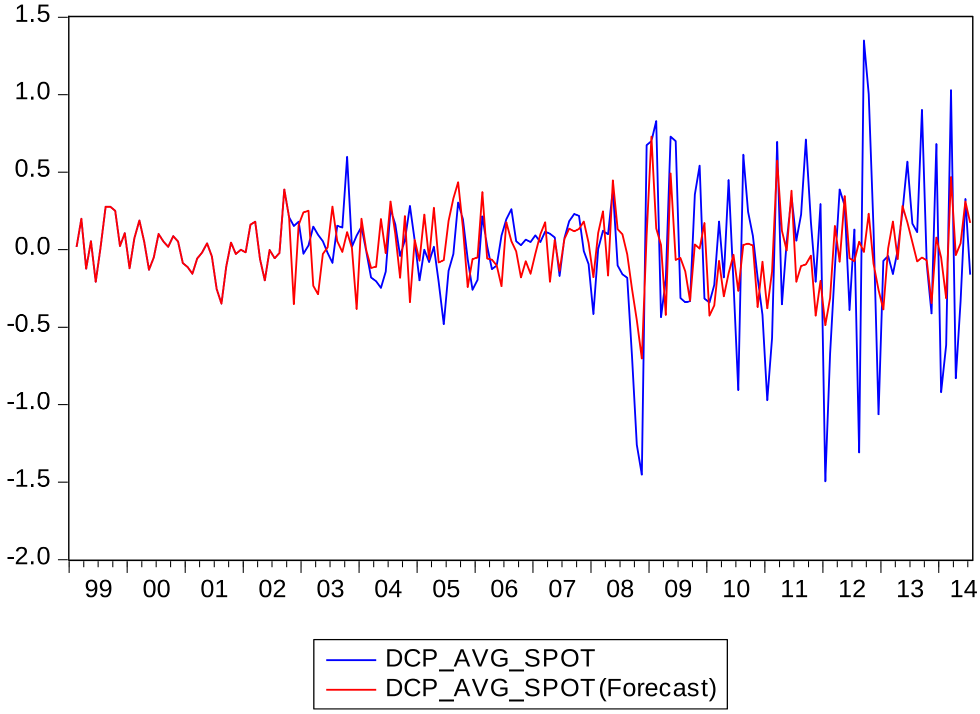


Figure 44: Capesize spot ex-post (VARX)

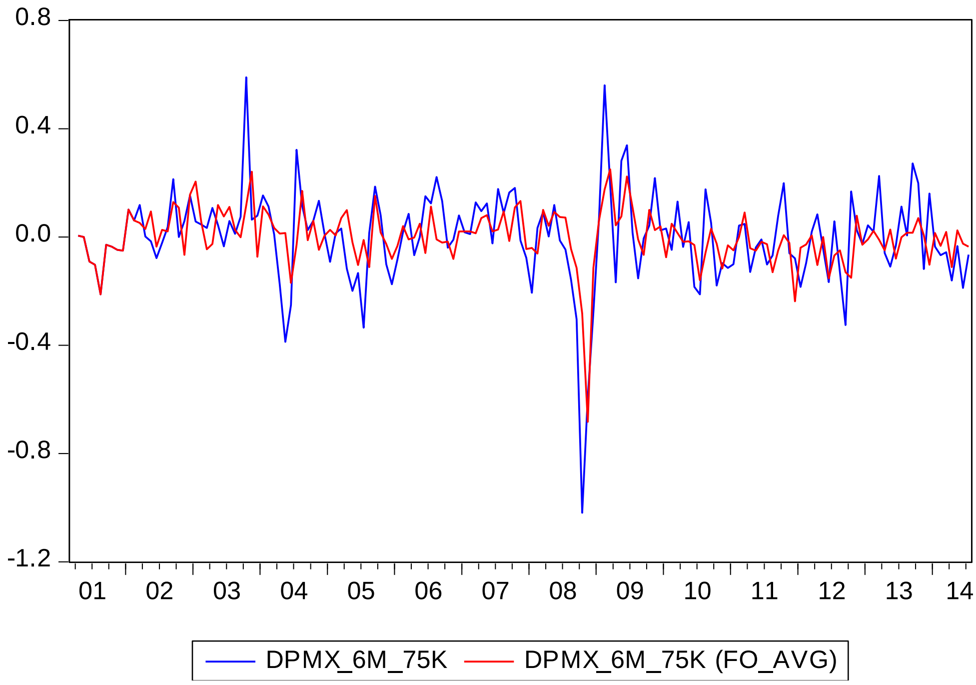


Figure 45: Panamax 6m t/c ex-post (VARX)

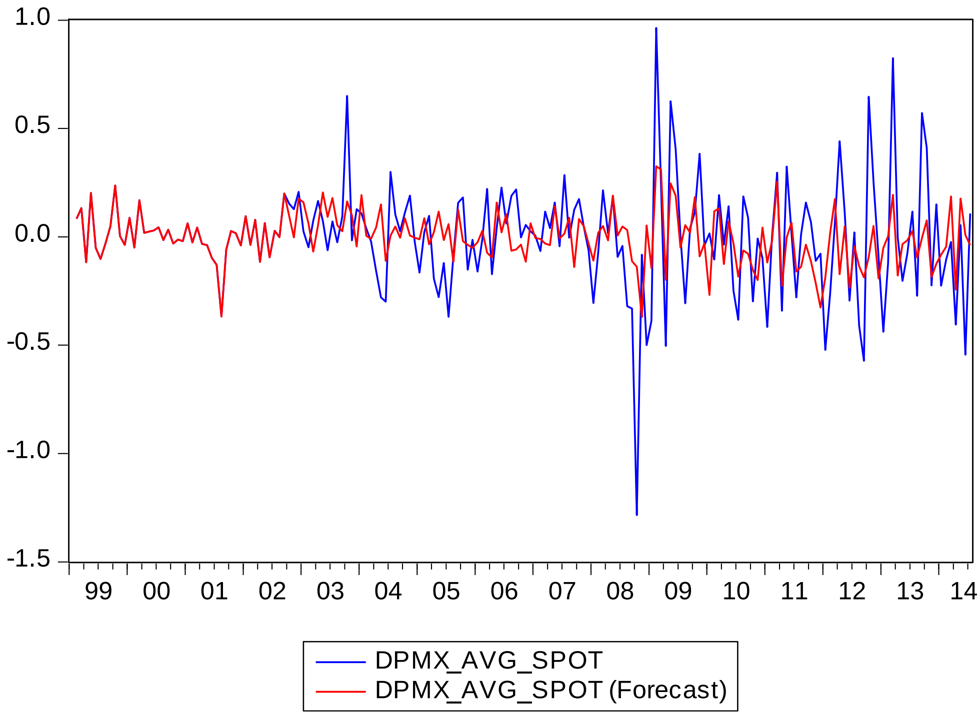


Figure 46: Panamax spot ex-post (VARX)

7.7.1. Ex-ante forecasts

Ex-ante forecasts require the specification of a sub-sample of the dataset and the remaining observations are considered unknown. Thus the data of the resized sample can be used to generate forecasts and then compare the forecasted values with the actual ones (which had been regarded as out-of-sample). This technique allows the evaluation of the forecasting accuracy of the model.

This analysis takes sub-samples of each dependent variable which end on December 2013 and uses them to produce ex-ante forecasts for seven months ahead.

The following figures depict the ex-ante forecasts for the dependent variables of this study.

7.7.1.1. ARIMA models

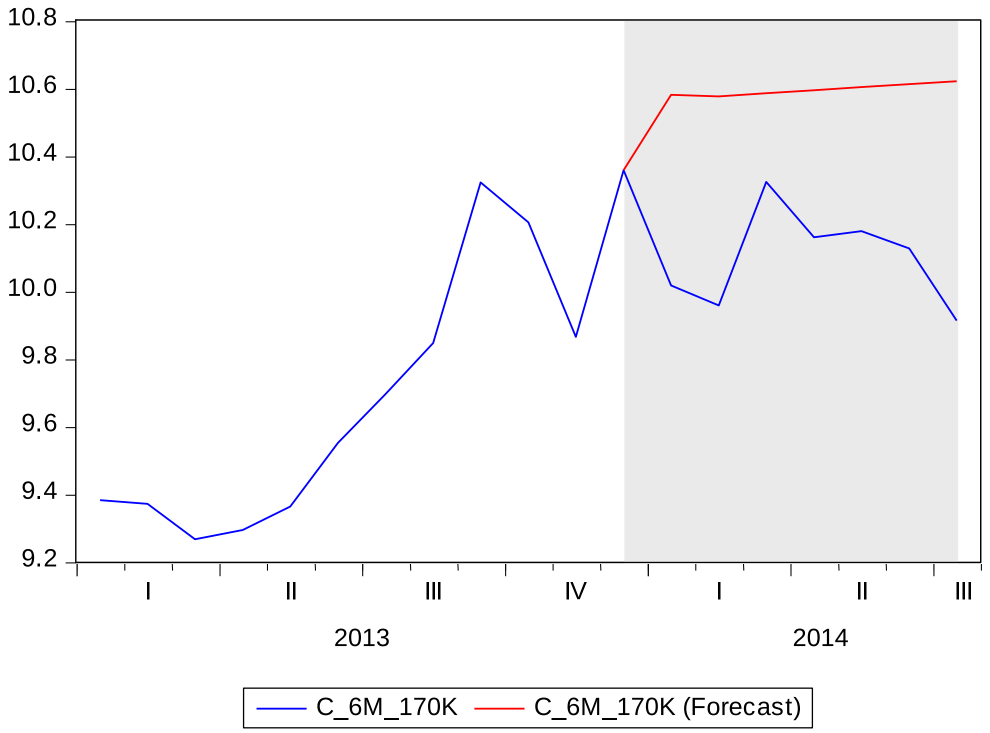


Figure 47: Capesize 6m t/c ex-ante (ARIMA)

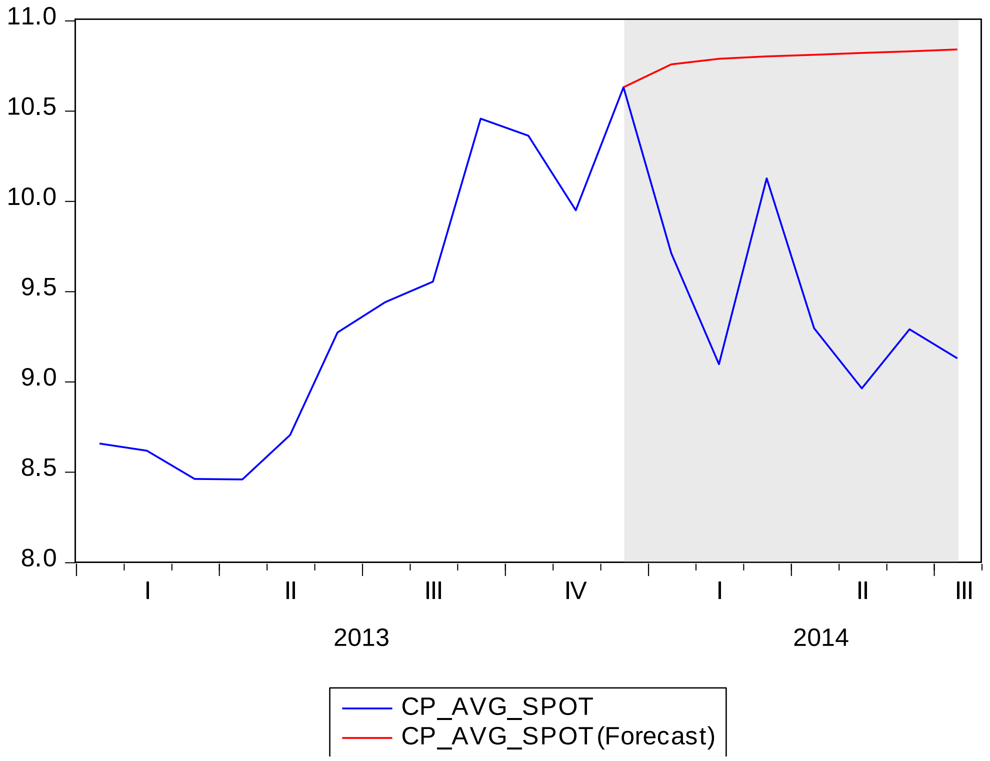


Figure 48: Capesize spot ex-ante (ARIMA)

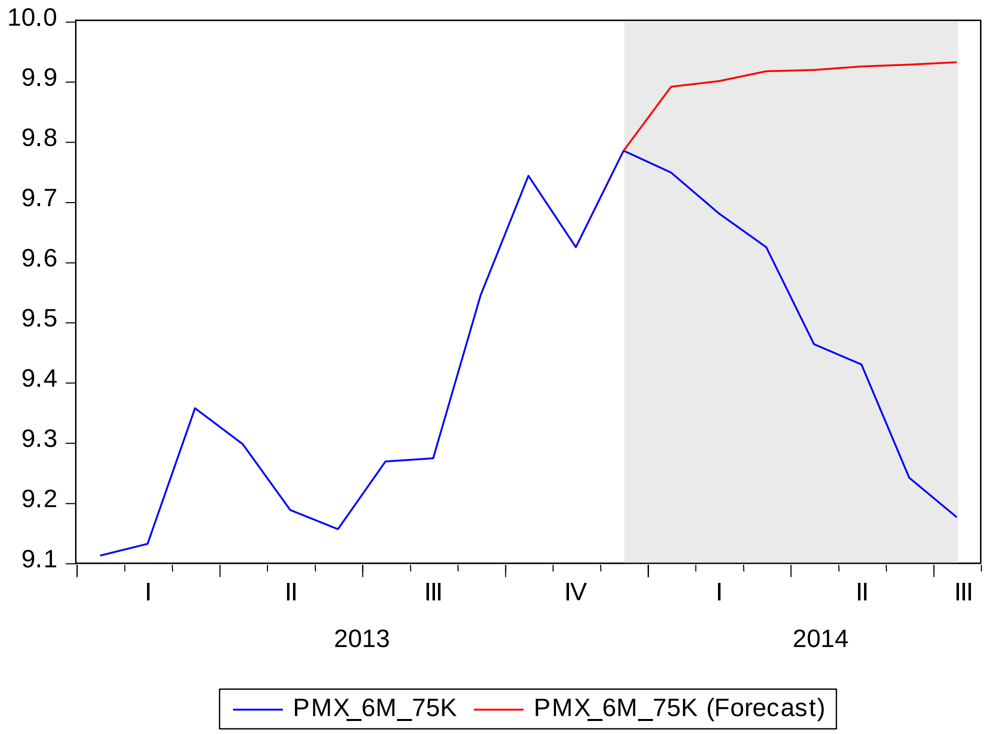


Figure 49: Panamax 6m t/c ex-ante (ARIMA)

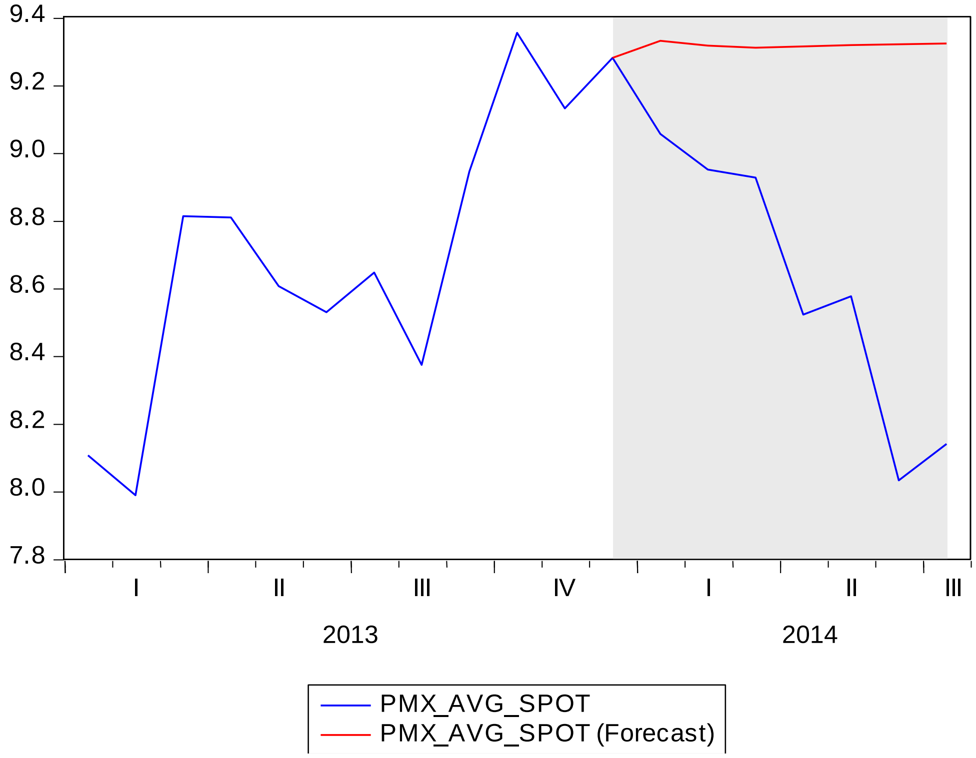


Figure 50: Panamax spot ex-ante (ARIMA)

7.7.1.2. VAR / VECM Models

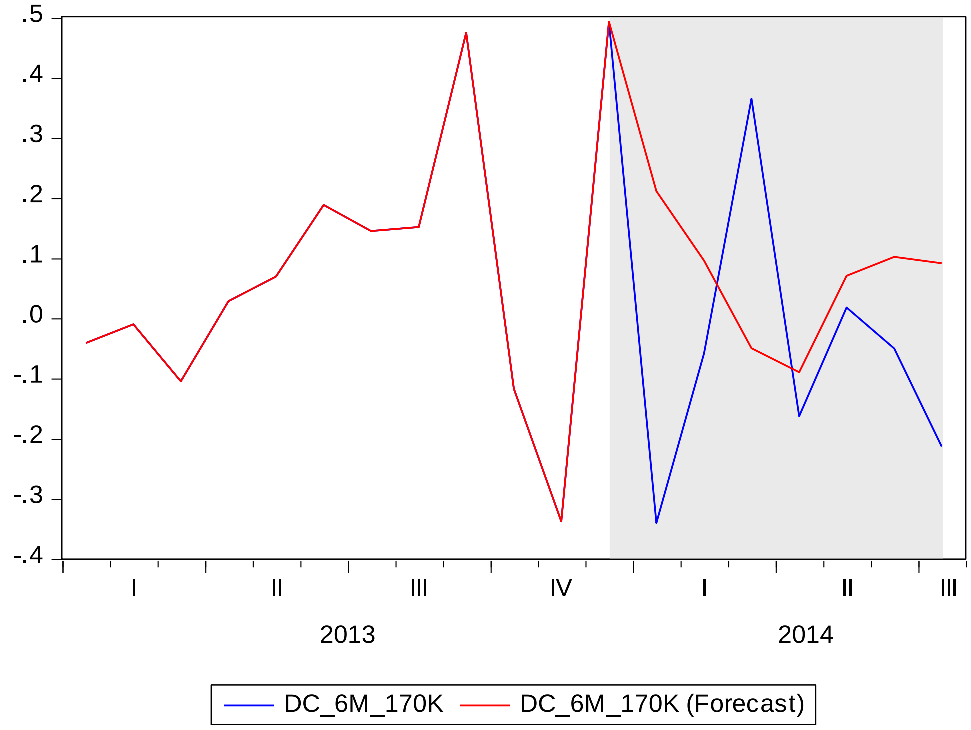


Figure 51: Capesize 6m t/c ex-ante (VAR)

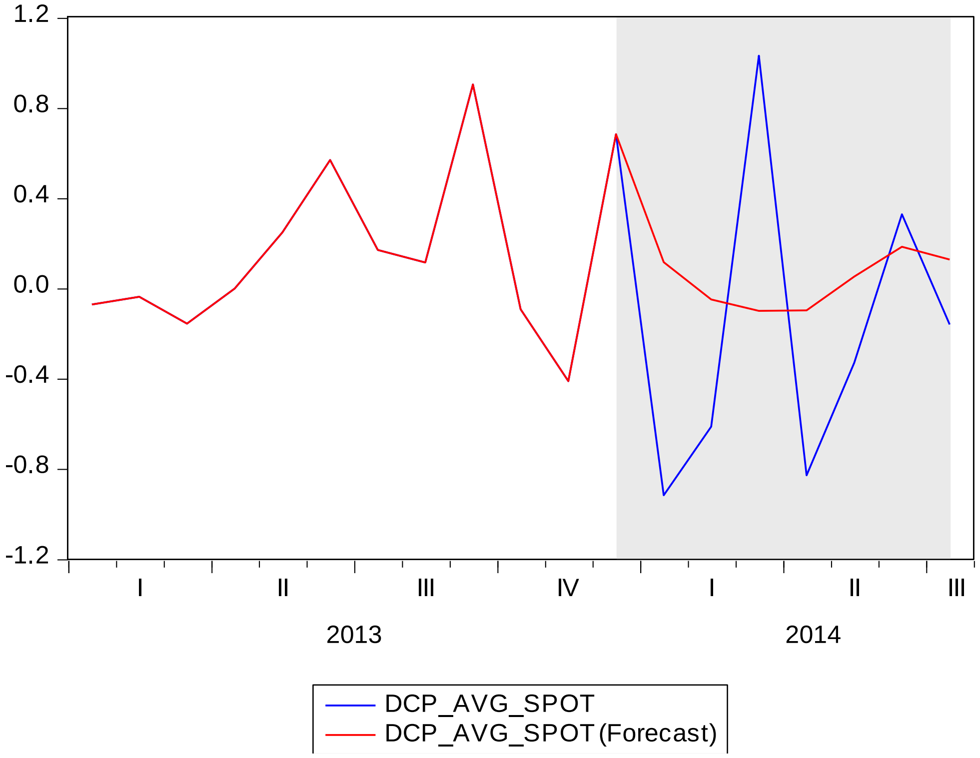


Figure 52: Capesize spot ex-ante (VAR)

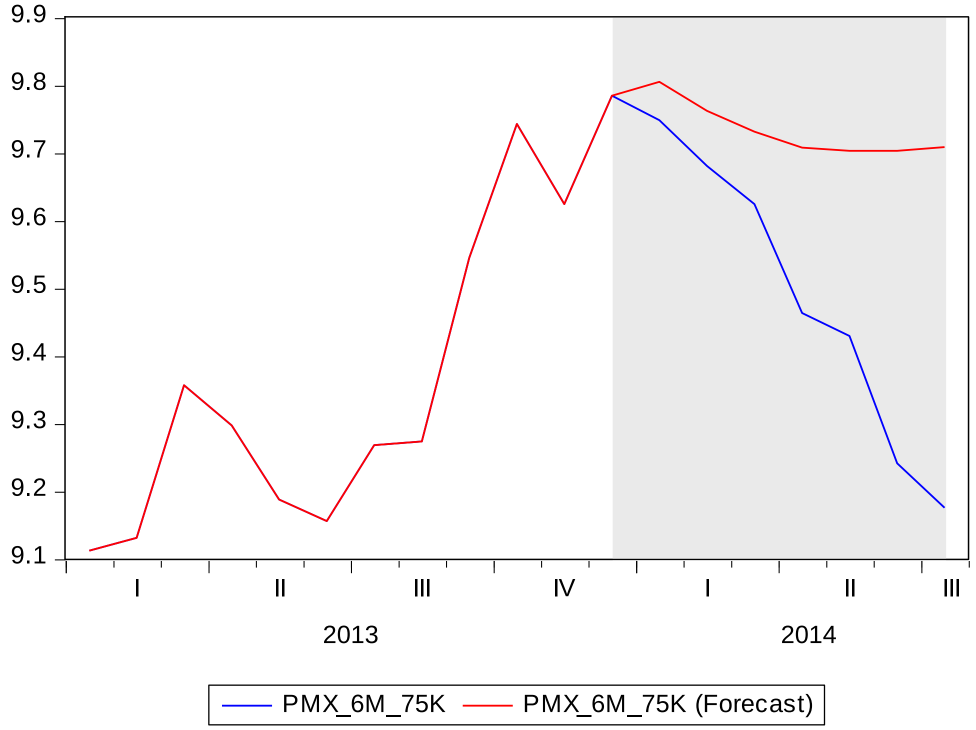


Figure 53: Panamax 6m t/c ex-ante (VECM)

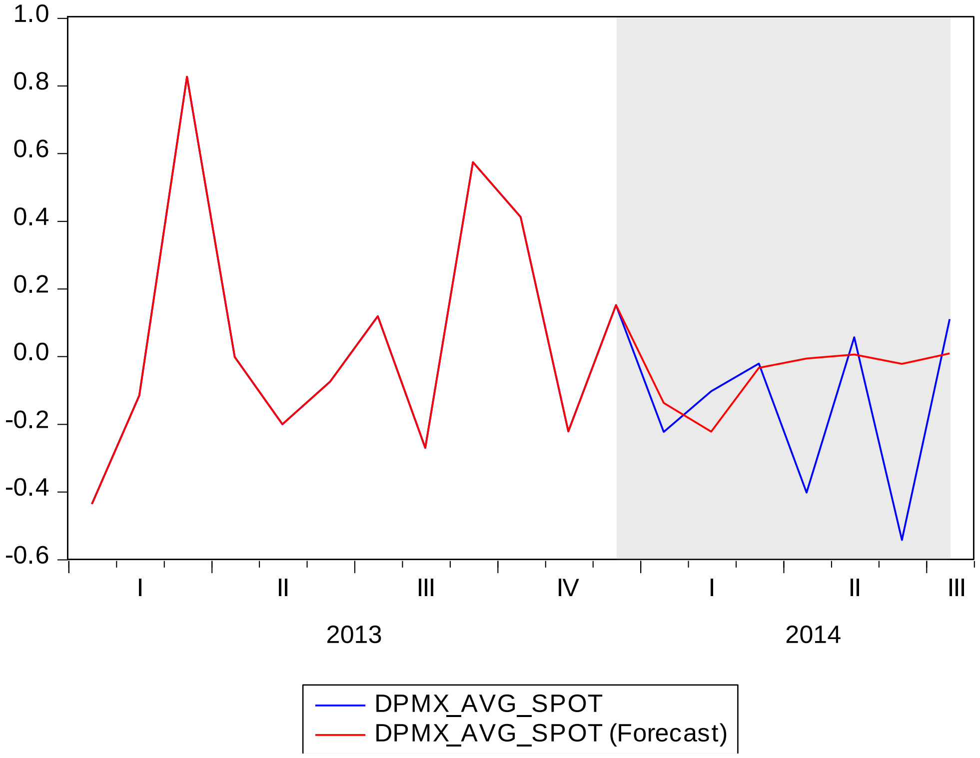


Figure 54: Panamax spot ex-ante (VAR)

7.7.1.3. VARX Models

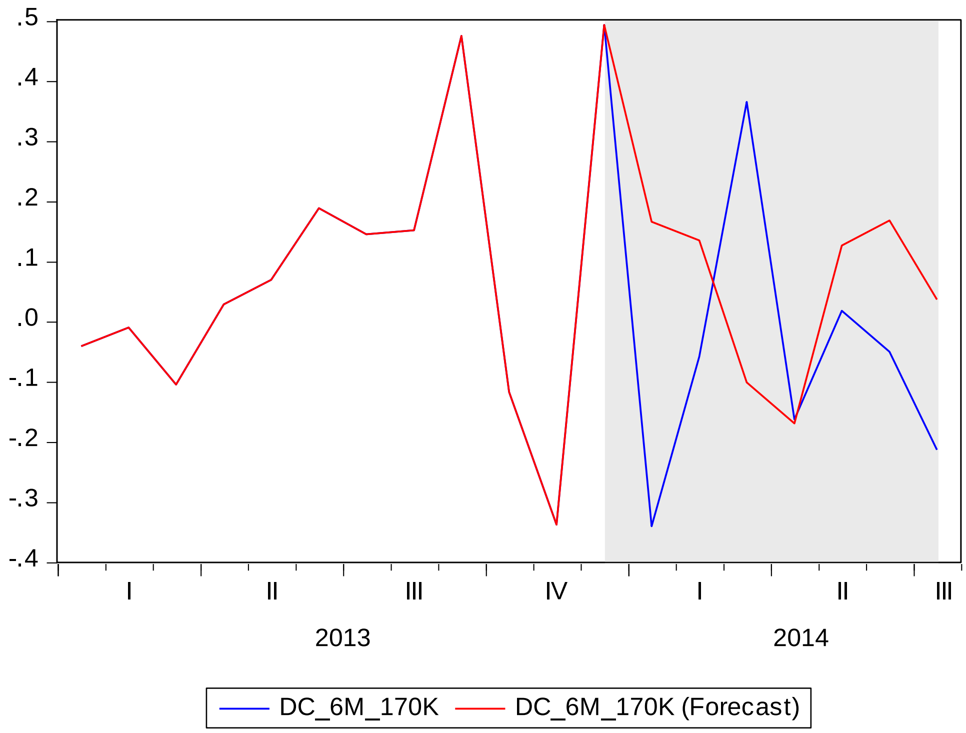


Figure 55: Capesize 6m t/c ex-ante (VARX)

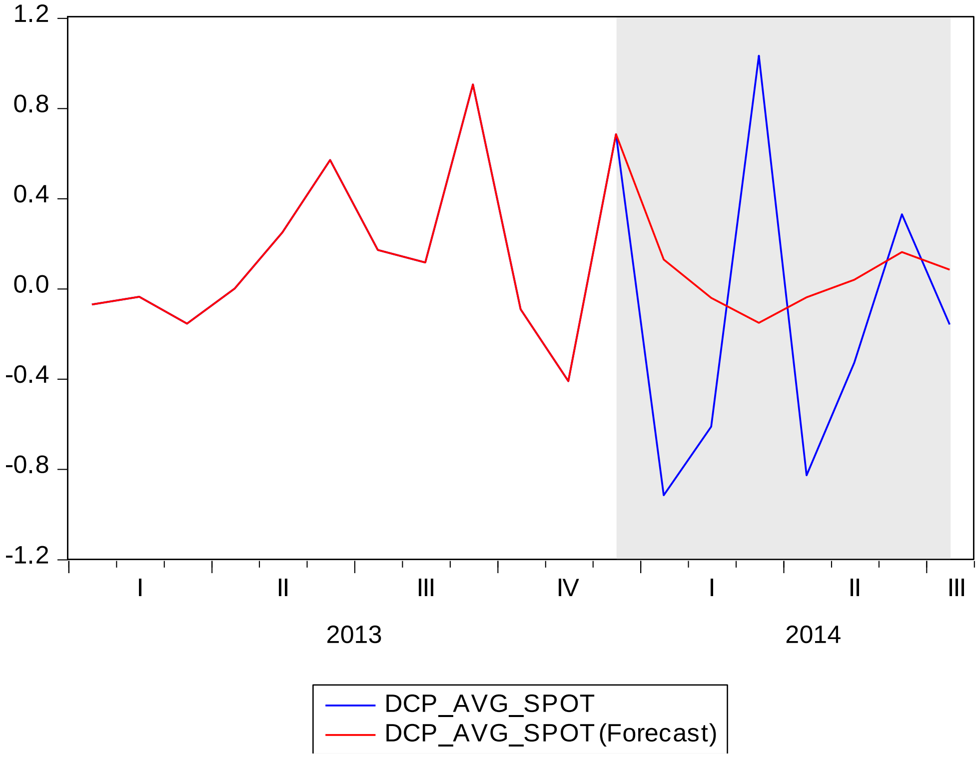


Figure 56: Capesize spot ex-ante (VARX)

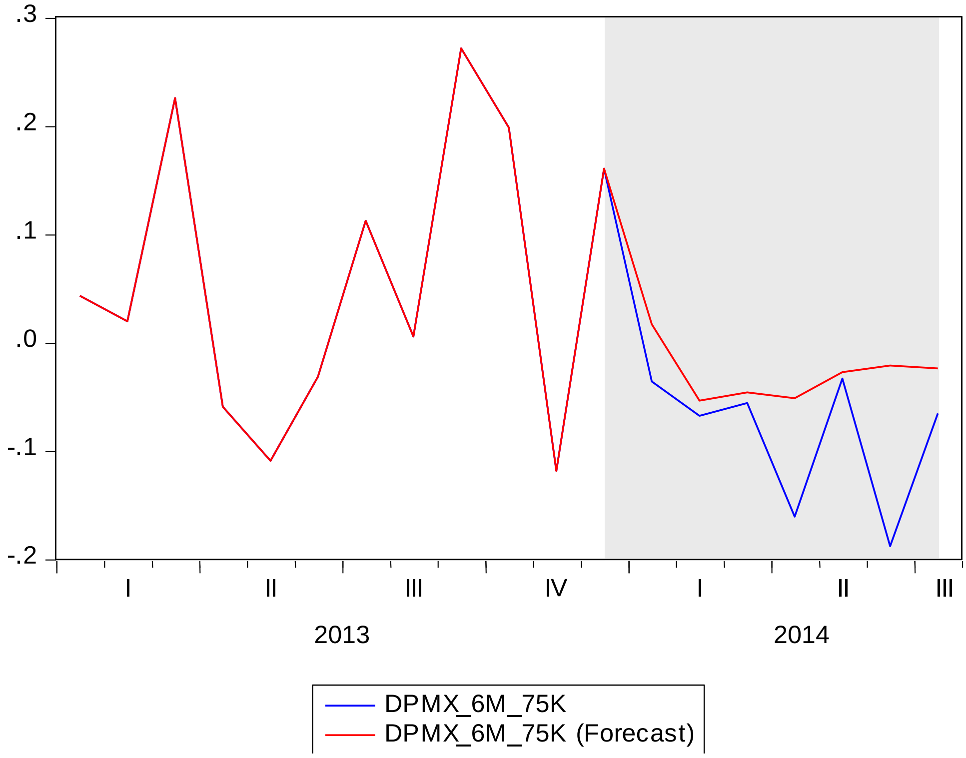


Figure 57: Panamax 6m t/c ex-ante (VARX)

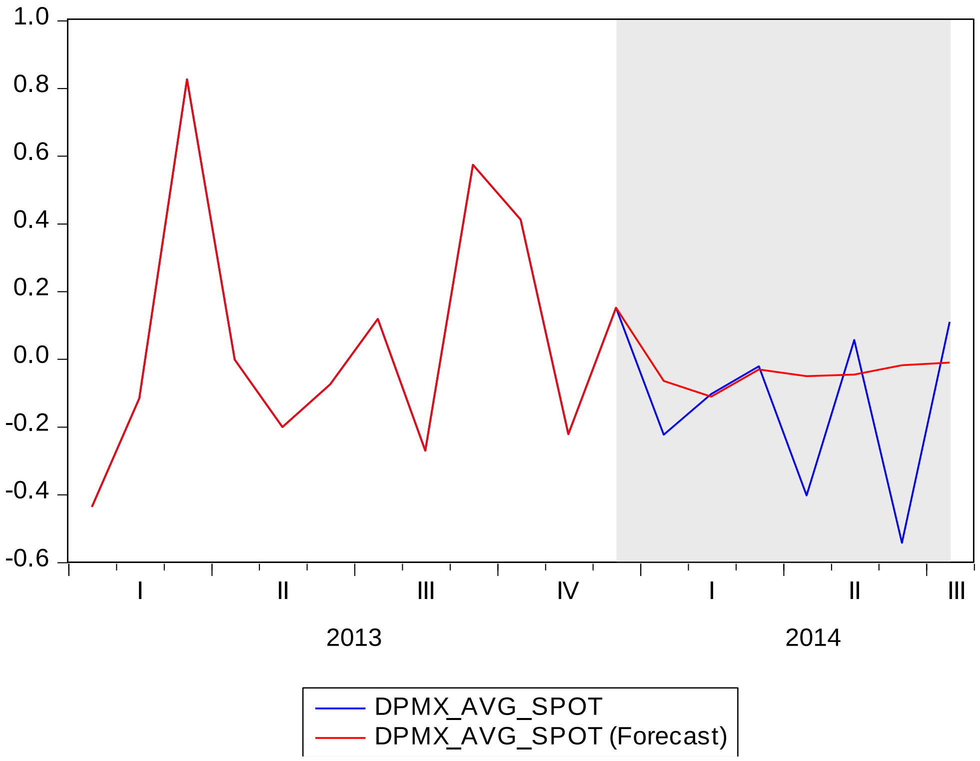


Figure 58: Panamax spot ex-ante (VARX)

7.8. Forecasting Evaluation and Comparison of Forecasts

Table 41 presents the forecast errors of ex-post forecasts and Table 42 the errors pertaining to ex-ante forecast. The values of the two tables measure the predictive accuracy and thus provide evidence for the forecasting performance of each approach.

	ARIMA		VAR / VECM		VARX / VECMX	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
Capesize						
avg spot	0.448270	0.309264	0.449230	0.312504	0.446092	0.311693
6-m tc 170k	0.236236	0.264612	0.224556	0.163695	0.205470	0.157780
Panamax						
avg spot	0.275938	0.193055	0.277866	0.194738	0.275371	0.192302
6-m tc 75k	0.156628	0.110822	10.555840	10.543080	0.172130	0.114670

Table 41: Forecast Errors (ex-post static forecasts)

	ARIMA		VAR / VECM		VARX / VECMX	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
Capesize						
avg spot	1.485375	1.433201	0.683148	0.611073	0.680953	0.608044
6-m tc 170k	0.517611	0.499697	0.298708	0.243342	0.300645	0.249803
Panamax						
avg spot	0.810306	0.718781	0.277466	0.210927	0.278017	0.206066
6-m tc 75k	0.485598	0.435513	11.170430	11.170230	0.107667	0.090387

Table 42: Forecasting Errors (ex-ante dynamic forecasts)

The above results are indicative of the superiority of the VARX approach compared both to VAR/VECM and to ARIMA. The values of most relevant criteria are much lower for the VARX models, revealing a higher level of accuracy. This can be attributed to their suitability for this kind of forecasts, which is enhanced by the incorporation of a new composite index, the DBECI, which reflects the economic conditions pertinent to the dry bulk market (DBECI). Moreover, the performance of VARX models is further improved by the utilization of the average bunker prices as a second exogenous variable. On top of that, as discussed in 7.5.3.4, the R-squared values are consistently higher in the case of VARX models than in the two alternative approaches (with only one exception).

Starting with the ex-post forecasting results, it is noticeable from Table 41 that the VARX model performs better than both the VAR/VECM and the ARIMA models in the prediction of spot Capesize rates, period Capesize rates and spot Panamax rates.

In contrast, while VARX easily outperforms the VECM in terms of Panamax period rates, the ex-post results indicate that the ARIMA model provides more accurate forecasts for this particular case. However, this is not confirmed by the ex-ante results, which reveal that ARIMA yields the largest forecast errors. Indeed, the values of both criteria are more than three time higher than the respective values for VAR and VARX models.

Table 42 presents the ex-ante results, which confirm the superiority of VARX models, as they yield the lowest forecast errors in all cases except the Capesize period rates, which are better predicted by VAR models. Also, there is a conflict between the RMSE and MAE in the case of Panamax spot rates, as the former criterion is in favour of VAR, while the latter points to VARX. Other than that, the VAR models perform better than their ARIMA counterparts. It should be noted that the predictive power of ARIMA models is significantly lower in all ex-ante forecasts. Given that the forecast horizon is 7 months, it appears that ARIMA models are not well suited for medium term forecasts.

Another important remark is that both ex-post and ex-ante forecasts, in all three modeling frameworks, yield more accurate predictions for the period than for the spot market. This is consistent with theory, considering that period rates are more reliant on future expectations than spot rates. The latter are also more volatile, as indicated by the descriptive statistics. Therefore, the formation of the current values of period rates embodies elements of market expectations, which ultimately facilitate their prediction. This also explains the relatively good performance of ARIMA models in the case of period rates, considering that this framework relies solely on its own past values for future predictions. The most notable example is the superiority of this approach for ex-post forecasts of Panamax period rates.

Overall, the lower forecast errors of VARX models manifest the influential role of the proposed index as a leading indicator of dry cargo freight rates.

7.9. Concluding Remarks

This chapter formulates three different modelling approaches and then evaluates the forecasting results using appropriate criteria. The ARIMA framework mainly serves as a benchmark for purposes of comparison. Co-integration tests determine the choice between VAR and VECM, and Granger causality analyses validate the selection of suitable explanatory variables. In this setting, each model is used to generate ex-post and ex-ante forecasts for the same sample size and over the same time horizon. According to the results, it arises that period rates can be predicted with significantly higher accuracy than spot rates. A further comparison of the forecast errors, points to the superiority of the VARX models in almost all cases. VAR models also outperform ARIMA, but they are less powerful than VARX. Those findings, combined with the higher R-squared values of VARX models, are a clear indication of the beneficial role of DBECI and average bunker prices as exogenous variables in forecasting models. All in all, it is evident that the addition of those two newly constructed variables enhances the robustness and the predictive success of the proposed models.

8. OPTIMAL CHARTERING DECISIONS

8.1. Introduction

The aim of this chapter is to investigate strategic chartering decisions in the spot market. In this respect, it studies the historical return performance of trip charters in comparison with their corresponding voyage charters using technical analysis rules. Considering first some of the most representative dry bulk t/c trip routes, the corresponding voyages are identified. In this context, a technical trading strategy is developed and then examined in terms of its ability to generate excess returns. The results show that the proposed approach outperforms the 'naïve' strategy of always chartering in vessels on t/c trip charters and perform the underlying voyage charters. Overall, the results reveal the existence of excess return opportunities in the spot market. This analysis can be used by ship operating companies as a guide to select voyages with the highest probability of excess returns and adapt their strategies accordingly.

It is worth noting, that the present analysis is performed under the assumption of semi-strong market efficiency, as it is assumed that the historical rates and all publicly available information are known. At this point a contradiction arises, since the existence of excess profit opportunities is not consistent with the EMH. Yet, as it is discussed in the EMH section of this thesis (2.12 – 2.15), it can be considered that market efficiency is restored in the long-run, if a long-term equilibrium exists. In this regard, it is of paramount importance to test for co-intergration and check if there are any equilibrium relationships.

According to the relevant literature review (3.3 -3.4), there have not been any studies investigating the relationship between trip charters and their underlying voyages. The body of the literature makes no distinction between trip charters and the Time Charter Equivalent (TCE) of voyages. They are rather used interchangeably to represent the spot market rates for purposes of comparison with the time charter period rates and FFAs (see 3.3). However, they constitute two different ways of chartering a vessel and it is interesting to study their dynamics. Hence this study extends the analysis to a new area of research, attempting to fill a gap in the literature.

As discussed in Chapter 2, a trip t/c is a short time charter, where the vessel is employed for a specified route only. On the contrary, under a standard (or period) t/c the operator is free to trade the vessel for an agreed period of time within specified trading areas. In general, under time charters (both trip and period) the ship owner hires out the vessel and remains responsible for paying the crewing costs, the maintenance costs and so on. In exchange, the shipowner receives a daily hire payment. On the other side, the time charterer (who becomes the operator) takes over the commercial control of the vessel and pays the voyages costs, such as bunker expenses, port disbursement accounts and so on.

A voyage charter occurs when a vessel is employed for a voyage between a load and a discharge port. The ship operator incurs the voyage expenses, while the charterer pays the operator an agreed freight on a per-ton basis. Some operators, described as 'Disponent Owners', hire in ships on a period t/c or a trip t/c from ship owners and try to secure a profit by trading them in the spot market, entering into voyage charter contracts. This study concentrates on those operators who charter in vessels for a single t/c trip and perform voyage charters.

The chapter begins with an extensive discussion of the characteristics of spot and period rates, including their formation mechanism and their relationship. Then the attention is turned to the spot market, which is the focal point of the current analysis. In this context, a technical trading method is developed and applied to some selected routes. The last step involves the evaluation of the proposed methodology and the analysis of the results.

8.2. Formation of spot freight rates

The dry bulk freight rates are determined by the balance between supply and demand. In turn, each of these functions is driven by several factors which have been identified and analyzed in the previous sections. The important point here is that freight rates are formed by this dynamic relationship. Therefore, in order to obtain a more solid picture of the freight rate mechanism, it is essential to look into the precise manner in which the supply and demand interact with each other.

This idea is illustrated by the supply and demand curves in Figure 59 below. To begin with, the demand for shipping services is inelastic. The shape of the demand curve reflects that higher freight rates may push down the demand, due to postponements of shipments or modifications of parcel sizes so that they can be carried by alternate vessel categories. In general, high transport cost is a significant disincentive for shippers.

The supply of ships has a characteristic "J shape" which represents the carrying capacity at different levels of freight rates. This particular shape implies that supply is elastic at low freight rates (within the interval specified by points A and B) and turns into inelastic when rates skyrocket (beyond point B). The elastic part of the supply curve is attributed to the overcapacity during periods of stagnating freight rates. In such periods, any increase in demand (for example from D1 to D2) is instantly absorbed by the available tonnage and limits the upside potential of freight rates. On the other hand, a possible shift of demand from D3 to D4, is expected to trigger a steep rise in freight rates, followed by a relatively small increase in supply. This inelastic behavior can be explained by the notion of full capacity utilization. The rising demand leads to high utilization rates of vessels and this enhances the negotiating power of shipowners. Therefore, when the demand keeps rising, charterers are usually compelled to concede to much higher freight rates. This creates the almost vertical supply line which is shown in the graph.

Finally, an increase in demand triggers an automatic rise in freight rates, which ultimately leads to surging supply in the short term. The latter is owed to the tendency of shipowners to speed up when rates are high in order to get the most out of the favorable market conditions, as well as to their possible decision to reactivate the laid-up vessels. The long term supply is also poised to be affected, since the cash that shipowners accumulate during the aforementioned market boom is likely to be invested in newbuilding vessels; especially when shipowners are driven by a positive sentiment. At the same time the scrapping rate drops, since even the old ships are able to cover their operating expenses. The combination of those factors leads to a sharp increase in supply over the long run, which is not easy to be absorbed by the market demand.

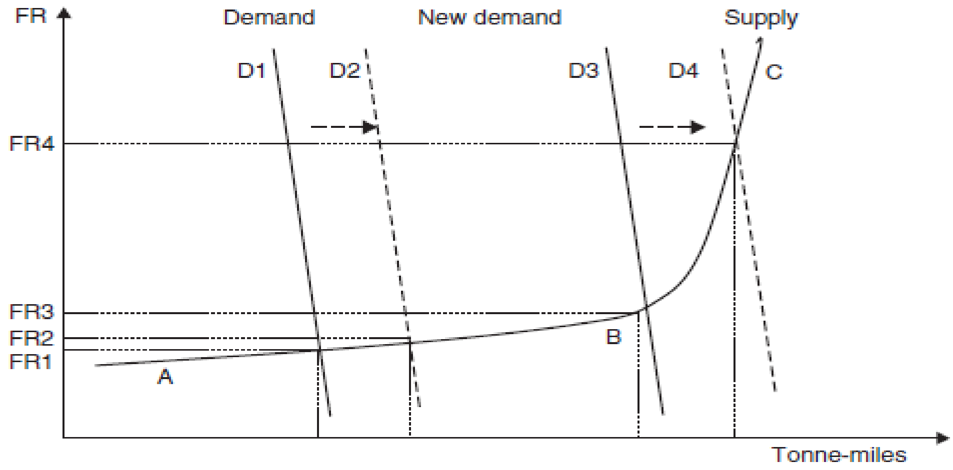


Figure 59: Supply – demand framework

Source: Alizadeh and Nomikos (2009)

8.3. Formation of time charter rates

Unlike voyage or spot freight rates, which are shaped by the interplay between demand and supply and are affected by various factors, in the case of time charter rates the market expectations about the future values of spot rates play a more important part. For instance, the 6-month t/c contract reflects the agents' expectations about the levels of spot rates over the duration of the charter.

In congruence with what was discussed in 2.12 - 2.15 and 3.3 – 3.4, it will be attempted to approach the formation of t/c rates within the spectrum of the term-structure relationship. The latter is connected with the no-arbitrage principle and the efficiency of the freight market.

This relationship implies that in an efficient market the present value of t/c rates equals the present value of the difference between the expected values of spot earnings and voyage expenses over the contract duration. This is mathematically represented by the following equation:

$$\mathrm{TC}=\frac{1}{T}\sum_{t=1}^{T}\frac{\left[\mathrm{E}\left(R_{t}\right)-\mathrm{E}\left(C_{t}\right)\right]}{(1+i)^{t}} \qquad (8.1)$$

where TC is the time charter rate, $E(R_t)$ denotes the expected earnings in the spot market, E(Ct) are the expected voyage costs, T is the maturity of the contract and i is the discount rate.

Drawing on the discussion about the existence of a time-varying risk premium which emanates from various risk factors (see 2.16), the risk premium, φ_t, is incorporated and equation 8.1 takes the form:

$$\mathrm{TC}=\frac{1}{T}\sum_{t=1}^{T}\frac{\left[\mathrm{E}\left(R_{\mathrm{t}}\right)-\mathrm{E}\left(C_{\mathrm{t}}\right)\right]}{(1+i)^{t}}-\varphi_t \tag{8.2}$$

where φ_t is the time-varying risk premium.

8.4. Time Charter Equivalent (TCE)

Voyage rates are converted into Time Charter Equivalents (TCE) so as to be comparable with the spot t/c rates which are measured in $/day. The TCE is calculated on the basis of standard ship types by deducting from the total net revenues: [freight rate x cargo intake x (1 – commission)] the total voyage expenses: (bunker cost + port charges + canal dues) and divide by the number of voyage days. The calculations do not include allowance for unforeseen expenses, waiting time at port and off-hire time. However they do account for the ballast trips in the estimation of the total voyage days. (Clarkson Research Services Limited, 2014)

8.5. Excess returns in the spot market

8.6. Motivation

The figures below (Figure 60 – 64) provide a graphical representation of the relationship between representative t/c trips and some of their corresponding voyages for different vessel sizes. It is illustrated that the respective pairs of variables co-fluctuate in the long run, while they are characterized by distinct deviations at some specific points in time over the short run. Therefore, it is essential to statistically confirm their co-integrating relationship and then develop a strategy in order to exploit the deviations and increase the excess returns.

In this respect, the series are first examined in terms of their stationarity, using two different tests, i.e. the Augmented Dickey Fuller (ADF) and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. If the series are found non-stationary Johansen test will be employed to test for co-integration.

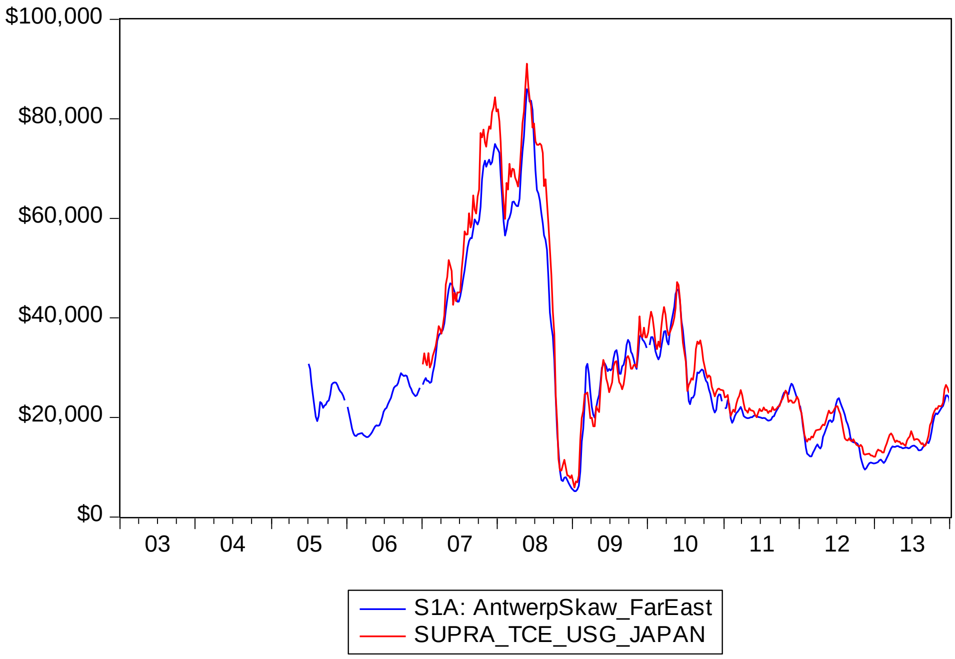


Figure 60: Supramax S1A and USG-Japan TARV

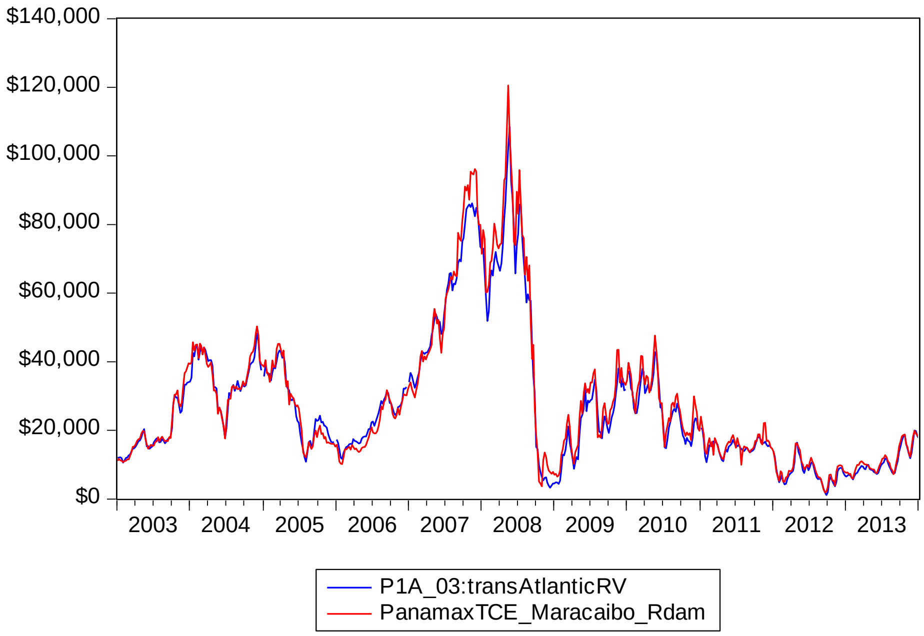


Figure 61: Panamax P1A_03 and Maracaibo-Rotterdam

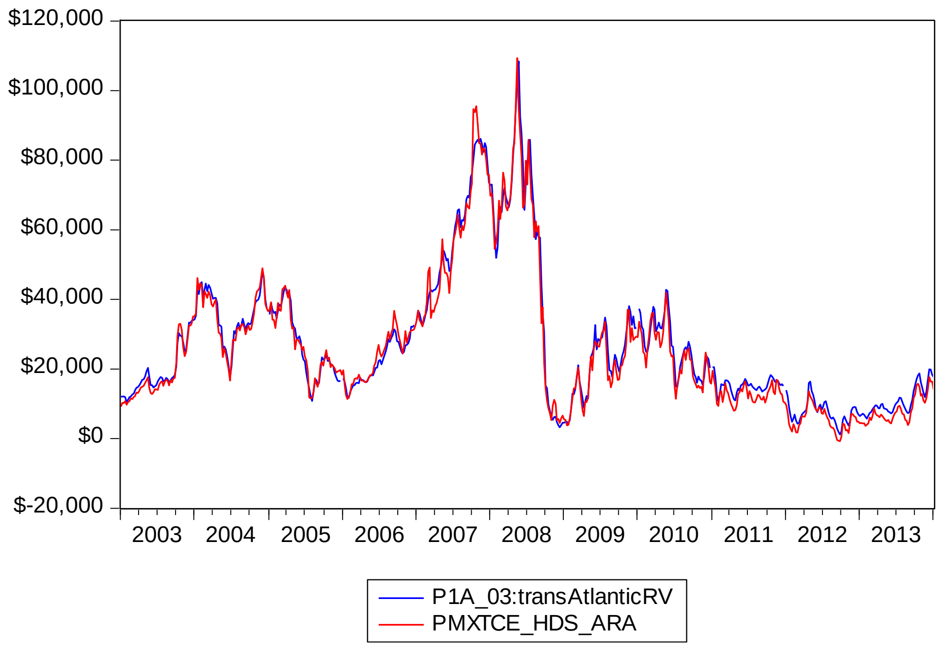


Figure 62: Panamax P1A_03 and Hampton Roads-ARA

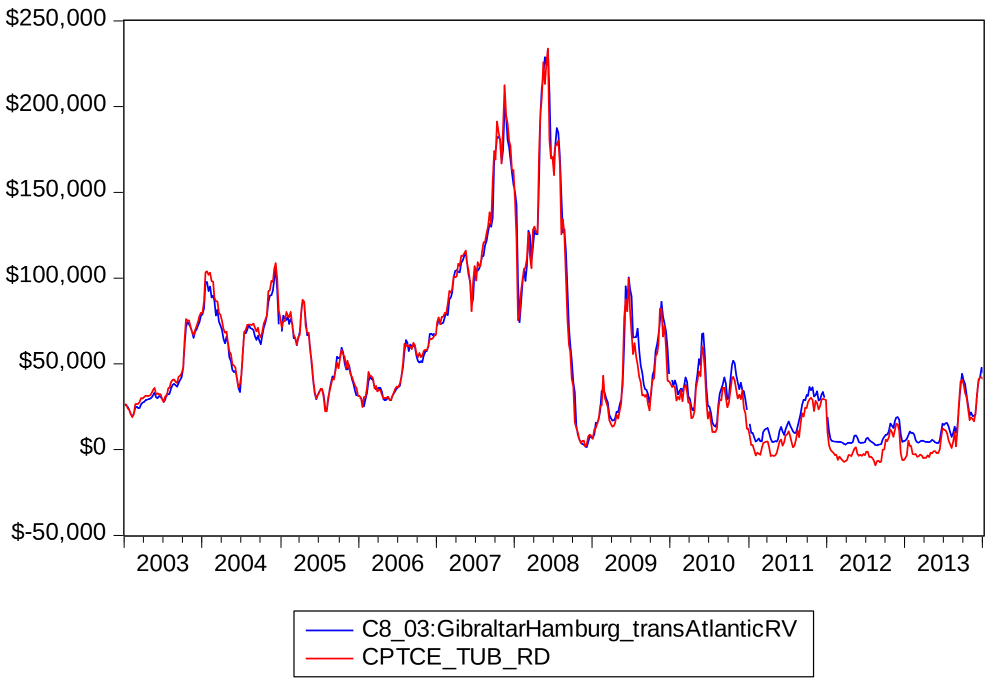


Figure 63: Capesize C8_03 and Tubarao-Rotterdam

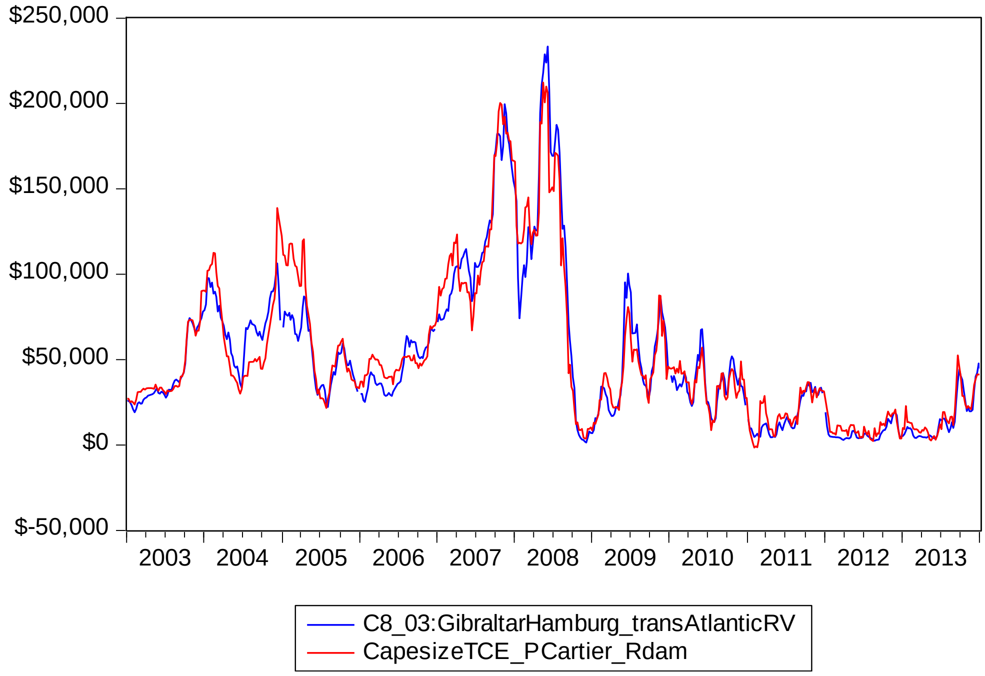


Figure 64: Capesize C8_03 and Port Cartier-Rotterdam

In essence, the figures show that there are signals at some specific times, emanating from the distinct (positive) divergence of voyage rates from t/c trip rates. The prime goal is to develop a new methodology which will be able to identify the optimal timing for entering the spot market.

8.7. Chartering Strategy Formulation

Subsequent to the establishment of the existence of a long-term relationship between spot t/c and voyages rates, the centre of attention shifts to the short run deviations and to the formulation of a chartering strategy based on technical trading rules. The main objective is to set up a new method and exploit the short-term opportunities as they arise. For this purpose, a new methodology is introduced, the Modified Momentum Trading Model (MMTM).

Widler (1978) was the first to introduce price momentum and RSI as a technical analysis tool. Furthermore, many other books dealing with technical analysis discuss both momentum and RSI; for example, Murphy (1999) and Kahn (2006).

In physics, momentum depends on the velocity of an object. Likewise, market momentum is the measurement of the velocity or speed of price movements. Momentum trading is a technical analysis method, employed to set up a chartering strategy. It is based on an index (the RSI), which reflects the momentum of upward and downward movements. The basic idea is the continuation of established trends in the market.

In the framework of the Momentum Trading methods, generally, when the RSI crosses some specified threshold values, indicates a decision signal. However, these barriers vary from case to case. Thus, this analysis takes as threshold the Moving Average MA(4). This modification makes the MMTM more aligned to the volatile nature of shipping freight markets, compared to the conventional Momentum Trading methods. The goal is to capture - as much as possible - the fluctuations and the market shocks of the dry bulk freight market, without compromising the flexibility of the methodology.

This model is based on the concept of the Momentum Trading model with necessary modifications in terms of the definition of its components and its thresholds. More specifically, a measure of the momentum (M_{t+1}) is defined as:

$$M_{t+1} = \sum_{t=1}^{n} u_t / \sum_{t=1}^{n} d_t$$

where u_t represents a positive spread at time t, namely voyage TCE > t/c trip rate and d_t a negative spread (TCE < t/c trip).

On this basis, the Relative Strength Index at time t+1 (RSI_{t+1}) is constructed using the following formula:

$$RSI_{t+1} = 100 - 100 / (1 + M_{t+1})$$

A move of the RSI above its 4-week Moving Average MA(4) is an indication of an upward momentum, as the recent sum of voyage TCEs is surpassing the respective sum of t/c trip rates. Hence, in this case, an operator should select this voyage as profitable. Conversely, a level below its MA(4) corresponds to a lack of excess return opportunities on voyage charters; Thus there will be no voyage in the latter case.

8.8. Data Description

This study employs weekly data from the Clarkson's Research Services Ltd (CRLS) database, which cover the period starting from January 2003 to January 2014. The dataset considers three separate sizes: Capesize, Panamax and Supramax. There were no historical data available on CRLS for voyage freight rates of the Hadysize-Handymax category, as these vessels perform various and usually short-distance voyages.

The freight rate data collection is carried out by Clarkson's Research team through a pro-forma where various brokers report last week's fixtures and then the data are crosschecked with published sources. Voyage rates are converted into Time Charter Equivalents (TCE) so as to be comparable with the spot t/c rates which are measured in $/day. The calculations do not include allowance for unforeseen expenses, waiting time at port and off-hire time. However they do account for the ballast trips in the estimation of the total voyage days.

The analysis focuses on the following t/c trips: the BSI S1A: 52,454 mt Antwerp/Skaw trip to Far East, the BPI P1A_03: 74,000mt trans-Atlantic round voyage and the BCI C8_03: 172,000mt Gibraltar/Hamburg trans-Atlantic round voyage. On this basis, the following corresponding voyages are identified: the US Gulf (USG) – Japan grain voyage for a 49,000dwt Supramax, the Maracaibo – Rotterdam coal voyage for a 70,000dwt Panamax, the Hampton Roads – Antwerp, Rotterdam or Amsterdam (ARA) coal voyage for a 70,000dwt Panamax, the Tubarao - Rotterdam iron ore voyage for a 165,000dwt Capesize and finally the Port Cartier – Rotterdam iron ore voyage for a 150,000dwt Capesize.

8.9. Descriptive Statistics

The data analysis begins with the descriptive statistics, as shown in Table 43 below.

	Mean	Min	Max	Standard Deviation	Skewness	Kurtosis	J-B
Supramax							
TC trip:							
S1A	10.1201	8.55256	11.3614	0.55078	0.04656	3.11129	0.386041 [0.824465]
Voyage TCE:							
USG - Japan	10.21325	8.683724	11.41939	0.572859	0.23501	2.576107	6.109208 [0.047141]
Panamax							
TC trip:							
P1A_03	9.94924	7.051856	11.59357	0.743091	-0.26554	3.077472	6.829129 [0.032891]
Voyage TCE:							
Maracaibo - Rdam	9.999021	7.549083	11.69975	0.714825	-0.045568	2.886465	0.507825 [0.775759]
HRds-ARA	9.861387	6.267201	11.60254	0.831001	-0.511187	3.546481	32.029340 [0.000000]
Capesize							
TC trip:							
C8_03	10.39242	7.286192	12.36059	1.059044	-0.593499	2.65294	36.259920 [0.000000]
Voyage TCE:							
Tubarao-Rdam	10.51904	4.488636	12.36211	1.092755	-1.499845	7.009585	530.752200 [0.000000]
Port Cartier - Rdam	10.49787	7.23201	12.26582	0.935939	-0.522867	3.038819	26.099040 [0.000020]

Notes:
Figures in [.] are p-values
The Jarque-Bera (J-B) test is used to check for normality. The J-B statistic is asymptotically $\chi^2(2)$-distributed

Table 43: Descriptive Statistics

According to Table 43, the historical mean voyage return of every route of the current analysis exceeds the respective t/c trip earnings, indicating the existence of excess return opportunities on voyage charters.

The unconditional volatility (standard deviation) of the majority of voyage charters is higher than the corresponding standard deviation of the respective t/c trips (e.g. Supramax USG – Japan, Panamax HRds – ARA and Capesize Tubarrao-Rotterdam routes). This suggests that the voyage rates generally fluctuate more than the t/c trip rates in all vessel sizes.

In addition, Table 1 reports that almost all rates are right-tailed (positive skew). The only exception is the P1A_03 t/c trip which is negatively skewed. A positively skewed distribution implies a large number of small losses and a few extreme gains, while the reverse occurs with negative skewness.

As far as the kurtosis is concerned, Table 1 indicates that most of the variables are leptokurtic (kurtosis greater than 3). This class includes the S1A t/c trip, the P1A_03 t/c trip, the Panamax HRds – ARA voyage charter, the Capesize Tubarrao - Rotterdam voyage and finally the Capesize Port Cartier-Rotterdam voyage charter. Therefore their distribution is characterised by heavy tails, which implies that there are it is more likely to come across values which fall quite far from their mean.

Lastly, the Jarque-Bera test suggests the data of Supramax S1A and Panamax Maracaibo – Rotterdam are normally distributed, whilst the low p-values of the Jarque-Bera reveal significant departures from normality for all other variables.

8.10. Empirical Results

8.10.1. Unit Root tests

The unit root tests are performed in the log-levels and log-differences of the voyage TCEs and t/c trip rates alike. The KPSS test examines the null hypothesis of stationarity under two different assumptions: First, the series have an intercept and, second, a constant and a linear trend. The results, which are presented in Table 45, reject the null hypothesis in all cases of level forms suggesting that the series are non-stationary. In contrast, the test shows that the log-first differences of the series are stationary, suggesting that the series are integrated of order 1 or I(1). In addition to KPSS, the ADF unit root test is also employed and the results confirm that all of the variables are integrated of order 1. The results are reported in Table 44. Therefore, it is essential to check the existence of a co-integration relationship between the time series.

	Log-Levels			Log-first differences		
	Intercept	Const. & trend	None	Intercept	Const. & trend	None
Supramax						
TC trip:						
S1A	-2.659634*	-3.086494	0.364146	-8.766217***	-8.754385***	-8.767417***
Voyage TCE:						
USG - Jpn	-2.151210	-2.815897	-0.260193	-11.76167***	-11.74577***	-11.77688***
Panamax						
TC trip:						
P1A_03	-2.903449**	-3.423322**	0.298413	-9.633108***	-9.623158***	-9.626778***
Voyage TCE:						
Maracaibo - Rdam	-2.764329*	-3.276459*	-0.033592	-13.45650***	-13.45446***	-13.46732***
HRds - ARA	-1.761125	-2.560573	-0.420973	-16.59231***	-16.59578***	-16.61070***
Capesize						
TC trip:						
C8_03	-3.049059**	-3.51147**	0.299807	-10.71809***	-10.71624***	-10.7093***
Voyage TCE:						
Tubarao - Rdam	-2.25417	-2.979141	-0.305744	-12.32811***	-12.20271***	-12.38802***
Port Cartier - Rdam	-2.246797	3.083134	-0.479262	-9.675934***	-9.672725***	-9.685169***

Notes:
*** indicates rejection of the null at 1% level, **at 5% and * at 10%
H_0: the series is non stationary, H_1: the series is stationary

Table 44: ADF Unit Root Test

	Log-Levels		Log-first differences	
	Intercept	Const. & trend	Intercept	Const. & trend
Supramax				
TC trip:				
S1A	0.732645**	0.185000**	0.034879	0.035711
Voyage TCE:				
USG - Jpn	1.204081***	0.064859	0.054382	0.054275
Panamax				
TC trip:				
P1A_03	0.981690***	0.292773***	0.058846	0.039725
Voyage TCE:				
Maracaibo - Rdam	0.884206***	0.319406***	0.063982	0.041485
HRds - ARA	1.237135***	0.361492***	0.042382	0.031735
Capesize				
TC trip:				
C8_03	1.418374***	0.312576***	0.035584*	0.035260
Voyage TCE:				
Tubarao - Rdam	1.394660***	0.323697***	0.240541	0.096436
Port Cartier - Rdam	1.431077***	0.326051***	0.037684	0.03247

Notes:
*** indicates rejection of the null at 1% level, **at 5% and * at 10%
H_0: the series is stationary, H_1: the series is non stationary
The bandwidth for each test is chosen on the basis of the Newey-West selection using Berlett kernel

Table 45: KPSS Unit Root Test

8.10.2. Co-integration tests

Pair of variables	Lags	Hypothesized No. of CE(s)	Trace	0.05 CV (trace)	Max Eigenvalue	0.05 CV (Max Eigen.)
Supramax						
S1A - USG/Jpn	5	None*	26.58220 [0.0059]	20.26184	21.95234 [0.0049]	15.89210
		At most 1	4.629857 [0.3265]	9.164546	4.629857 [0.3265]	9.164546
Panamax						
P1A_03 - Marac/Rdam	5	None*	44.0479 [0.0000]	20.2618	35.9685 [0.0000]	15.8921
		At most 1	8.07943 [0.0800]	9.1646	8.0794 [0.0800]	9.1646
P1A_03 - Hrds/ARA	5	None*	25.4389 [0.0088]	20.2618	18.0416 [0.0227]	15.8921
		At most 1	7.397308 [0.1070]	9.1646	7.3973 [0.1070]	9.1646
Capesize						
C8_03 - Tub/Rdam	5	None*	47.7464 [0.0000]	20.2618	29.6836 [0.0002]	15.8921
		At most 1*	18.06278 [0.0009]	9.1646	18.06278 [0.0009]	9.1646
C8_03 - Pcartier/Rdam	4	None*	52.3159 [0.0000]	20.2618	41.8916 [0.0000]	15.8921
		At most 1*	10.4243 [0.0287]	9.1646	10.4243 [0.0287]	9.1646

Notes:
* denotes rejection of the hypothesis at the 0.05 level.
Figures in [.] are MacKinnon-Haug-Michelis (1999) p-values.
The tests assume a restricted intercept in the co-integrating equation and no deterministic trends in the series
The trace statistic tests H_0: r cointegrating relations against H_1: k cointegrating relations.
The max eigenvalue statistic tests H_0: r cointegrating relations against H_1: r+1 cointegrating relations.

Table 46: Johansen Co-integration test for log - tc trips and log - voyage tce

Based on various lag selection criteria (see Appendix D), the Johansen Co-integration test investigates the existence of equilibriums and the results are presented in Table 46. Both the trace and the max eigenvalue statistics show that there exists at least one co-integrating relation in all cases. This suggests that the t/c trip and the voyage TCE rates are linked through a long-term equilibrium relationship. In the short term though, there are deviations which are brought back to their equilibrium condition in the long run.

8.10.3. Performance of Chartering Strategy

Table 47 reports the overall excess return of each strategy when it is applied to the historical data of each individual route. The results are indicative of the superiority of the proposed methodology relative to the benchmark strategy. Specifically, it is shown that the MMTM can even double the excess return, i.e. on the Capesize Port Cartier - Rotterdam route where it yields a 30.9% return versus 14.9%. Similarly, it increases the return of the Panamax Maracaibo/Rotterdam route from 6.2% to 10.0%. Another striking characteristic of this method is its ability to reverse a negative return and turn it into positive. This is illustrated in Table 47, which demonstrates that the return for the Capesize Tubarao - Rotterdam route increased from a negative rate (-28.6%) to a positive (3.6%) and for the Panamax Hampton Roads - ARA route from -8.7% to 1.1%.

On the Supramax front, the proposed methodology spurs an equally meaningful increase in the excess return. Although the naïve strategy provides a positive return (7.8%), the MMTM based strategy fosters the anticipated performance and can lead to a remarkable 11.7% excess return in the case of the USG – Japan route.

	Benchmark Strategy	MMTM
Supramax		
Route:		
USG - Jpn	7.8%	11.7%
Panamax		
Route:		
Maracaibo - Rdam	6.2%	10.0%
HRds-ARA	-8.7%	1.1%
Capesize		
Route:		
Tubarao-Rdam	-28.6%	3.6%
Port Cartier - Rdam	14.9%	30.9%

Table 47: Overall return of chartering strategies

At the same time, it appears that the two Capesize iron ore routes have substantial differences with regard to the respective excess returns of their benchmark strategy. The Tubarao - Rotterdam route realizes a negative return of -28.6%, implying that an operator may incur enormous losses if they decide to charter in a vessel for a Transatlantic Round Voyage (TARV) and then perform continuous voyages on the Tubarao - Rotterdam route. Yet the proposed strategy, which determines the momentum of this type of chartering decisions and considers only the voyages with positive expectations, enhances the total excess return for this route (3.6%). On the other hand, as mentioned, the Port Cartier / Rotterdam route provides positive excess returns, even under the benchmark strategy, but the MTMM is able to provide a further boost and raise the expected return to 30.9%. The difference in returns between these two iron ore routes can be attributed to the fact that Tubarao generally exports much larger quantities of iron ore than Port Cartier and this creates port congestion in periods of high demand. In general, when the waiting time for a berth to become available is too long, the demurrages do not always cover the ‘hidden’ costs arising out of operational needs at the waiting anchorages, such as bottom fouling cleaning costs, crew repatriation expenses for seamen with expiring contract, cost for launch boats and costs for additional supplies and provisions. Therefore, even though congestion has a positive effect on the levels of freight rates, when considering the relative return between t/c trip and voyage charters, it seems to have a negative impact. At times, the freight earnings (even after the addition of demurrages) cannot counterbalance the extra running costs (coming from congestion), and this usually makes the original shipowners to factor them in and seek higher t/c trip rates. This eventually results in lower profit margins for ship operators, due to the narrower differential between t/c trip and voyage rates. Yet, Table 47 demonstrates that operators who will act as dictated by the MTMM strategy stand a good chance to generate a positive return of about 3.6% for this particular route.

The standard deviations in Table 43 suggest that in all three sectors, voyage rates are more volatile than t/c trip rates. This justifies the practice discussed in this study, whereby an operator charters in a vessel on the less volatile t/c trip market and then trades it on the riskier market of voyage charters hoping to make profit.

Furthermore, the two Panamax coal routes of this analysis are characterized by similar differences. While the Hampton Roads - ARA route is subject to severe losses under the benchmark strategy, the Maracaibo - Rotterdam route realizes gains. In a similar fashion, a combination of various factors such as weather conditions, strikes and waiting time, interact in such a way as to lead to overvalued voyage rates. The results show that the presence of such opportunities is more evident on the Maracaibo - Rotterdam route, where the benchmark strategy yields a total excess return of 6.2%. In contrast, the respective return for the Hampton Roads - ARA route is negative, revealing much fewer excess return opportunities. In both cases, the proposed methodology manages to identify the periods of mispricing and boost the excess returns.

Finally, it is worth noting that the proposed methodology provides higher margins for the Capesize than for the Panamax and Supramax vessels. This can be explained by the higher volatility of Capesize freight rates relative to the other two sectors. This is demonstrated in Table 43 which reports much greater standard deviations in the case of Capesize rates. The Panamax standard deviations come second and the Supramax rates appear the most stable across the three vessel categories. These particular findings are in line with the theoretical expectations, as they are presented in Chapter 2. The volatile nature of Capesizes increases the possibility of higher returns but also of bigger losses. Overall, the results indicate that the proposed strategy is capable of detecting positive spreads in the spot market and use them to foster the profitability of ship operators

8.11. Concluding Remarks

This chapter investigates the excess freight return dynamics between trip charters and their underlying voyage charters in the dry bulk spot market. It first establishes co-integrating relations between time charter (t/c) trip and their underlying voyage charters reflecting the existence of long-run equilibriums. On this basis, it focuses on the short-term deviations and describes the construction of a new chartering strategy in the context of technical analysis. In particular, it introduces the Modified Momentum Trading Model and uses it to form an appropriate chartering strategy. Finally, it tests the robustness of this approach against the simple rule of entering into a voyage charter every week. The results show that the proposed methodology outperforms the benchmark strategy, suggesting that the appropriate exploitation of rate deviations in the spot market can yield considerable excess returns. Overall, this approach intends to improve the decision making techniques in the spot freight market. The analysis of this chapter is of interest to academics and maritime practitioners alike. It can be used by ship operating companies as a guide to select voyages with the highest probability of excess returns and adjust their chartering strategies accordingly.

9. CONCLUSIONS

9.1. Summary of results and managerial implications

The present study aims to fathom the dry bulk sector, providing an unwavering picture of the underling market dynamics. Drawing on an in-depth analysis of the dry market fundamentals, the thesis develops appropriate forecasting models and eventually proposes a novel chartering strategy.

The analysis begins with a thorough investigation of the key determinants of the dry bulk freight market. This leads to the identification of several variables which frequently attract the attention of chartering decision makers, but the exact impact of most of those factors has never been documented at an empirical level. Thus, this study undertakes to examine the lead-lag relationship between the selected variables and various Baltic Exchange indices using causality and impulse response analysis. The findings confirm the hypothesis for Chinese steel production, DBECI, average bunker prices, congestion and some selected commodity prices. Notably the DBECI and the average bunker prices exhibit the strongest causality with each of the Baltic indices (1%). This justifies their utilization as explanatory variables in the multivariate forecasting model developed in Chapter 8.

This particular study is of interest to academics and market practitioners for a variety of reasons. First, the impact analysis of major bulk prices contributes to the understanding of the dynamics between commodity prices and freight rate movements. At the same time, it can support decision making in freight and commodity markets. Furthermore, at the practical level, this study sheds some light on the dynamic relationship between freight rates and several external factors, such as Chinese steel production, bunker fuel prices and congestion. Thereby it can considerably improve operational management and budget planning decisions.

Importantly, the preceding analysis also constitutes the groundwork for the ensuing forecasting methods. Chapter 7 formulates VAR/VECM and VARX models, by drawing on the findings and of the theoretical discussion of the previous sections. The building blocks of those models involve explanatory variables which are perceived to be intrinsically significant. The latter point is empirically illustrated by means of pertinent causality tests. Additionally, ARIMA models are developed for the same dependent variables and sample size, and primarily serve as benchmarks for comparison purposes. Eventually, the relative performance of those forecasting models is assessed using appropriate criteria, which reveal that the VARX approach provides the most accurate results and is followed by the VAR/VECM models that outperform the ARIMA framework in most ex-post and ex-ante forecasts.

The construction of the DBECI intends to summarize several dimensions of the economic environment revolving around the dry cargo market. In other words, the development of this new composite indicator aspires to capture the overarching impact of various economic factors that affect the dry market. The empirical analysis provides evidence that there is significant causality between the DBECI and each of the Baltic Exchange indices under consideration. Furthermore, as the comparison of forecast errors illustrates, the incorporation of the DBECI in a VARX model results in a substantial improvement of the forecasting accuracy. Overall, it turns out that the novel idea to construct a new index tailored to the dry bulk freight market enhances the reliability of forecasting models and adds value to their role as a decision support tool.

Another important finding of this study is that period rates can be predicted with greater accuracy than spot rates. To this point, the analysis puts under scrutiny both the spot and the period freight market. Next, the focus is placed on the spot market and the aim is to identify excess return opportunities. Given that this would be inconsistent with the EMH, the freight market is assumed semi-strong efficient. This perspective calls for co-integration tests between the rates of some selected t/c trips and the rates of the corresponding voyage charters. In this setting, a new technical trading method is developed (i.e. the Modified Momentum Trading Model), which lays the foundation for the subsequent formulation and implementation of a pertinent chartering strategy.

The results show that the proposed chartering strategy is able to identify excess return opportunities in the short term and increase the profitability of ship operators who engage in the spot freight market. Furthermore, the tests support the existence of a co-integrating relation (for each pair of variables), which translates into a long term equilibrium. The latter, combined with the presence of short-term deviations, confirms the initial hypothesis of semi-strong efficiency in the spot freight market. The same analysis is applied to three different sectors (Capesize, Panamax and Supramax) and the outcomes are consistent in all respects. All in all, the empirical results suggest that the appropriate exploitation of rate deviations in the spot market can yield considerable excess returns.

This last part of the thesis is of interest to academics and maritime practitioners alike. In particular, it can be used by ship operating companies as a guide to select voyages with the highest probability of excess returns and adjust their chartering strategies accordingly. After all, the very existence of many ship operating companies relies on this kind of speculative opportunities in the spot market. Overall, the proposed approach intends to improve the decision making techniques in the spot freight market.

9.2. Limitations

A major limitation stems from the route assessments of the Baltic Exchange. Even though the reporting panels strive to ensure an objective valuation of the current freight rates for each route, at times it is inevitable to exercise some personal judgment. This is particularly prevalent in cases of routes with little activity at a given point in time, and as a result they cannot base their assessments on factual information.

In addition, it should be taken into consideration that the agreed terms usually vary from fixture to fixture, even if the underlying route and vessel type are the same. Thus, the panellists resort to averaging.

The Baltic Exchange indices, as well as the freight rate and t/c rate time series correspond to typical vessels of each category. Given that even ships belonging to the same category vary with respect to age, technical specification and so forth, it is impossible to obtain data that reflect the prevailing rates of every single vessel in the market. Thus the present thesis relies on the assessment of data providers, who select the most representative ships from each category.

Along these lines, there is a mismatch between the appropriate size categorization of bulk carriers and the classification of Clarksons. Owing to the unavailability of sufficient historical data for certain sizes, such as Ultramax and Kamsarmax, they provide aggregate data and include those types under the umbrella of Supramax and Panamax respectively.

In general, the studies involving secondary data, such as the current one, are subject to severe data limitations. The agencies collecting data could not possibly provide a high degree of customization, so that they can suit the needs of each individual study.

Therefore, the researchers often have to make compromises and adjust their analysis to the existing dataset.

9.3. Recommendations for Future Research

The thesis raises several issues for further research. First of all, more determinants of the freight market could be identified and then undergo a similar causality analysis. However, this is subject to data availability and it is unfortunate that there are serious data limitations. Provided that pertinent data become available, a future study could shed more light on the critical factors affecting freight rates and ultimately lead to even more accurate forecasting models. Along these lines, a potential study could also factor in FFAs, but again this requires sufficient data.

In light of the findings, it would be interesting to develop alternative modelling frameworks, such as Artificial Neural Networks, and evaluate their predictive success against the approach of this thesis.

Another possible avenue for future investigation is to apply the proposed methodology to specific trade routes and generate freight rate forecasts. In that case, it would be useful to attempt to embed certain regional characteristics of each route. This could lead to more targeted forecasts, but it entails the danger of model overfitting. Therefore, the selection and inclusion of additional variables should be very careful and in line with the process adopted in the current thesis.

Furthermore, the methodology of Chapter 9 can be extended to include more routes and support strategic chartering decisions in the entire dry bulk market. Therefore, a suggestion for future research is to use this approach and conduct a comparative analysis of the profitability of the proposed technical-based strategy for all major trade routes.

Finally, the methods of the thesis can potentially be expanded to a fleet scale and analyze the dynamics of arbitrary fleets rather than individual vessels. This will also allow the investigation of diversification strategies.

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APPENDICES

Appendix A

VAR Residual Portmanteau Tests for Autocorrelations (Chapter 6)

- **BCI and Steel Production (China)**

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1999M01 2014M07

Included observations: 181

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.026324	NA*	0.026471	NA*	NA*
2	0.566120	NA*	0.572298	NA*	NA*
3	1.376115	NA*	1.395944	NA*	NA*
4	17.88538	0.0013	18.27830	0.0011	4
5	19.97333	0.0104	20.42557	0.0088	8
6	25.91078	0.0111	26.56658	0.0089	12
7	31.32998	0.0122	32.20380	0.0094	16
8	41.64606	0.0031	42.99692	0.0020	20
9	42.59837	0.0111	43.99906	0.0076	24
10	49.10144	0.0081	50.88243	0.0051	28
11	56.47184	0.0048	58.72974	0.0027	32
12	117.5787	0.0000	124.1755	0.0000	36

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

- **BPI and Steel Production (China)**

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1999M01 2014M07

Included observations: 184

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.071095	NA*	0.071484	NA*	NA*
2	1.377088	NA*	1.391829	NA*	NA*
3	2.024006	0.9585	2.049469	0.9571	7
4	13.82358	0.2429	14.11125	0.2269	11
5	15.01852	0.4501	15.33957	0.4272	15
6	20.71040	0.3530	21.22331	0.3246	19
7	22.91198	0.4659	23.51196	0.4312	23
8	26.84465	0.4722	27.62339	0.4306	27
9	27.14042	0.6651	27.93437	0.6246	31
10	31.65311	0.6305	32.70641	0.5793	35
11	41.61542	0.3576	43.30217	0.2928	39
12	97.33266	0.0000	102.9067	0.0000	43

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

- **BSI and Steel Production (China)**

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1999M01 2014M07

Included observations: 105

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.084600	NA*	0.085413	NA*	NA*
2	2.430557	NA*	2.476923	NA*	NA*
3	3.269860	NA*	3.340912	NA*	NA*
4	12.56322	0.0136	13.00233	0.0113	4
5	14.64439	0.0664	15.18755	0.0556	8
6	17.68157	0.1257	18.40880	0.1038	12
7	20.48384	0.1992	21.41124	0.1632	16
8	23.36331	0.2713	24.52819	0.2201	20
9	30.39515	0.1720	32.21926	0.1216	24
10	31.48053	0.2962	33.41889	0.2207	28
11	41.94624	0.1121	45.10931	0.0621	32
12	60.84659	0.0060	66.44843	0.0015	36

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

- **BCI and DBECI**

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1999M01 2014M07

Included observations: 176

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.331726	NA*	0.333622	NA*	NA*
2	1.163052	NA*	1.174503	NA*	NA*
3	2.614704	NA*	2.651328	NA*	NA*
4	4.743147	NA*	4.829270	NA*	NA*
5	5.311848	NA*	5.414600	NA*	NA*
6	5.593686	NA*	5.706385	NA*	NA*
7	7.384775	NA*	7.571661	NA*	NA*
8	9.552778	NA*	9.842902	NA*	NA*
9	12.06163	0.0169	12.48696	0.0141	4
10	14.47853	0.0701	15.04946	0.0582	8
11	25.77645	0.0115	27.10057	0.0075	12
12	52.68168	0.0000	55.97448	0.0000	16

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

- **BPI and DBECI**

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1999M01 2014M07

Included observations: 178

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.139201	NA*	0.139987	NA*	NA*
2	0.460673	NA*	0.465113	NA*	NA*
3	1.939380	NA*	1.969169	NA*	NA*
4	6.396127	NA*	6.528369	NA*	NA*
5	6.767946	NA*	6.910935	NA*	NA*
6	6.855454	NA*	7.001495	NA*	NA*
7	8.922323	NA*	9.152974	NA*	NA*
8	9.587998	NA*	9.849974	NA*	NA*
9	12.18988	0.0160	12.59042	0.0135	4
10	17.32509	0.0269	18.03129	0.0210	8
11	27.15724	0.0073	28.51108	0.0047	12
12	52.35313	0.0000	55.52835	0.0000	16

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

- **BSI and DBECI**

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1999M01 2014M07

Included observations: 103

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.240977	NA*	0.243339	NA*	NA*
2	0.325806	NA*	0.329849	NA*	NA*
3	1.070149	NA*	1.096522	NA*	NA*
4	2.128588	NA*	2.197725	NA*	NA*
5	2.505522	NA*	2.593892	NA*	NA*
6	4.039532	0.7752	4.222788	0.7538	7
7	7.587972	0.7497	8.029969	0.7106	11
8	16.55470	0.3462	17.75179	0.2759	15
9	19.78454	0.4076	21.29087	0.3210	19
10	23.46053	0.4342	25.36213	0.3319	23
11	25.91282	0.5234	28.10763	0.4054	27
12	31.97765	0.4178	34.97222	0.2849	31

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

- **BCI and iron ore price**

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1999M01 2014M07

Included observations: 126

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.147234	NA*	0.148412	NA*	NA*
2	0.767543	NA*	0.778725	NA*	NA*
3	1.368896	NA*	1.394746	NA*	NA*
4	3.495569	0.4786	3.591146	0.4642	4
5	6.693460	0.5700	6.921181	0.5452	8
6	20.92636	0.0515	21.86573	0.0391	12
7	33.13138	0.0071	34.78869	0.0042	16
8	34.81142	0.0211	36.58263	0.0131	20
9	42.76108	0.0106	45.14381	0.0056	24
10	48.98384	0.0084	51.90301	0.0039	28
11	57.26284	0.0040	60.97391	0.0015	32
12	58.52371	0.0102	62.36751	0.0041	36

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

- **BCI and coal price**

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1999M01 2014M07

Included observations: 182

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.173190	NA*	0.174147	NA*	NA*
2	2.147619	NA*	2.170514	NA*	NA*
3	4.737426	0.3153	4.803726	0.3080	4
4	17.17979	0.0283	17.52569	0.0251	8
5	22.49524	0.0323	22.99130	0.0278	12
6	24.33442	0.0825	24.89317	0.0717	16
7	31.31324	0.0512	32.15115	0.0417	20
8	53.33125	0.0005	55.18148	0.0003	24
9	58.90758	0.0006	61.04791	0.0003	28
10	61.26900	0.0014	63.54662	0.0007	32
11	64.92112	0.0022	67.43367	0.0012	36
12	69.56227	0.0026	72.40243	0.0013	40

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

- **BSI and coal price**

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1999M01 2014M07

Included observations: 106

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.004110	NA*	0.004149	NA*	NA*
2	0.321639	NA*	0.327785	NA*	NA*
3	5.846642	0.5578	6.013710	0.5381	7
4	15.72430	0.1517	16.27873	0.1311	11
5	16.72135	0.3358	17.32513	0.2998	15
6	18.58853	0.4835	19.30434	0.4375	19
7	22.28458	0.5031	23.26173	0.4456	23
8	32.36558	0.2188	34.16568	0.1613	27
9	38.24838	0.1735	40.59430	0.1162	31
10	42.05800	0.1918	44.80075	0.1240	35
11	48.26776	0.1468	51.72954	0.0834	39
12	60.76258	0.0383	65.81944	0.0141	43

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

- **BPI and wheat price**

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1999M01 2014M07

Included observations: 184

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.005819	NA*	0.005851	NA*	NA*
2	0.023414	NA*	0.023640	NA*	NA*
3	1.023503	0.9062	1.040304	0.9036	4
4	5.285539	0.7267	5.397052	0.7144	8
5	7.874085	0.7949	8.057904	0.7806	12
6	8.862741	0.9190	9.079885	0.9101	16
7	15.22881	0.7632	15.69772	0.7352	20
8	20.79275	0.6509	21.51457	0.6082	24
9	25.03388	0.6260	25.97381	0.5745	28
10	33.21887	0.4076	34.62921	0.3435	32
11	35.50763	0.4918	37.06349	0.4197	36
12	44.01707	0.3054	46.16662	0.2325	40

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

- **BCI and AVG_IFO**

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1999M01 2014M07

Included observations: 181

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.041958	NA*	0.042191	NA*	NA*
2	0.357495	NA*	0.361254	NA*	NA*
3	1.394476	NA*	1.415712	NA*	NA*
4	8.002142	0.0915	8.172703	0.0855	4
5	9.722843	0.2850	9.942288	0.2691	8
6	11.44908	0.4909	11.72771	0.4678	12
7	15.63573	0.4787	16.08279	0.4472	16
8	26.63254	0.1459	27.58812	0.1195	20
9	27.37686	0.2872	28.37138	0.2447	24
10	30.38712	0.3450	31.55768	0.2929	28
11	38.17430	0.2092	39.84874	0.1605	32
12	42.45916	0.2126	44.43785	0.1579	36

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

- **BPI and AVG_IFO**

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1999M01 2014M07

Included observations: 182

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.002237	NA*	0.002249	NA*	NA*
2	0.130061	NA*	0.131493	NA*	NA*
3	0.288601	NA*	0.292691	NA*	NA*
4	0.523341	NA*	0.532706	NA*	NA*
5	1.540875	0.8194	1.578984	0.8126	4
6	2.947486	0.9376	3.033547	0.9322	8
7	4.673844	0.9680	4.828960	0.9634	12
8	9.188274	0.9055	9.550949	0.8890	16
9	9.773559	0.9721	10.16668	0.9650	20
10	15.54236	0.9039	16.27088	0.8781	24
11	23.51420	0.7069	24.75552	0.6411	28
12	24.48044	0.8265	25.78997	0.7728	32

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

- **BSI and AVG_IFO**

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1999M01 2014M07

Included observations: 106

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.806741	NA*	0.814425	NA*	NA*
2	6.826260	NA*	6.949703	NA*	NA*
3	11.17927	0.1310	11.42950	0.1210	7
4	22.22125	0.0227	22.90450	0.0182	11
5	26.26481	0.0353	27.14824	0.0276	15
6	27.15336	0.1011	28.09010	0.0817	19
7	30.41044	0.1380	31.57748	0.1093	23
8	33.84844	0.1705	35.29613	0.1315	27
9	39.86636	0.1321	41.87241	0.0920	31
10	40.37457	0.2448	42.43356	0.1812	35
11	45.55345	0.2181	48.21210	0.1480	39
12	57.76784	0.0655	61.98577	0.0304	43

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

- **BCI and Cong_Cape**

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1999M01 2014M07

Included observations: 53

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.053390	NA*	0.054417	NA*	NA*
2	0.881992	0.9965	0.915513	0.9961	7
3	3.687345	0.9782	3.889188	0.9730	11
4	8.473598	0.9034	9.066154	0.8740	15
5	16.80680	0.6030	18.26740	0.5046	19
6	21.79854	0.5324	23.89638	0.4096	23
7	29.07205	0.3574	32.27673	0.2220	27
8	36.44550	0.2301	40.96102	0.1088	31
9	38.22174	0.3253	43.10057	0.1634	35
10	41.09025	0.3791	46.63618	0.1872	39
11	42.32029	0.5006	48.18838	0.2710	43
12	47.63625	0.4467	55.06023	0.1960	47

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

- **BPI and Cong_Pmx**

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1999M01 2014M07

Included observations: 53

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.366726	NA*	0.373779	NA*	NA*
2	3.611805	0.8232	3.746116	0.8085	7
3	6.962507	0.8021	7.297860	0.7745	11
4	7.964586	0.9252	8.381741	0.9076	15
5	11.52768	0.9048	12.31599	0.8717	19
6	11.90414	0.9719	12.74051	0.9574	23
7	15.85489	0.9557	17.29246	0.9237	27
8	17.96038	0.9701	19.77226	0.9406	31
9	24.35850	0.9112	27.47908	0.8137	35
10	25.85624	0.9475	29.32514	0.8696	39
11	29.61077	0.9400	34.06300	0.8331	43
12	33.63207	0.9287	39.26127	0.7814	47

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

- **BSI and Cong_Hmx**

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1999M01 2014M07

Included observations: 53

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.029173	NA*	0.029734	NA*	NA*
2	1.204679	0.9908	1.251338	0.9897	7
3	3.774654	0.9761	3.975512	0.9706	11
4	4.836533	0.9934	5.124075	0.9910	15
5	9.050452	0.9726	9.776944	0.9582	19
6	11.91562	0.9718	13.00787	0.9518	23
7	13.52689	0.9855	14.86434	0.9713	27
8	14.41450	0.9951	15.90975	0.9886	31
9	16.99186	0.9955	19.01429	0.9873	35
10	18.64041	0.9976	21.04623	0.9916	39
11	24.73660	0.9885	28.73904	0.9532	43
12	28.73181	0.9836	33.90358	0.9238	47

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

Appendix B

Lag order Selection Criteria (Chapter 6)

Pair of variables	LR	FPE	AIC	SC	HQ
BCI - Stl_Prd_Ch	7	8	8	2	3
BPI - Stl_Prd_Ch	3	3	3	2	3
BSI - Stl_Prd_Ch	3	3	3	3	3

Pair of variables	LR	FPE	AIC	SC	HQ
BCI - DBECI	8	8	8	2	2
BPI - DBECI	8	5	5	2	2
BSI - DBECI	5	5	5	2	3

Pair of variables	LR	FPE	AIC	SC	HQ
BCI - Coal_Aus	5	3	3	2	2
BCI - Iron_Aus	5	3	3	2	3
BPI - Wheat	2	2	2	2	2
BSI - Coal_Aus	2	2	2	2	2

Pair of variables	LR	FPE	AIC	SC	HQ
BCI - AVG_IFO	3	3	3	4	3
BPI - AVG_IFO	4	4	4	2	4
BSI - AVG_IFO	4	4	4	2	4

Pair of variables	LR	FPE	AIC	SC	HQ
BCI - Cong_Cape	8	8	8	1	1
BPI - Cong_Pmx	1	1	1	1	1
BSI - Cong_Hmx	1	1	1	1	1

Appendix C

ARIMA Specification

Dependent Variable: D(CP_AVG_SPOT)

Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)

Sample (adjusted): 1999M03 2014M07

Included observations: 185 after adjustments

Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000105	0.032951	0.003191	0.9975
AR(1)	0.105426	0.073543	1.433544	0.1534

R-squared	0.011105	Mean dependent var	0.000219
Adjusted R-squared	0.005701	S.D. dependent var	0.402079
S.E. of regression	0.400931	Akaike info criterion	1.020699
Sum squared resid	29.41652	Schwarz criterion	1.055514
Log likelihood	-92.41467	Hannan-Quinn criter.	1.034809
F-statistic	2.055049	Durbin-Watson stat	1.956568
Prob(F-statistic)	0.153409		

Inverted AR Roots	.11

Dependent Variable: D(C_6M_170K)

Method: Least Squares

Sample (adjusted): 2002M02 2014M07

Included observations: 150 after adjustments

Convergence achieved after 8 iterations

MA Backcast: 2002M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003721	0.022486	0.165465	0.8688
AR(1)	-0.604204	0.095345	-6.337037	0.0000
MA(1)	0.904643	0.049325	18.34038	0.0000

R-squared	0.125455	Mean dependent var	0.004124
Adjusted R-squared	0.113557	S.D. dependent var	0.246455
S.E. of regression	0.232040	Akaike info criterion	-0.064017
Sum squared resid	7.914854	Schwarz criterion	-0.003804
Log likelihood	7.801272	Hannan-Quinn criter.	-0.039554
F-statistic	10.54372	Durbin-Watson stat	1.871490
Prob(F-statistic)	0.000053		

Inverted AR Roots	-.60
Inverted MA Roots	-.90

Dependent Variable: D(PMX_AVG_SPOT)

Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)

Sample (adjusted): 1999M04 2014M07

Included observations: 184 after adjustments

Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.003676	0.017811	-0.206409	0.8367
AR(1)	0.080401	0.073882	1.088228	0.2779
AR(2)	-0.113515	0.074822	-1.517142	0.1310

R-squared	0.017616	Mean dependent var	-0.004056
Adjusted R-squared	0.006761	S.D. dependent var	0.250428
S.E. of regression	0.249580	Akaike info criterion	0.078096
Sum squared resid	11.27452	Schwarz criterion	0.130513
Log likelihood	-4.184808	Hannan-Quinn criter.	0.099341
F-statistic	1.622865	Durbin-Watson stat	1.966458
Prob(F-statistic)	0.200190		

Inverted AR Roots	.04-.33i	.04+.33i

Dependent Variable: D(PMX_6M_75K)

Method: Least Squares

Sample (adjusted): 2001M06 2014M07

Included observations: 158 after adjustments

Convergence achieved after 10 iterations

MA Backcast: 2001M05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000997	0.020461	-0.048750	0.9612
AR(1)	-0.264438	0.193559	-1.366190	0.1739
AR(2)	0.201452	0.128965	1.562069	0.1203
MA(1)	0.763274	0.168657	4.525610	0.0000

R-squared	0.208705	Mean dependent var	-0.001106
Adjusted R-squared	0.193290	S.D. dependent var	0.172755
S.E. of regression	0.155163	Akaike info criterion	-0.863691
Sum squared resid	3.707634	Schwarz criterion	-0.786157
Log likelihood	72.23160	Hannan-Quinn criter.	-0.832204
F-statistic	13.53924	Durbin-Watson stat	1.980342
Prob(F-statistic)	0.000000		

Inverted AR Roots	.34	-.60
Inverted MA Roots	-.76	

Lag order Selection Criteria (Chapter 7)

- **VAR / VECM**

Pair of variables	LR	FPE	AIC	SC	HQ
Capesize					
Avg spot ***vs*** {Cp fleet devel Ch_steel prod}	7	7	7	2	3
6-m tc 170k ***vs*** {Cp fleet devel Ch_steel prod}	5	5	5	3	3
Panamax					
Avg spot ***vs*** {Pmx fleet devel Ch_steel prod}	7	5	5	3	3
6-m tc 75k ***vs*** {Pmx fleet devel Ch_steel prod}	5	5	5	2	3

Notes:

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

- **VAR X**
-

Pair of variables	LR	FPE	AIC	SC	HQ
Capesize					
Avg spot ***vs*** {Cp fleet devel Ch_steel prod} {DBECI IFO_avg}	7	7	7	2	3
6-m tc 170k ***vs*** {Cp fleet devel Ch_steel prod} {DBECI IFO_avg}	7	7	7	3	3
Panamax					
Avg spot ***vs*** {Pmx fleet devel Ch_steel prod} {DBECI IFO_avg}	7	5	5	1	3
6-m tc 75k ***vs*** {Pmx fleet devel Ch_steel prod} {DBECI IFO_avg}	5	5	5	2	3

Notes:

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

Appendix D

Lag order Selection Criteria (Chapter 8)

VAR Lag Order Selection Criteria					
	LR	FPE	AIC	SC	HQ
Supramax					
Route:					
USG - Jpn	5	5	5	4	5
Panamax					
Route:					
Maracaibo - Rdam	5	5	5	2	3
HRds-ARA	5	5	5	2	2
Capesize					
Route:					
Tubarao-Rdam	5	5	5	5	5
Port Cartier - Rdam	4	4	4	2	2

Notes:

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion