Essays on the econometric modelling and forecasting of shipping market variables

by

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Submitted to Newcastle University
in partial fulfilment of the requirement for the degree of
Doctor of Philosophy in Applied Econometrics

September 2011

Abstract

This thesis uses econometric modelling and forecasting to investigate a number of important topics associated with economic and financial aspects of the global shipping market.

The thesis is made up of five chapters. Chapter 1 introduces the structure of the shipping market; it covers a wide range of topics, including the shipping sub-markets, shipping stock and shipping market information. It introduces the different types of freight rates involved, and discusses the economics behind the formation of spot and time-charter freight rates. It also introduces the new-build ship market and explains some of the different shipbuilding models. In addition, it discusses the market for second-hand ships. Finally, it reports and discusses the correlations of different shipping variables with each other and with the S&P500 stock market index.

Chapter 2 focuses on forecasting the freight rate for ship operators. Since time-charter rates depend on market participants' expectations about future spot rates, under market efficiency the ship operator should not be able to make abnormal profits by choosing a specific chartering strategy. The chapter investigates whether this is true by exploring the economic value of freight rate forecasts, using a regression-based recursive switching approach based on two sets of macroeconomic and commodity data. The ship operator is assumed to allocate the ship between a trip-charter and time-charter market according to forecasts of the quarterly excess freight rate. The Handymax and Capesize classes of ship are analysed, the analysis showing that this type of investment strategy does not generate significantly abnormal profits for the Handymax class, but does for the Capesize class. Forecasting with commodity variables is more profitable than forecasting with macroeconomic variables.

Chapter 3 quantifies and discusses the volatility of index returns in the dry bulk freight rate market for freight traders and investors. The daily freight rate indexes of three ship classes, Baltic dry index (BDI), Baltic Panamax index (BPI) and Baltic Capesize index (BCI) from 14 January 2000 to 14 January 2010 are analysed. Some of the findings from applying variations of autoregressive conditional heteroskedasticity (ARCH) models suggest that the volatility of shocks is very persistent and that a unit root might exist in the conditional variance. No evidence of any asymmetry in the conditional variance is found. Volatility forecasting for one day ahead and multiple days ahead is also performed using a variety of ARCH models. At the end of the chapter the risk exposure of the freight rate index is assessed using the Value at Risk (VaR) technique.

In Chapter 4 it is argued that if risk premiums are time-varying and correlated with macroeconomic variables, macroeconomic variables might have forecasting power for shipping stock returns. This issue is investigated using the recursive regression-based approach of Pesaran and Timmermann (1995) and it is concluded that allowing for different combinations of macroeconomic variables generally does not help forecasting. This may be because the model selection criteria do not seem to work efficiently when there is a structural break in the data. The model which includes all variables (AV) is found to be the best performing model. A data set is employed which includes four shipping stocks and the S&P500 index for comparison, and this shows that a trading strategy using the AV model generates 93% to 500% more wealth than a buy-and-hold strategy. When the explanatory variables are analysed individually, the US Treasury bill and NYMEX oil price are shown to have the most forecasting power.

Chapter 5 concludes the thesis. It presents a review of the original findings and puts forward recommendations for future research.

Main supervisor: Professor Robert Sollis

Second supervisor: Dr. Bartsoz Gebka

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Chapter 1

Introduction

1.1 Introduction to shipping economics

The main aim of this chapter is to explain the nature of the shipping industry. It provides an overview of the different segments and aspects of the market and the way in which they interact with each other. It introduces different types of freight rate contracts as well as the economics of freight rates formation. It also introduces the new-build ship market and explains some of the static models of shipbuilding. In addition, it introduces the market for the sale and purchase of second-hand ships. It also describes the sources of shipping market information, in particular the Baltic Exchange. The data samples in this chapter include the super-boom period that began in 2003 and peaked in mid-2008. For this reason, several time series are compared with S&P500 as a benchmark.

The shipping industry facilitates global trade by connecting the sources of supply and demand regarding raw materials and goods. The history of the shipping industry is linked with the world economy, as Adam Smith notes in his famous book *The Wealth of Nations* (1776):

> shipping is one of the major catalysts of economic development shipping is a cheap source of transport which can open up wider markets to speculation, offering shipment of even the most everyday products at prices far below those that can be achieved by any other means.

It is estimated that the contribution of merchant ships to the global economy in terms of freight rate is around 5% of world trade.[1] This percentage is increasing along with the progress in ship design and port technologies. The total numbers of ships involved in the world seaborne trade have increased significantly during the past few decades. This is due to the discovery of new geographical sources of raw materials, including oil, and to changes in the locations of refineries, as well as to the creation of new sources of supply and demand throughout the world. By far the most important factor for the increase in sea transportation had been the liberalization in international trade which had allowed manufacturers to outsource their operations to countries where costs are lower and then to transport their products to their destination markets. This trade liberalization has resulted in economic growth throughout the world, specifically in poorer countries,

[1] See UNCTAD (2009), Ch. 1, available at www.unctad.org

which has increased demand for manufactured products and goods and increased in turn the need for more raw materials with which to produce them.

For the purposes of research, international seaborne trade is classified into liquid bulk, dry bulk, general cargo, and container trade. There are also several other types of cargoes, such as natural gas and refrigerated cargoes. Economic cycles are the vital issue in the shipping business. Shipping has a highly cyclical nature where large profits can be made quickly and can be lost even more quickly. Economic and political factors influence the shipping markets, while seaborne supply and demand increase or decrease freight rates. Volatility in freight rate can be massive, and changes in ship prices from trough to peak can be tenfold. The effects on profit are magnified by leverage, which is usually 25% of the ship price. Shipping operates in a truly global environment and the dependence of it on global trade requires a wealth of skills and knowledge in order to cope with its market. This complexity has made ship owners such as Onassis, Pao and McKinsey-Maersk into some of the most successful classical entrepreneurs in the world.

Classically speaking there are five markets in shipping: freight, new-build, second-hand, scrap, and the finance market. The factors affecting the shipping market are: world economic structure, shipping supply & demand, and fleet changes. Shipping is obviously a derived demand and depends on the state of the seaborne trade. The latter is primarily affected by seaborne trade conditions and commodity demand and prices. Overall, demand can be ascertained by the movement of commodity prices. Seaborne trade conditions play an important role in relation to port facilities and terminal efficiencies, trade restrictions, war and political factors, and route-specific characteristics. An example of these trade conditions is the closure of the Suez Canal in 1967, which increased shipping demand and brought about a record high in freight rates.

Demand in shipping changes quickly, but supply of ships only slowly. The freight rate information is available to anyone through Baltic Exchange and there is no barrier to entry or leave the bulk market with a large number of buyers and sellers at any time, this means the bulk shipping industry is very close to perfect competition. This is in contradistinction to liner shipping, which has an oligopolistic structure. During the super-boom which started in 2003 and lasted until mid-2008 the industry experienced a steep increase in demand owing to rapidly growing economies. In the rest of this chapter, we briefly analyse the different sub-markets and their growth. We also analyse the shipping fleet, freight rate, the new-build and second-hand market, the demolition market, and shipping companies' stock market performance. The relevant static models will be mentioned in every case. Although some of these models may not help the econometrics of this research, they may help to bring about a quicker understanding of the market mechanisms involved.

1.2 Motivation

Investment decisions in the shipping market depend on the future movement of freight rates. For this reason a good understanding of the decision making mechanism in the shipping market provides an efficient decision making tool for market participants. We aim to investigate the forecasting of shipping market variables, these includes the forecast of freight rates, the volatility of freight rate indexes and the forecast of shipping companies' stock prices. The results are used to provide optimal policies for chartering and investment in different sectors of the shipping market. For instance the future prices of freight rates affect the valuation of time charter contracts and ship prices; it also affects the valuation of freight rate contingent claims and freight rate swaps. Likewise the expected freight rate volatility can affect the pricing of options. While the topics of this thesis are mainly of theoretical interest the obtained results can be applied in decision making and modelling in shipping economics for investors and other market participants. There is a large potential for exploring the results in commercial and academic sense. While investigating all the scenarios of applying the results of these chapters is hard to achieve, the theoretical foundations that we investigate are based on the following hypothesis. We check the validity of these hypotheses.

1- Time Charter (TC) rates are formed by the market participants' expectations about future spot rates. There is a term-structure relationship between spot and TC rates. The term-structure is derived from no-arbitrage models this means a ship operator should not be able to make abnormal profit by contracting the ship in the TC market in comparison to contracting it in spot market for a series of voyages charters equal to the length of the TC. The results can be used to investigate whether the Efficient Market Hypothesis hold in this scenario or not.

2- Since different freight rate indexes address different ship sizes and routes, we investigate if the responses of three freight rate indexes are similar to each other or not and if the specification of their GARCH forecasting model is identical or not.

3- We use macroeconomics and financial variables to analyse the predictability of the shipping stock return. We argue that if risk premiums are time varying and correlated with macroeconomic variables then macroeconomic variables should have forecasting power for shipping stocks.

We illustrate some scenarios that can outline the importance of these forecasts. The first chapter forecasts the freight rate, the ship operator can decide if he can make more money by contracting the ship in the TC or spot market and make a proper decision according to the forecast. The application of this forecast technique has a direct impact on the level of cash flow of the shipping company. This is even more crucial for the ship mortgage lenders especially in the case of the single ship company, the cash flow from a single ship should always be sufficient to pay the mortgage repayment. Therefore the future cash flow can potentially be maximised by adopting a correct forecasting strategy. Suppose that the bank wants to repossess the vessel or sell its loan to another institution, the prices of both the ships and the loans are related to the future cash flows, if the bank expects the next quarter freight rate prices will rise then the value of the loan or the vessel can change significantly in the short term therefore the bank can wait a few months before making such a decision with the intention of having a better valuation on the ship or the loans. It is not however sufficient to rely in the freight rate forecast as an expectation of the cash flow. Another important issue is also the probability that any future cash flow becomes insufficient to pay the mortgage, this issue depends on volatility and value at risk estimates which is investigated in the fourth chapter. Consider the case that a speculator or an oil company buys a portfolio of the forward freight rate; this allows them to hedge against the volatility of freight rates, in order to price this deal it is necessary to estimate the value at risk and forecast the volatility. Consider an investment company or a hedge fund that has a portfolio of shipping companies stocks. It is important to document the impact of different macroeconomics variables on different shipping companies stock's to behave strategically and take into account the different reaction and prices impacts on every kind of shipping company, these are the motivation behind chapter 4 in which we study the trading strategies in shipping companies' stock market.

1.3 Development of the shipping fleet

Figure 1.1 compares the natural logarithms of US GDP, merchant shipping fleet, S&P500 and a freight rate index. Merchant shipping fleet is the index of the total weight the ships can carry. Freight rate is a price that is paid to the ship owner by the charterer for the use of the ship; here the Baltic dry index (BDI), which is an aggregated index of freight rates, is used.[2] The logarithms of US GDP grew by 8.6% between 1970 and 2009. The merchant shipping fleet grew by 6.1% during the same period, and so the shipping fleet has experienced a slower growth than US GDP. The S&P500 composite has the lowest growth of the four time series, at 5.8%. Data for BDI are available from 1986, and the growth rate is 7.4%. Table 1.1 presents the correlation coefficient between the variables. The correlations of freight rates are discussed later in this chapter. The first column shows the correlation of the return series and the second that of the price series. In the return series there is a relationship of -17% between US GDP and the fleet. The relationship between the fleet and S&P500 is 18%. There is a 98% correlation between US GDP and the fleet price series. However, the correlation of prices cannot be relied on because the series have non-stationary characteristics.

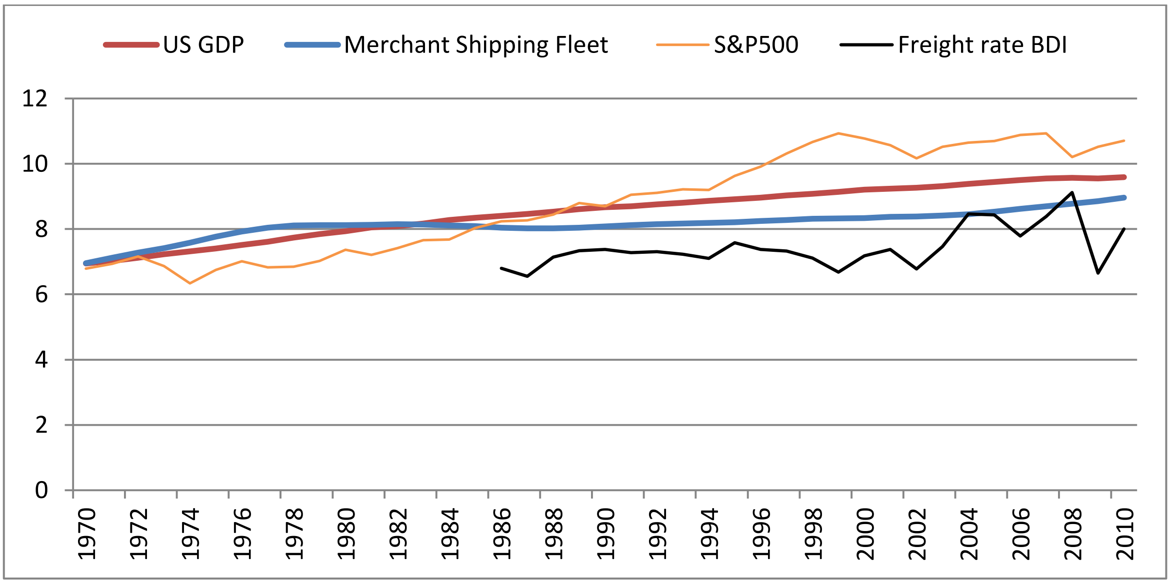


Figure 1.1 Natural logarithms of US GDP, S&P500 and shipping fleet
(Growth rates= US GDP:8.6% – shipping fleet:6.1% – S&P500:5.8% – freight rate:7.4%)

[2] Sections 1.14 and 1.19 comprehensively explain the nature of different freight rates and the freight indexes.

Table 1.1 Correlation panel of US GDP, shipping growth and S&P logarithms

r	*Returns*	*Prices*
Fleet, GDP	-17%	98%
Fleet, S&P500	18%	89%

The shipping fleet in Table 1.1 includes tankers and bulk carriers only. Figure 1.1 shows a slight change of phase in the shipping fleet around 1978. The most important reason for this could be the consequences of the Suez Canal closure from 1967 to 1975, which resulted in a massive growth of the fleet. The freight rate reached a record high, with tanker rates reaching 280 on the World Scale.[3] Most of the shipbuilding yards were making tankers during this period as the period was very profitable for them, but this changed when OPEC raised oil prices. At this time there was a huge drop in tanker freight rates and the need for more tankers started to diminish. The tanker fleet had to be reduced by demolition to match current demand. This was the consequence of an over-supply of tankers during the early 1970s and an increase in the price of crude oil between 1973 and 1979. Figure 1.2 presents the world shipping fleet pattern between 1996 and 2010.[4]

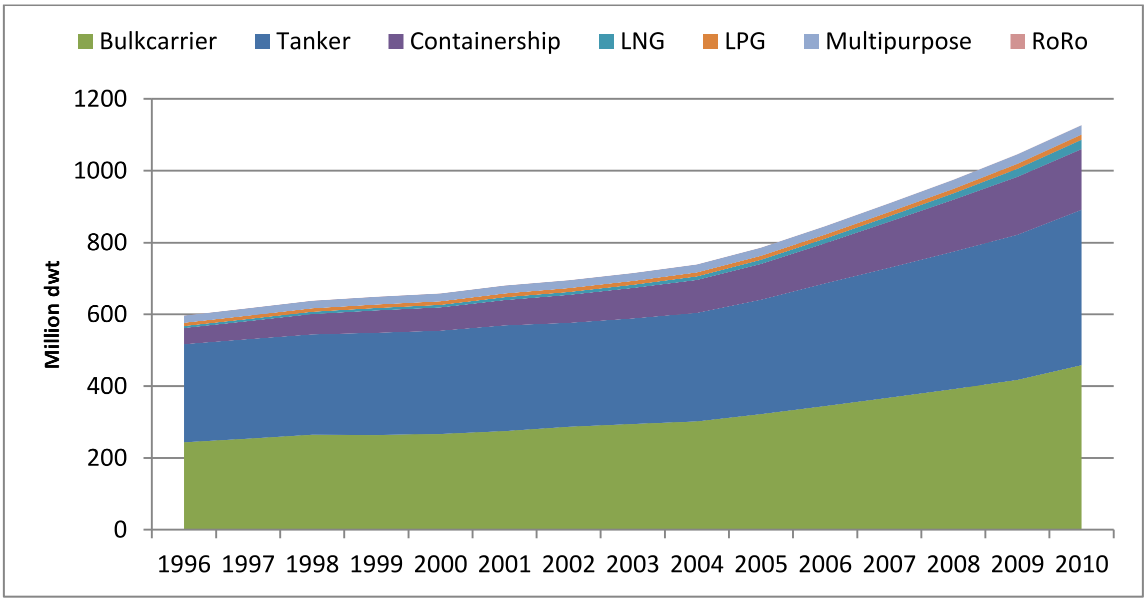


Figure 1.2 World shipping fleet pattern 1996–2010

[3] World Scale (WS) is a system of freight rate payment for oil tankers.

[4] Only ships bigger than 10,000 dwt are included. dwt is the abbreviation for 'deadweight'. It is a measure of how much weight a ship can carry and is given in tonnes.

Fleet data for the tanker and dry bulk variable are from 1970. Taking the period 1970–2010 into consideration, we can see that dry bulk has experienced growth of 5.27% and tanker (excluding chemical tankers) has grown by 1.23%, but including chemical tankers the fleet has grown by 3.45%. Data for chemical tankers are only available from 1996. The size of the shipping fleet after the Second World War has expanded from around 120 dwt to around 1,200 dwt. The dry bulk and tanker fleets constitute around 80% of the merchant fleet. The rest of the fleet consists of 13% container ships and 7% other ship types, such as LNG (Liquid Natural Gas) carriers, LPG (Liquid Petroleum Gas) carriers, multi-purpose carriers and RoRo (roll on/roll off) ships.

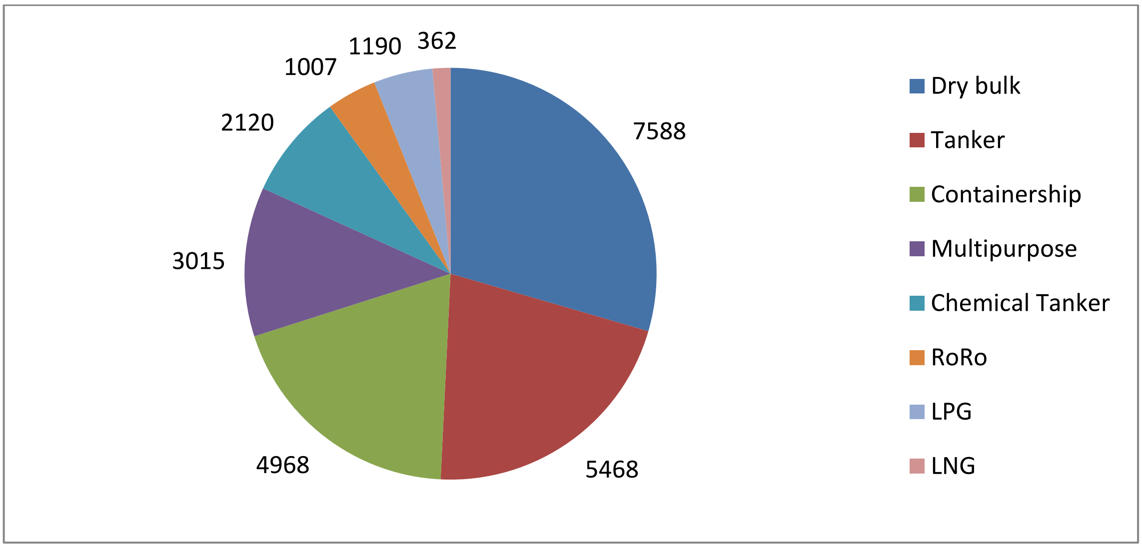


Figure 1.3 World fleet size: number of ships

At the end of 2010 there were more than 25,720 ships around the world; this figure covers ships of more than 10,000 dwt. Dry bulk and tankers, including chemical tankers, constitute about 40% of the dwt of the world fleet, but they constitute more than 60% of the number of ships. The correlation coefficient, which has been estimated for several time series in this chapter, is the Pearson product-moment correlation coefficient, typically referred to as r, which measures the linear dependence between two variables. The coefficient is between +1 and -1 and is presented in percentage format. The Pearson formula for two series of x and y is:

$$r_{xy} = \frac{\sum(x-\bar{x})(y-\bar{y})}{\sqrt{\sum(x-\bar{x})^2 \sum(y-\bar{y})^2}} \tag{1.1}$$

The correlation coefficient will be calculated for many prices and return series, for purposes of comparison, not for analysis of statistical significance. The high degree of correlation does not necessary mean there is strong causality between two variables.

1.4 Shipping market segments

The types of ships needed for each cargo and route depend on several factors, such as type of commodity transported, type of loading and discharging facilities available at ports, and draught restrictions. The shippers and charters always try to minimize costs by chartering the best possible size of vessel. A ship should be certified by classification societies to be of a specific type and size. Classification societies are organizations that provide a survey and classification of ships from the time they are built. These organizations represent the means whereby standards of constructions and maintenance are enforced. Classification societies are licensed by Flag States to survey and classify on their behalf. The classification society in the UK is Lloyd's Register of Shipping.

Table 1.2 Classes of major ship types

Type	*Size*	*Type*	*Size*
Tanker	*dwt 000,*	*Container ship*	*TE0U[5] 00*
ULCC-VLCC	160-550	ULCV	145 higher
Suezmax	130-160	New Panamax	100-145
Aframax	80-120	Post Panamax	50-100
Panamax	50-80	Panamax	30-50
Handysize	20-50	Feedermax	20-30
small tanker	10-20	Feeder	1-30
Type	Size	Type	
Bulk Carrier	dwt 000	Others	
Capesize	80-300	Reefer Ships	
Panamax	60-75	PCC	
Supermax	40-50	PCTC	
Handymax	30-50	Ferries	
Handysize	20-30	Barges	

Table 1.2 presents the general classification of ships. This table has four columns, representing the four types of ship: tankers, bulk carriers, container ships, and others.

[5] The twenty-foot equivalent unit (TEU) is the unit of cargo capacity which is used to calculate container ship capacity.

The last columns list specialized ships. In Chapter 2, two types of freight rates, deriving from the Handymax and Capesize classes, are used. In Chapter 3 we use three freight rate indexes, which include the Capesize and Panamax classes. The stock prices given in Chapter 4 are those issued by the companies that own different types of tankers.

1.5 The dry bulk market

The dry bulk fleet constitutes around 40% of the total world shipping fleet in terms of capacity, with more than 6,600 ships. Dry bulk ships are usually involved in the transportation of dry bulk, which includes iron ore, coal, grain, bauxite, alumina and phosphate rock. Tables 1.4 and 1.5 present the pattern of dry bulk ship capacity and fleet numbers between 1970 and 2010.

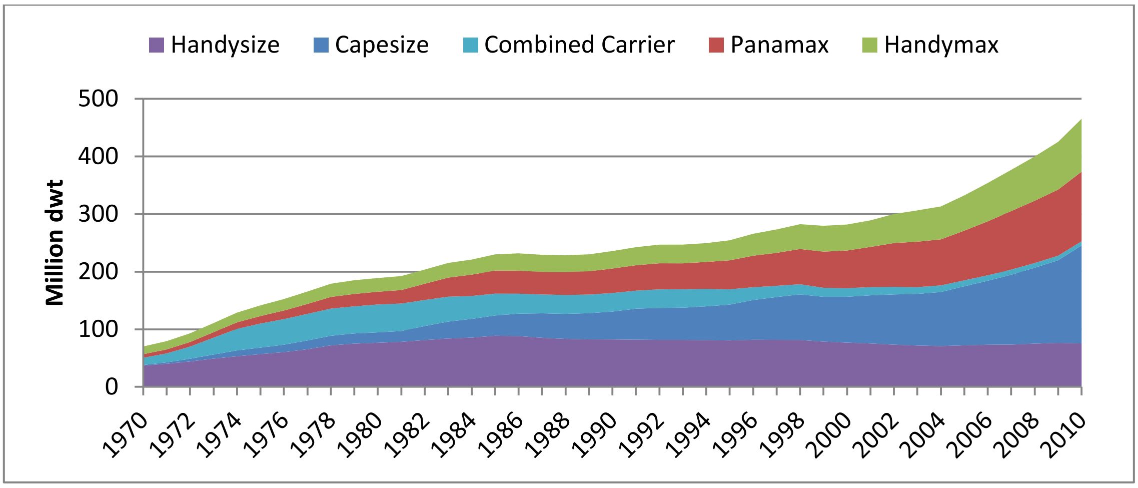


Figure 1.4 Bulk carriers' fleet capacity

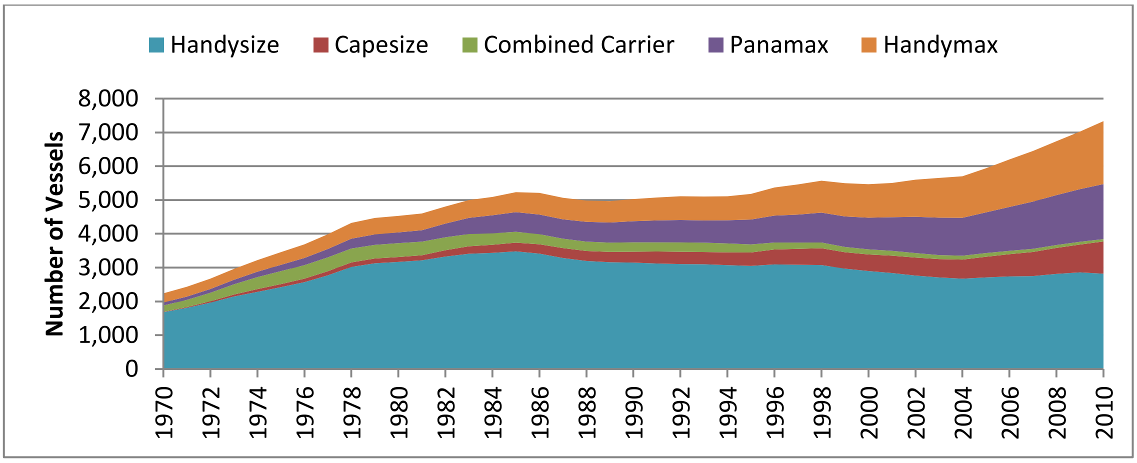


Figure 1.5 Bulk carrier fleet: numbers of ships

Most bulkers are currently built in Japan, with South Korea ranked the second-largest builder. Most of the fleet capacity is of the Capesize type; however, the Capesizes constitute a relatively much lower number of ships. Figure 1.5 shows that Handysize and Combined Carriers are experiencing diminishing fleet capacity and numbers. The pattern of the dry bulk fleet is very different from that of the tankers fleet, shown in Figure 1.6.

1.6 The tanker market

Tankers are designed to transport liquids in bulk; the majority of tankers are either oil or chemical tankers. Tankers carry a wide range of products: crude oil, liquefied petroleum gas (LPG), liquefied natural gas (LNG), refined petroleum, drinking water, and others. The country of Panama has the largest number of tankers and dry bulk registers. The USA, Japan and Greece are the top three tanker owners. Table 1.5 presents the pattern of tanker fleet capacity, showing that capacity in 1978 is similar to that for 2005. Table 1.7 presents the pattern of tanker fleet numbers. Small tankers represent the highest numbers of ships and the lowest total capacity. Data for small and chemical classes are available from 1996.

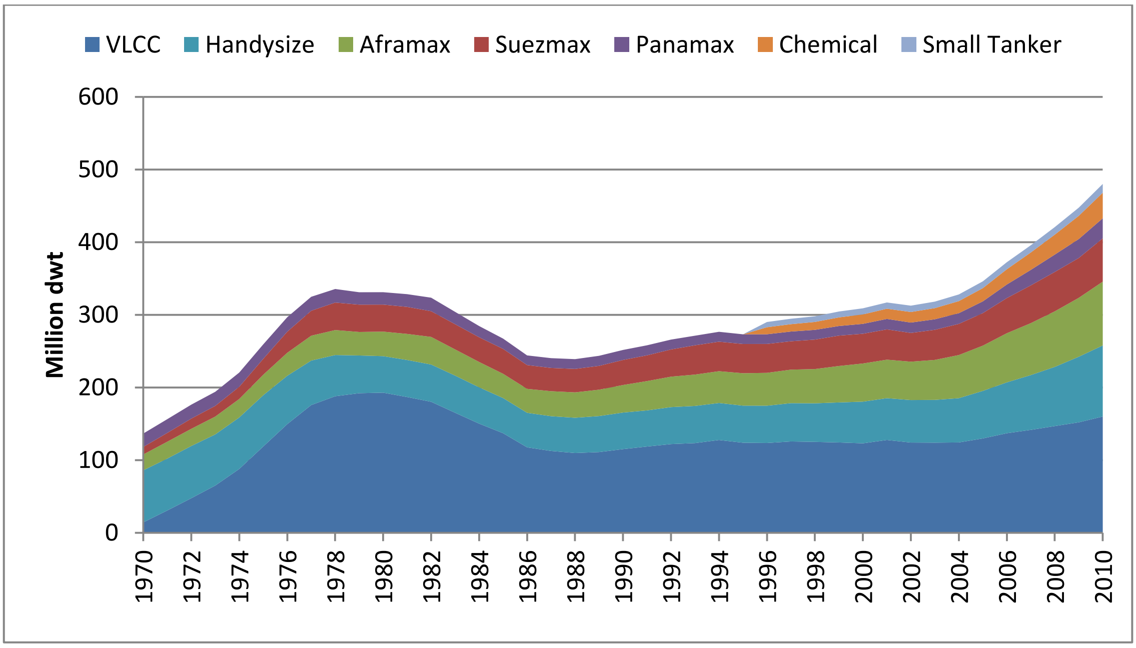


Figure 1.6 Tanker fleet capacity (16% growth a year for chemical and small tankers)

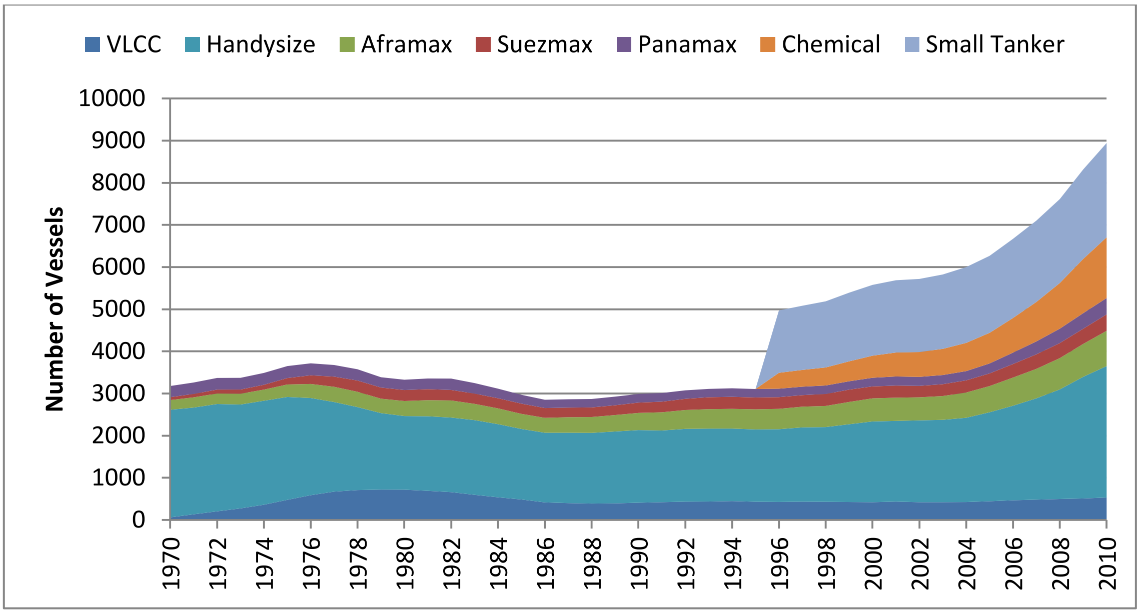


Figure 1.7 Pattern of tanker fleets: number of ships

Over 70% of tankers are built in Japan, South Korea or China. Large tankers are usually involved in the transportation of crude oil. As Figure 1.7 shows, the VLCCs, with a relatively small number of ships, have the largest share of the fleet. Small tankers, which are very flexible because they are subject to less restriction in ports and terminals, constitute a small part of the capacity, with a relatively large number of vessels. The size of the tanker fleet (excluding that of chemical and small tankers) grew by 3.42% between 1996 and 2010, chemical and small tanker fleet growth during the same period being 16%.

1.7 The container market

Container ships carry their loads in lorry-sized containers. Containers were introduced first in the USA, and revolutionized intermodal transport. Containerization has changed shipping and world trade. Containers can be loaded and unloaded much faster than the alternatives, meaning reduced labour costs, shipping times and packaging. Containers have also reduced the numbers of breakages and thefts. Modern container ships can carry 15,000 TEU (20-foot equivalent units). Panama, Liberia and Germany are the three top Flag States for container ships, and South Korea the largest producer of container ships. Figures 1.8 and 1.9 present the pattern of the container ship fleet. In

Figure 1.9 part of the graph relevant to the number of ships in 2010 is flat, but fleet capacity has grown during this time. This indicates that the new ships are becoming larger. Container ship has the highest average fleet growth, which stands at 19% per year and constitutes around 19% of world shipping fleet tonnage. Chemical and small tankers have the second highest average growth at 16%, and constitute around 4% of world fleet tonnage. Dry bulk and tankers collectively have less than 5% growth, but constitute more than 50% of the world fleet.

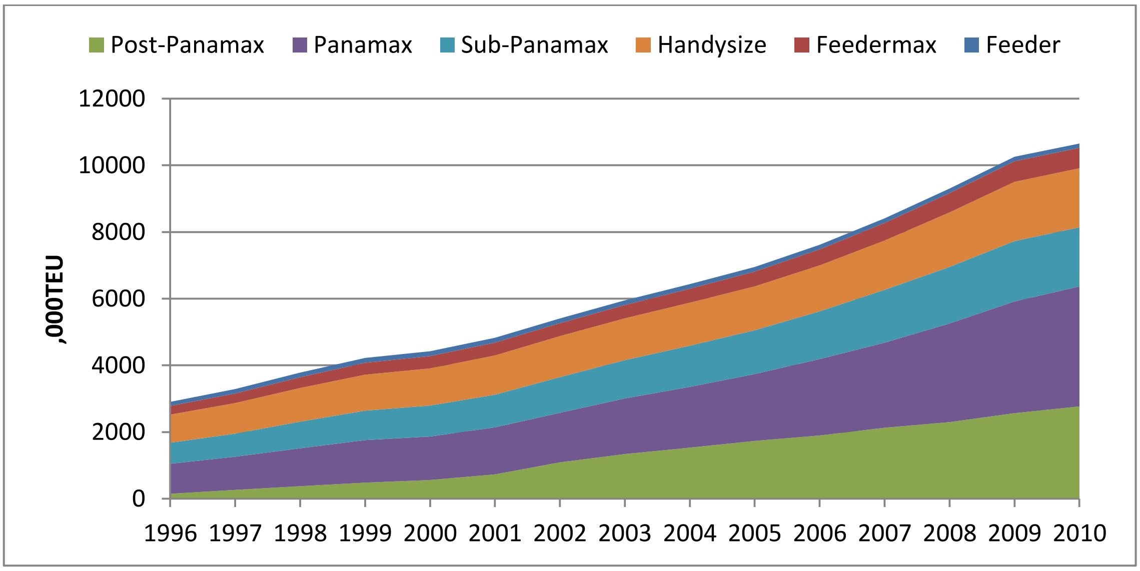


Figure 1.8 Pattern of containership fleet capacity, 19% growth a year

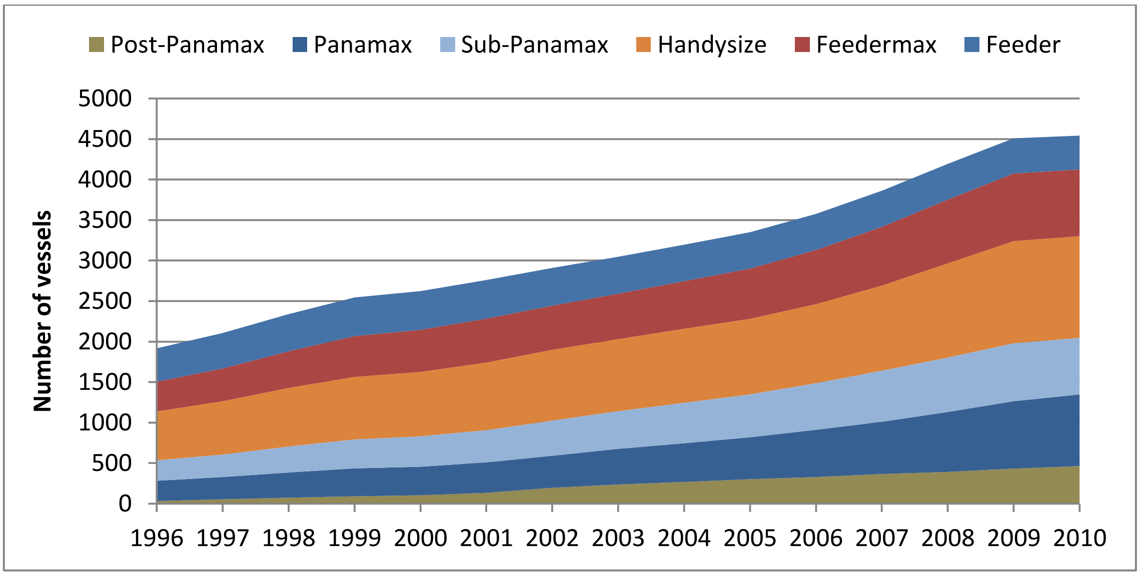


Figure 1.9 Pattern of containership fleets: number of ships

1.8 Other ship types

The other main merchant ship types are: LNG, LPG, multi-purpose carriers, pure car carriers, and reefers. LNG ships transport natural gases, LNG being natural gas which has been converted into liquid for transport. Russia and Iran hold more than 40% of the world's natural gas reserves, while Japan and Europe are the two biggest importers of LNG. The LPGs transport chemical gases produced by chemical plants, and gases for domestic and commercial use. These gases need to be liquefied so as to reduce their volume by 99.8%. Two of the major cargoes of LPG tankers are Propane and Butane. Multi-purpose vessels carry different kinds of cargoes such as liquid and general cargoes. Pure car carriers are a type of roll-on/roll-off vessel that carry new-build automobiles. Reefer ships carry perishable commodities that require temperature control. LNGs constitute the fastest-growing market. Multi-purpose ships constitute most of the shipping fleet between these classes. Figure 1.10 presents the capacity pattern of the above ship types. Multi-purpose carriers constitute 12%, RoRo 4%, LPG 5% and LNG 1% of the world shipping fleet. Growth per year for all these ships averages 1.7%, which is much less than that for any other major ship type. Figure 1.11 presents the pattern of ship numbers. Multi-purpose carriers constitute the highest number and LNGs the lowest number of ships.

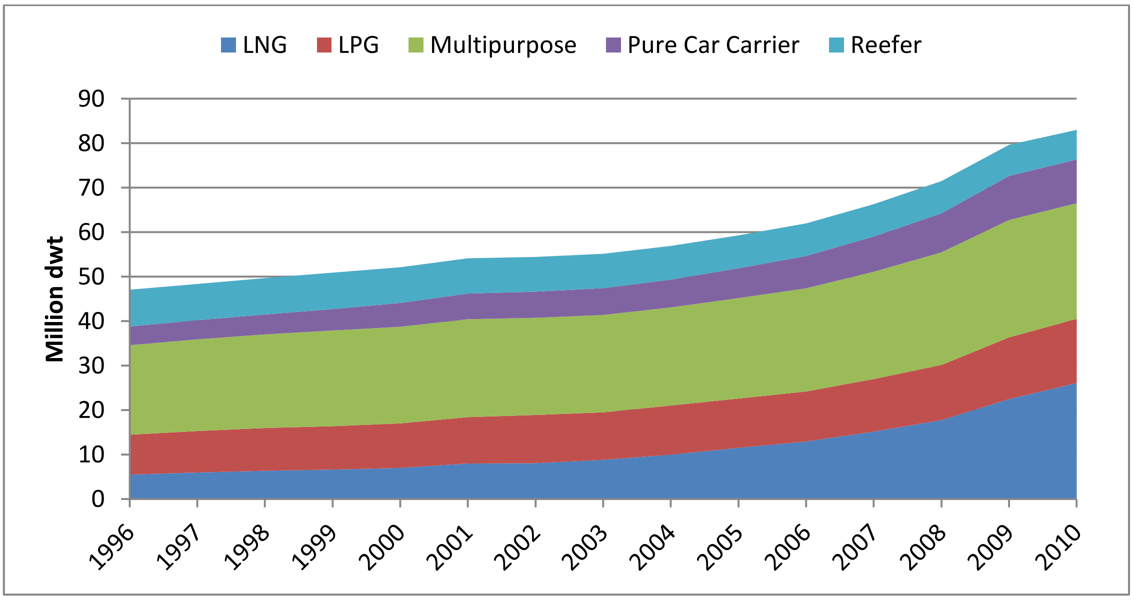


Figure 1.10 Pattern of other ships fleets, 1.7% growth a year

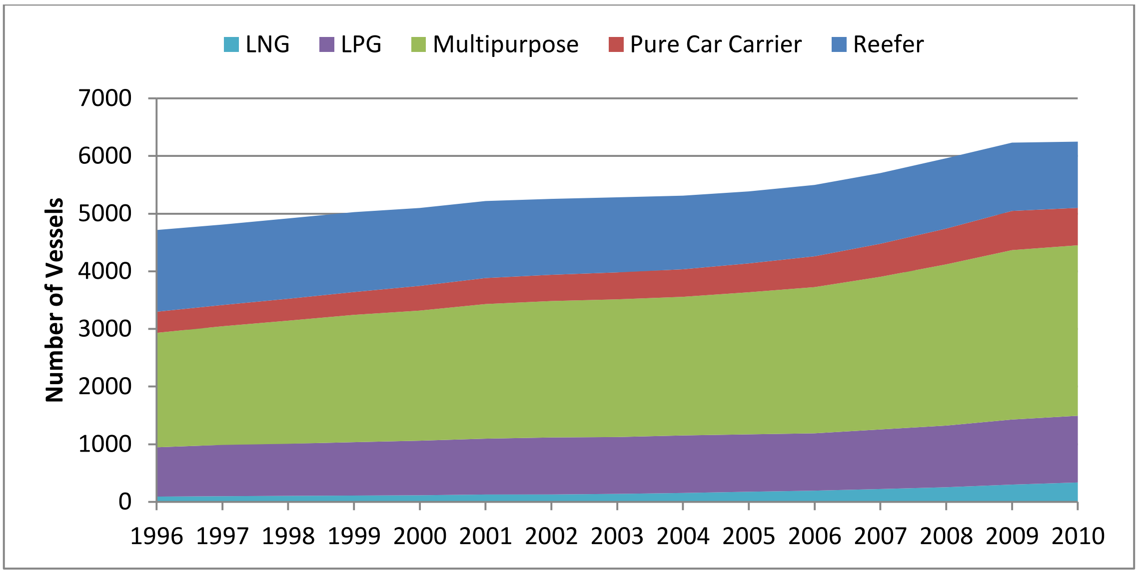


Figure 1.11 Pattern of other ships fleets: number of ships

1.9 Shipbuilding order book

The new-build ships are ordered by shipping companies and are built in shipyards. The shipbuilding order book has a different pattern from that of fleet growth: we may expect the order book to look regular and similar to fleet growth, but in fact it is very volatile. Figure 1.12, which presents the pattern of orders by Compensated Gross Tonnage (CGT),[6] clearly shows that during the economic boom and high freight rate there is a tendency to order new-build ships; however, these orders are based on the current ordering time of the market and the freight market could be very different a few years later when they are delivered. The fleet will be adjusted by scrapping or demolition. New-build and second-hand ship prices are determined differently, and this will be discussed below. The most important factor in creating the shipping market cycle is the time lag between new-build orders and actual delivery. There is also a second-hand market for already available ships, conducted through specialist brokers. Figure 1.12 indicates that the super-boom in orders began in 2003 and peaked in 2008. From late 2007 there was a massive fall in ship orders. The correlation coefficients of returns in Table 1.3 show that the order book is correlated by about 50% with the average time-

[6] CGT indicates the amount of work needed to build a ship.

charter freight rate and second-hand ship price. Time-charter freight rate has the highest correlation with the order book. The order book is correlated to S&P500 by 9.4%, which is not significant. The order book and fleet development correlated with each other by only 9%. There is a strong relationship between second-hand, time-charter and order book returns.

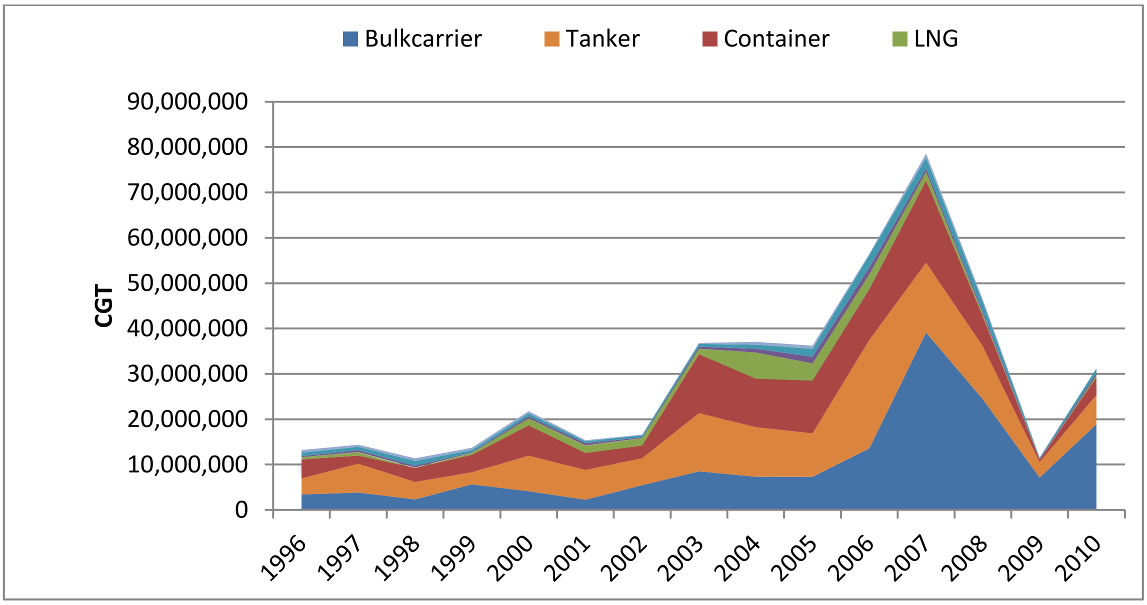


Figure 1.12 Pattern of shipbuilding orders

Table 1.3 Ship order book correlation

r	*Returns*	*Prices*
Order book, S&P500	9.4%	30%
Order book, time-charter rate	52%	86%
Order book , fleet development	9%	64%
Order book , second-hand prices	49%	85%

1.10 Shipbuilding and freight rate models

In this section, the static models that have been used to analyse the determinants of the order book are discussed. The freight rate and assets in bulk shipping industry is volatile and perfectly competitive; therefore, the market freight rate is determined by the marginal cost of the marginal vessel required to satisfy the demand for transportation. The short-term supply curve indicates the amount of transportation willingly supplied by the fleet at a given freight rate. (The characteristics of the shipping supply curve were first introduced by Koopmans, 1939.) Figure 1.13 presents an example of a supply and demand curve in shipping similar to the Koopmans curve. Depending on the level of ship employment, the shape of the curve may indicate a very flexible reaction to change in demand. In the steep part there is no possibility of expanding the supply. Because of the specific shape of the supply and demand curve in this example the freight rate could be extremely volatile.

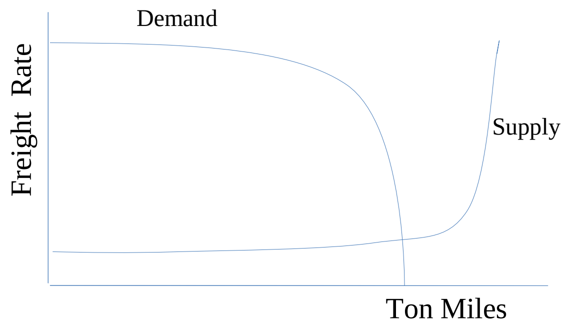


Figure 1.13 Supply and demand in bulk shipping

1.10.1 Tinbergen’s (1931) model

According to Tinbergen (1931), shipbuilding depends on the amount of freight. Freight, consequently, depends on the shipping tonnage present in the market. This leads to an endogenous shipbuilding market cycle, which is caused by the time lag between the demand for shipping capacity and the actual availability of fleet. Tinbergen also remarks that there is evidence of exogenous disruption, causing the cycle to act unpredictably at different periods of time. Tinbergen (1931) adopts a supply–demand approach to analysing the new-build market based on the cobweb theorem; he describes a model where supply adjusts to price with a specific time lag. More specifically, low total tonnage leads to high freight rates. Ships ordered during a period of expansion will be delivered many months later, thus increasing the total tonnage. After modelling the statistical data for the years 1875–1913, Tinbergen (ibid.) posited an endogenous shipbuilding period of around eight years.

1.10.2 Tinbergen's (1934) freight rate model

In another investigation, Tinbergen (1934) estimated the cyclic variations of the freight rate by means of multi-correlation by a linear combination between freight rates (F), the level of the demand for shipping (Q_n), and the total fleet $\left(B_f\right)$, as well as the fuel price $\left(T_p\right)$, as follows:

$$F = 1.7\, Q_n - 1.6\, B_f + 0.4\, T_p \qquad (1.2)$$

The size of the current shipping fleet reflects the influence of the freight rate of the previous period. This mechanism seems to have a very limited effect, however, as the economic cycles have a major effect on shipping cycles. According to Tinbergen (1934), the influence of the trade cycles on shipping appears in two variants: through change in the coal price, which can be compared to the fuel price; and through change in the fleet of the coal carrier. This model is actually the freight rate model, that investigates the sensitivity of freight rates to changes in the level of demand on the one hand, and the factors affecting the supply on the other. Beenstock and Vergottis (1993) have specified the Tinbergen model to be

$$Q^s = f_1(F_R, P_B, F) \qquad (1.3)$$

where

$Q^s = supply$

$F_R = freight\ rate$

$P_B = price\ of\ bunkers$

$F = fleet$

where freight rate moves to set demand equal to supply $Q^D = Q^S$. The two expressions imply that equilibrium freight rate can be written as a function of demand, fleet and bunker costs by replacing the first equation with the second one; then it reflects the relationship between equilibrium freight rates and level of demand, size of fleet, and bunker prices. Therefore, the freight rate is to be:

$$F_R = f_2(F, Q^D, P_B) \qquad (1.4)$$

Other factors, such as operating costs, are also specified as influencing rates, but since they remain more or less unchanged during the cycles in relation to other variables their effects are assumed to be constant. This model assumes that demand is inelastic, but supply reacts positively to freight rates and will result in changes to fleet size or bunker price. An increase in fleet size increases the supply of ships. An increase in the price of bunkers will cause supply at the constant freight rate to decrease as ships find it more economical to move more slowly to save fuel. A major problem with these static models is that the determinant variables are not clearly separated and hence the freight rate model includes equations with variables that mix up supply and demand.

1.10.3 Koopmans' (1939) model

Koopmans (1939) assumes that ton miles supply is directly proportional to fleet size, while the supply and demand generated by a unit of capacity depends on the reaction of freight rates to bunker prices and other operating costs. Taking into account the fact that in equilibrium demand must equal supply, the following relationship between rates, fleet demand and cost is specified:

$$Q^D = F\left(\frac{FR}{P_B}\right)^{\gamma} \tag{1.5}$$

γ was estimated from data and was found to be about 0.15, suggesting that supply become very inelastic as lay-up falls. Koopmans (1939) believes that shipbuilding is influenced by expectations concerning the degree of equilibrium between the transportation capacity of the world fleet and the aggregate demand for its services. Koopmans is the first to note the peculiar shape of the supply curve. He distinguished two situations in the supply of tankers, namely the cases of full and of partial employment. The elastic part of the supply curve shows the possibility of flexible fleet reactions to demand changes; the steep part shows the non-flexibility of fleet expansion in the short run when it is fully employed.

According to Koopmans, the specific shape of the supply curve is the main cause of freight rate volatility. If only part of the fleet is active and there is an idle fleet, the demand curve intersects with the elastic section of the supply curve. In this case, changes in demand do not influence freight rates because the fleet can engage with such demand changes. On the other hand, if the full fleet is actively trading a demand increase cannot be met by the existing fleet, and as a result freight rate increases. Figure 1.14 illustrates the Koopmans supply curve.

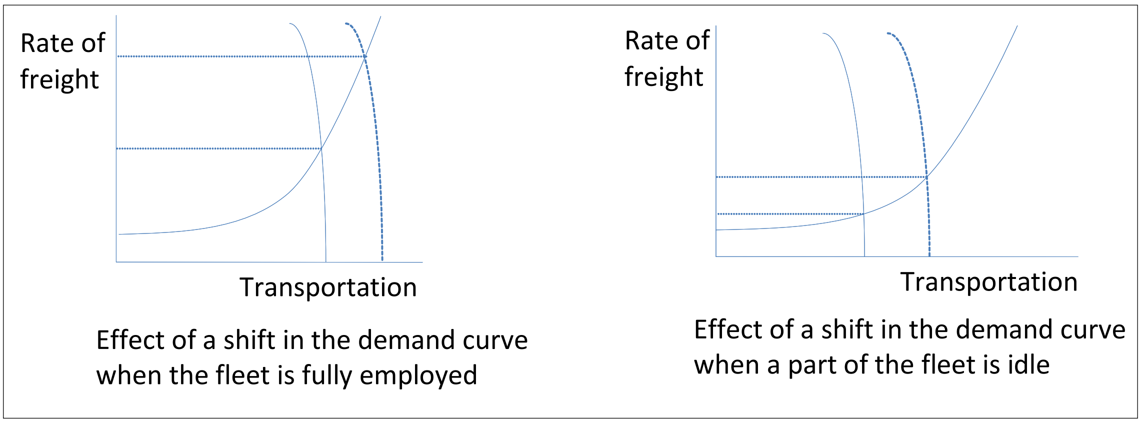


Figure 1.14 Koopmans' shipping supply curve

For new-build ships there is a time lag between the ordering and the delivery of a new ship. Koopmans suggests that the time lag in shipbuilding is the main reason behind business cycles in the shipping market. It is assumed that the higher the time-charter rate the higher will be the ship's profitability, and as a result the more interested the ship owners will be to invest in new ships. It can be said that time-charter rate also determines the order book; however, the new ships will be delivered with a time lag and usually by the time of delivery market conditions will have changed and the market may have become depressed. In the shipping market demand is volatile and quick to change, but supply is slow to change. According to Koopmans (1939), the shipbuilding market is influenced by expectations concerning the degree of equilibrium between the transportation capacity of the world fleet and the aggregate demand for its services. The reason for relying on expectation is the time lag between ordering and delivery, which indicates that past orders will shape the market situation.

1.11 The demolition market

The demolition market deals with scrapping. During a recession, or when vessels are old, vessels are sold to scrap dealers and demolition yards. Speculators sometimes operate between the ship owners and demolition merchants. Figure 1.15 shows the demolition pattern of bulkers and tankers between 1985 and 2010. There is a -62% correlation between LME index return (London Metal Exchange index) and the dwt quantity of demolition return. There is also a -26% correlation between demolition and S&P500 return series. Negative correlations suggest that there is a strong relationship in an opposite direction between the two variables. Table 1.4 and Figure 1.15 indicate that at a time when metal prices are high there is less evidence of scrapping. Scrapping activity scales up during times of low metal prices and economic recession. At times of economic boom, and when metal prices are high, old ships can still make money, and operators are keen to continue trading.

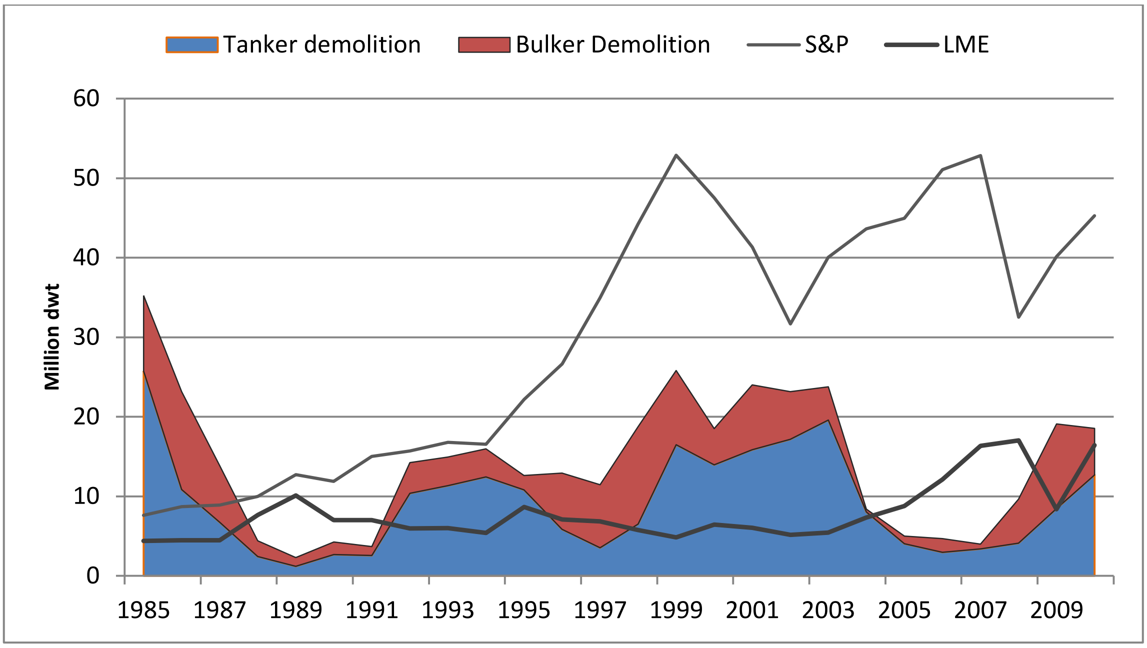


Figure 1.15 Pattern of ship demolition for tankers and bulkers

Table 1.4 Demolition correlation with S&P500 and London Metal Index (LME)

r	*Prices*	*Returns*
Demolition, LME	-62%	-46%
Demolition, S&P	-26%	0.04%

1.12 Economic cycles in the shipping market

In this section we explain some of the models relating to the behaviour of the shipping market's economic cycles.

1.12.1 Zuellig's (1942) model

Zuellig (1942) examines the development of freight rate and the economic turnovers in freight rate during World War II. His study shows characteristics similar to those of studies published before the War. As a primary cause of the variations in economic trends, he refers to the slight adaptability of supply to quantitative variations in demand for ships.

1.12.2 Hampton's (1987) model

Hampton (1987) has analysed the economic trend cycles of the shipping market for 40 years following the end of World War II. His analysis consists of two types of cycle, short-term and long-term. Figures 1.16 and 1.17 present the movements of these cycles.

The long-term cycles in the shipping market for a period of 20 years are divided into two phases, the construction phase and the correction phase. The construction phase lasts 8–12 years and is marked by high freight rate. The correction phase also lasts 8–12 years; it is a long period with low freight rates.

The short-term cycles in the shipping market have a duration of 3–4 years. The construction phase of the long cycle consists of three regular short cycles with, respectively, a high point in the freight rate around every 3–4 years. In addition, there are also short cycles during the correction phase of the long cycle. During the construction phase (8–12 years) freight rates are higher and tonnage is expanding strongly.

Hampton (1987) argues that the freight rate depression in the correction phase is required in order to demolish the excess supply created at the end of the construction phase. Hampton believes that the behaviour of market participants in the long and short cycles has a regular pattern and emphasizes that short cycles occur in the construction phase of a long cycle. Hampton (1991) believes that market environment is an important cause of the cycles, and the main reason market agents repeatedly overreact to price patterns.

Hampton (1991) argues that in any market,

> including the shipping market, the participants are caught in a struggle between fear and greed, because we are human beings, influenced to varying degrees by those around us, the psychology of the crowd feeds upon itself until it reaches an extreme that cannot be sustained. Once the extreme has been reached, too many decisions have been made out of emotions and a blind comfort which comes from the following the crowd rather than objective fact.

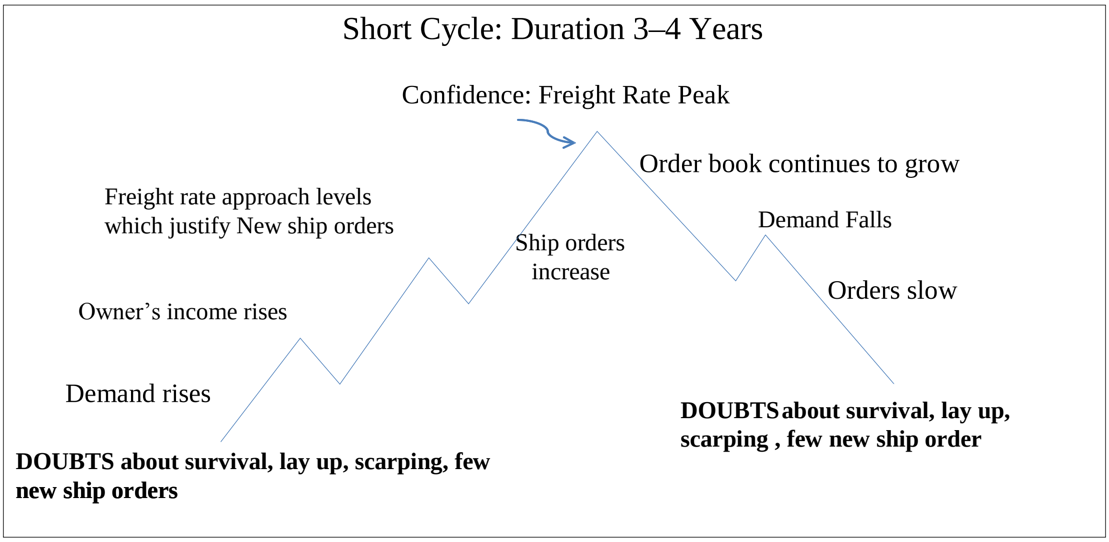


Figure 1.16 Short economic trend cycles of the shipping markets

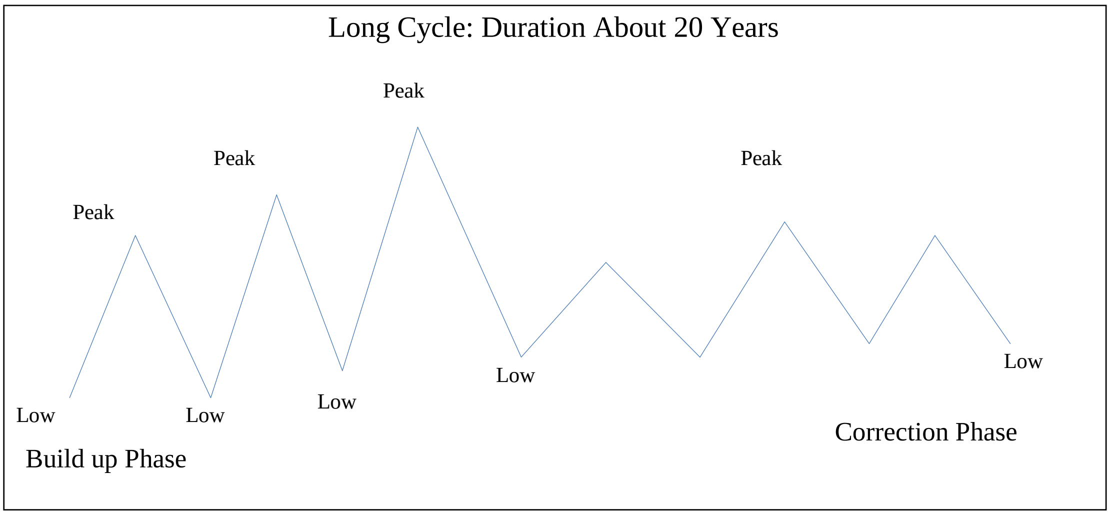


Figure 1.17 Long economic trend cycles of the shipping markets (source: Hampton 1987, p.23)

1.12.3 Volk (1994)

Volk (1994) formulated four hypotheses for market cycles in shipbuilding. He argues that shipping cycles are the result of development in freight rates, shipping innovations, psychological and speculative factors in shippers' attitudes to the market, and the limited influence of replacement orders. Of these factors, the freight rate is measurable while the others have stochastic behaviour and cannot be modelled. Volk's model combines an asset pricing model with a cost-based model, but in practice these factors are not actually quantifiable and cannot be used. Volk (1992) set up his four hypotheses through the analysis of statistics that were not available in earlier models. Volk assumes that the politico-economic causes, such as canal closings, wars and strikes, influence the freight rate achievable in the market. Also, strong economic growth can lead to a lack of supply and cause an increase in freight rate. He also assumes that the shipbuilding cycle is affected essentially by dry and wet bulk orders, and only slightly by other ship types. The explanation for this is that demand for raw materials is stronger than that for finished goods.

1.12.4 Stopford (1997)

Stopford (1997) found four cycles before World War II, but does not consider the major cycles. His analysis gives an average peak-to-peak duration of 9.8 years. He argues that in the short run, economic activity and world economic cycles are the major determinants of shipping cycles. There is more asymmetry between shipping cycles and economic cycles during peaks than during troughs. Stopford (1997) suggests that the cycles retain similar features through time, and have an average duration of 7.2 years in the post-war period. This is also in line with the previous literature discussed in earlier sections.

1.13 New-build ship prices

The new-build market relates to ships that do not currently exist, and so is conceptually different from the second-hand market. The ships need first to be ordered and then are built in shipyards, and this process takes 2–3 years. There may be several reasons for a purchaser ordering a new ship rather than buying one second-hand. For instance, a specific design and size may be needed which are not available in the second-hand market. Speculators may also be attracted to the market. The new-build prices of similar ships can vary depending on the country of build, the degree of advancement of design, the engine, fuel efficiency, and general quality, as with any other product, but in the main prices depend on steel prices and on the general conditions of the world economy.

Figure 1.18 presents the average monthly new-build price correlation for bulk carriers, container ships and tankers between 1985 and 2010. Container ship prices are available from 1996. There are two series of peaks, one between 1989 and 1992, and the other between 2006 and 2009. All the new-build ship price returns are significantly correlated. The ships are made of steel, and we can observe a strong relationship with the LME index. The new-build prices are not significantly correlated to the S&P500 index. Container ships are 56% correlated to LME, but only 1% to S&P500.

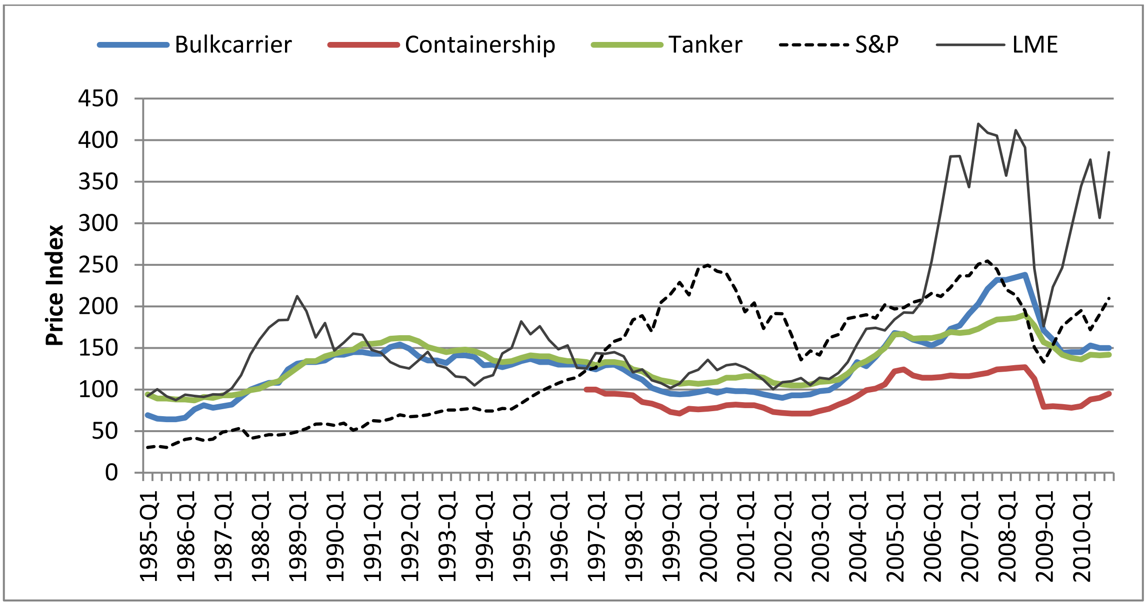


Figure 1.18   Average new-build prices

Table 1.5   Correlation of new-build prices

r	*Returns*	*Prices*
Bulk, tanker	78%	95%
Bulk, container	67%	86%
Tanker, container	76%	91%
S&P500, LME	16%	48%
Bulk, LME	32%	80%
Tanker, LME	31%	68%
Container, LME	56%	68%
Bulk, S&P500	6%	35%
Tanker, S&P500	1%	30%
Container, S&P500	1%	30%

1.14 The sale and purchase market

The sale and purchase of second-hand ships are conducted by specialist ship brokers. In certain situations, the second-hand price can be more than the new-build price. Ships are usually divided into 64 shares. The process of ship sale and purchase is very similar to that for real estate. The deposit is usually 10%, and ship brokers charge around 1% of the whole deal. Figure 1.19 presents the average monthly second-hand prices. There is a 19% correlation between second-hand returns and S&P500 return, as against 2.3% in new-building. Second-hand returns correlate to LME more than to new-build returns. Tanker and bulk carrier returns are significantly correlated to the S&P500 index; this is not the case with new-build returns. All the second-hand returns are significantly correlated to the LME index.

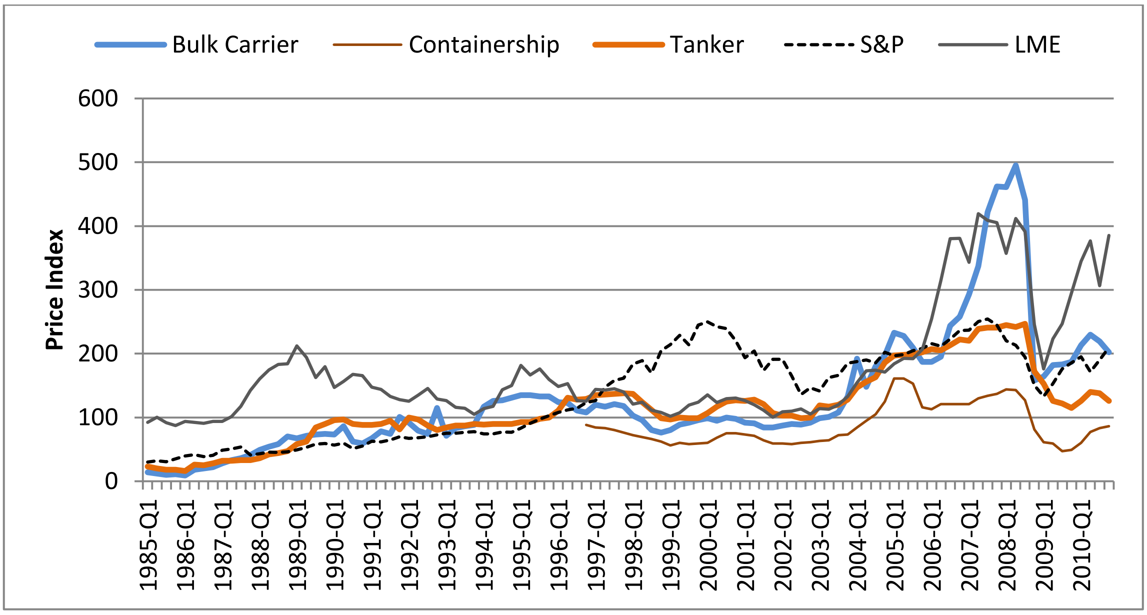


Figure 1.19 Average second-hand ship prices

Table 1.6 Correlations of second-hand prices

r	*Returns*	*Prices*
Bulk, tanker	48%	88%
Bulk, container	59%	74%
Tanker, container	67%	91%
Bulk, LME	56%	85%
Tanker, LME	43%	71%
Container, LME	48%	58%
Bulk, S&P500	25%	63%
Tanker, S&P500	16%	78%
Container, S&P500	17%	37%

Comparing the visual characteristics of Figures 1.18 and 1.19, we can see that container ships and tankers follow a similar path, but that the bulk carrier prices in Figure 1.19 show a much bigger price spike than new-build during 2006–8. In this period, the second-hand prices of dry-bulk carriers can reach twice the new-build prices. Figure 1.20 compares the new-build and second-hand prices. The correlation structure in Table 1.7 confirms that there is a high correlation of between 87% and 93% between the prices. There is a much lower, but significant, correlation between the returns.

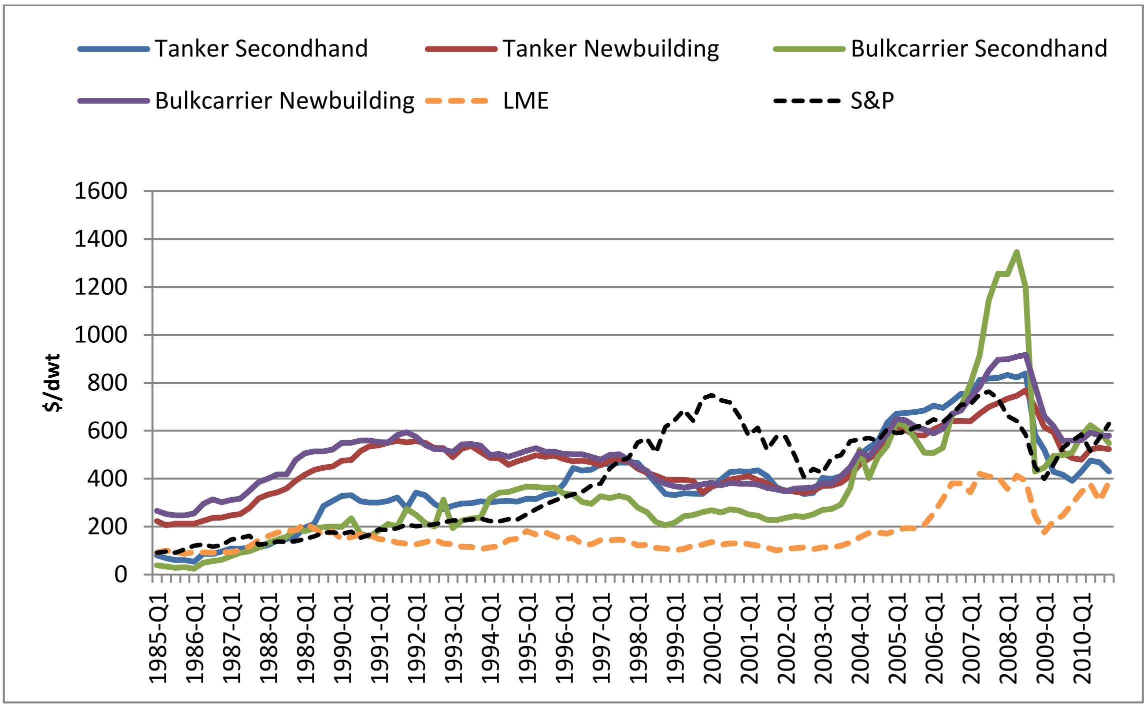


Figure 1.20 Comparison of new-build and second-hand ship prices

Table 1.7 Correlation of new-build and second-hand

r	*Returns*	*Prices*
Tanker second-hand, tanker new	32%	87%
Bulker second-hand, bulker new	42%	87%
Tanker second-hand, bulker second-hand	49%	90%
Bulker new, tanker new	70%	93%

There is only a 32% correlation between the average returns of a new-build and second-hand tanker; however, there is 70% correlation between the two ship types' new-build prices. This may suggest that the prices of new-builds and second-hand ships are differently constituted. There are several studies examining the modelling of ship prices.

Alizadeh and Nomikos (2003) have tested the relationship between ship price volatility and trading activity in the sale and purchase market. They found that ship prices are inversely related to trading volume. Alizadeh and Nomikos have also concluded (2009, p. 450) that volatility in the ship prices is directly related to volatility in freight rate. They argue that this could be because ship prices are believed to be determined through a discounted present value model in which revenue from freight operations is the main pricing factor.

1.15 The freight market

Different types of charter party contract exist in which a charterer, who may or may not be the owner of a cargo, buys the ship owner services in return for a price, which is called freight rate; the freight rate could be on a dollar per tonne or a dollar per day basis. The charter party may be the owner of a cargo and employ a ship broker to find a ship for the cargo. The charter party could also be a merchant who takes out a charter party agreement for a specific period in order to carry cargoes at a profit or sell the charter party contract in a rising market. The charter party agreement, as with any other legal document, is subject to interpretation in a court of law in the event of any dispute. There are different types of charter party agreement, as follows:

1- *Voyage charter (spot charter).* Under this contract the ship is chartered for one voyage between specific ports with a specified cargo. The charterer pays the freight to the ship owner on a dollar per tonne basis, and the owner pays the port, fuel and crew costs.
2- *Trip charter.* The ship is chartered for a specified period, on a specified trip. The charterer pays the freight on dollar/day basis ($/day). The ship owner controls the vessel and the charterer pays the voyage costs. The difference between this type of charter and voyage charter is that the voyage charter is on a $/day basis rather than a $/tonne basis, while the allocations of cost operate as in a time-charter contract.
3- *Time charter.* The vessel is chartered for a specific period of time such as six months or a year, though it could be 3–5 years. The charterer chooses the routes and cargoes and the owners manage the ships. The charterer pays the freight on a dollar per day basis, and will also pay the fuel, crew and port expenses.

4- *Contracts of affreightment (CoA).* This is a contract whereby the ship owner agrees to transport a cargo of a specified size, which is usually more than the ship's capacity. The cost allocations resemble those of the voyage charter agreement.

5- *Bare-boat charter*. In this type the charterer has full control of the ship commercially and operationally. This is less frequent in a commercial environment, and is sometimes used as a lease with which to buy agreements.

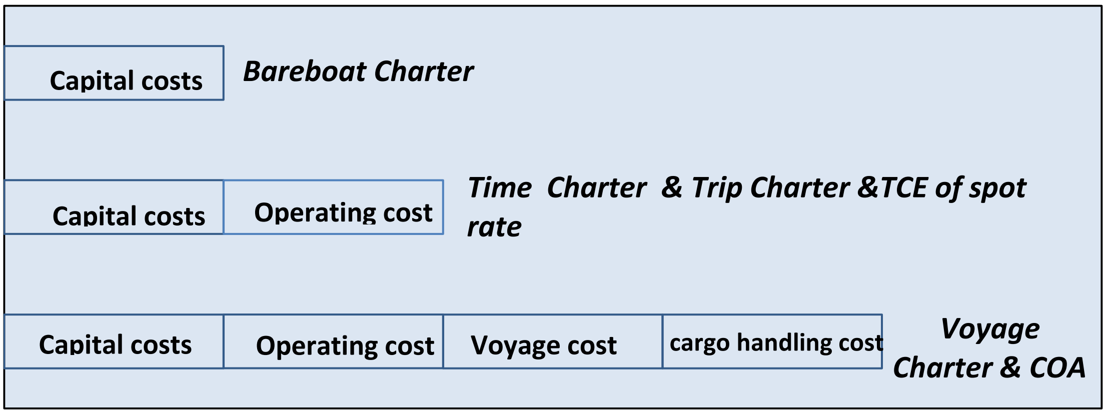


Figure 1.21 Charter party cost commitments

The capital cost includes mortgage and debt repayments, interest and dividends. Operating cost includes insurance, administration, repair and maintenance, including periodic maintenance, stores and lubricants, and manning costs. Voyage cost includes fuel oil cost, diesel oil cost, and port and canal costs. As Figure 1.21 shows, the pattern of cost is different in time-charter and spot contracts. In Chapter 2 we compare these two freight rates to ascertain whether the ship operator can make any extra money by predicting the market and implementing a correct chartering strategy. When there is a need for comparison the time-charter equivalent of spot freight rate (TCE) will be calculated. The time-charter equivalent is derived by subtracting the voyage costs from net freight (i.e. freight rate per tonne of cargo loaded minus commissions) and dividing it by the voyage days, as follows:

$$TCE = \frac{(Freight\ rate\ \times Tonnes\ loaded) - (Voyage\ cost + Commision + Freight\ tax)}{Voyage\ days}$$

(1.6)

TCE = *Time Charter Equivalent*

$Freight\ rate$ = *Freight rate per tonne of cargo*

1.16 Economics of spot freight rate

The formation of freight rates through the interaction of supply and demand was discussed in the previous section. Figures 1.22 and 1.23 present the spot freight rates of tankers and bulk carriers. Figure 1.22, illustrating dry bulk spot freight rate, shows the rates for two vessels, Capesize and Panamax. These are the voyage charter rates. Visually the price movements look very similar; however, in the short run the movements can be very different. The differences in the short movement can be due to the availability of fleet in a specific region, and other political conditions, and port facilities.

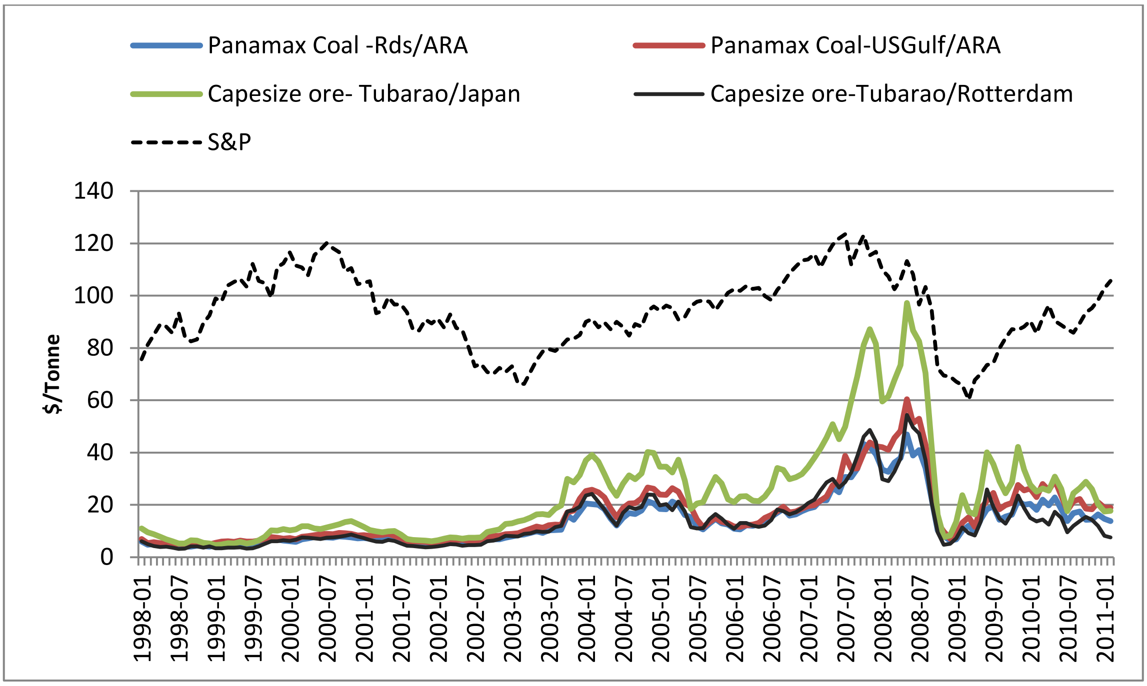


Figure 1.22 Spot freight rate for bulk carriers

Table 1.8 Correlation of spot freight rates for Panamx and Capesize bulkers

r	*Prices*	*Returns*
Panamax Coal-Rds/ARA & US Gulf/ARA	94%	98%
Capesize ore-Tubarao/Japan & Tubarao/Rott	93%	99%
Panamax Coal-Capesize ore U/G,T/J	65%	96%
Panamax Coal-Capesize ore Rds/ARA,T/R	69%	97%
Panamax Coal Rds/AR, T/R, S&P500	14%	47%
Capesize oreT/R, S&P500	15%	46%

As we can see, the freight rate of a Panamax vessel can be the same as or higher than a bigger vessel's. This can be explained by the fact that the larger vessels have a greater economy of scale and costs are lower. Correlations of prices are all more than 95%. The correlations of returns in any of the two classes are very similar to each other. The two routes, of Capesize and Panamax, are more than 90% correlated with each other. Dry bulk spot returns are about 15% correlated to S&P500 return, while S&P500 return is 25% correlated to dry bulk second-hand.

1.17 Wergeland's (1981) spot freight rate model for dry bulk

Wergeland (1981) has proposed a model for dry bulk ships known as Norbulk. In this model, shipping is a homogeneous market. The model consists of supply function similar to the Tinbergen (1934) model, as well as a demand for ton miles function that is assumed to be related positively to the level of world trade and negatively to freight rates. The structure of the model was described as follows:

$$Qnd = Vd_{a1}Fd_{a2} \tag{1.7}$$

$$Qad = Fd_{a3}Bfd_{a4}Foi_{a5} \tag{1.8}$$

Qnd = *Demand for dry bulk (tones per nautical mile)*

Qad = *Supply for dry dry bulk (tons per nautical mile)*

Vd = *Volume of the sea trade of dry goods by tonne*

Fd = *Average freight rate index of dry bulk ships*

Bfd = *dwt of the trading dry bulk ships*

Foi = *Average price of fuels in eight different harbours*

Through the use of the natural logarithm on both sides of both equations, a linear model is obtained. This linear model is based on the data for 1965–74 using econometrics methods, as follows:

$$Qnd = 1.379Vd - 0.077\,Fd \tag{1.9}$$

$$Qad = 0.485\,Bfd + 0.272\,Fd - 0.127\,Foi \tag{1.10}$$

The elasticity of demand with regard to freight rate is reported to be 0.077. Thus, demand is affected by freight rate very slightly. It was concluded that freight rate and fuel price are also inelastic variables by ship supply. Wergeland (1981) has also proposed the Norship model, a model for measuring both the freight and the second-hand market. Each of these markets is divided into two sectors, the wet and the dry, and large and small ships, and the aggregated demand is a function of the economic activities, as follows:

$$Qn_i = a_{1i} P_P^{a21} \left(\frac{P_r}{P_p}\right)^{a3i} F^{a4i} \tag{1.11}$$

Qn : *Demand for shipping as a function of goods production*

$\frac{P_r}{P_p}$: *The activity level of production*

F: *Freight rate*

i *=1,2 (wet and dry goods)*

$a_1, a_2, a_3, a_4 =$ *Coefficient*

A separate supply function was formulated for the respective ship types:

$$Qa_{ij} = Bf_{ij} Ds_{ij} \left(12 - AZ_{ij}\right) Ar_{ij} \tag{1.12}$$

Bf *= Available seaborne trade*

Lf *= Residual factor*

Ds *= Transport distance (nautical mile)*

Az *= Average lay time of ship*

Ar *= Amount of round trip each month*

i *=1,2,3,4,5 (small tanker, large tanker, combined carrier, small bulk, large bulk)*

j *= 1,2 (market for wet and dry ships)*

$Qa_{12} = Qa_{22} = Qa_{41} = Qa_{51} = 0$

This model is to a large extent similar to the other freight rate models such as the Tinbergen model. It represents a good attempt, but is too general to be of any practical use.

The dry bulk freight rate was analysed above. Now, we analyse tanker rates, which are shown in Figure 1.23 and Table 1.9. The reported rates for tanker vessels are for the Suezmax type and are in World Scale format. World Scale (WS) is a system of freight rate payment for oil tankers. A notable point is that the tanker freight rates look highly seasonal. In fact, many of the commodities have a seasonal trade pattern, and oil-related products may also have a seasonal trade pattern which affects the tanker freight market. The tanker spot freight rate prices of different routes are more than 90% correlated to each other, and the freight rates returns of different routes about 73% correlated. On the basis of the correlation structures presented in Tables 1.9, only the second-hand prices have a strong relation with S&P500.

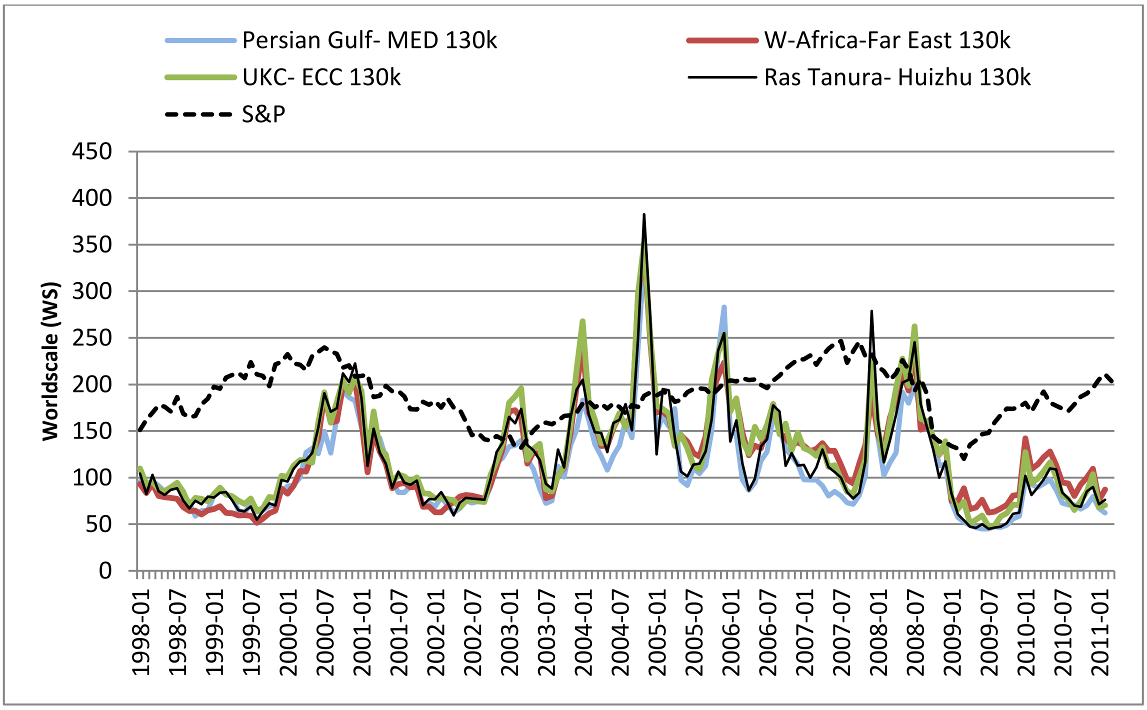


Figure 1.23 Suezmax tanker spot freight rate

Table 1.9 Suezmax tanker spot freight rate

r	*Returns*	*Prices*
Route PG-Med & Afri-FE	67%	91%
Route PG-Med&RT-Huiz	84%	96%
Route PG RT-UKC	70%	93%
PG, Afri – S&P500	5%	20.5%
Afri, FE – S&P500	1%	20.1%

1.18 Seasonality in freight rate

Seasonality has an important implication for market participants. The freight rate graph presented in Figure 1.23 shows that the evidence of seasonality is very clear in tanker freight rates; however, dry bulk does not show visible seasonality in freight rate. Stopford (1997) argues that dry bulk freight rates exhibit seasonal behaviour owing to the commodities periodically transported. These seasonal behaviours have been investigated by Kavussanos and Alizadeh (2001, 2002b) in dry bulk and tanker rates. Their study suggests that there is a significant deterministic seasonality in dry bulk freight rates for the period 1980–96.

1.19 Spot freight rate models for tankers

1.19.1 Zannetos' (1966) model

Zannetos (1966) suggests that spot tanker rates should be related to the long-run marginal cost of providing tanker services. These could be above or below the marginal cost level in the short run. Lengthening the period of charter fixture could mean that the rate itself would have no convergence towards this long-run marginal cost either above in boom periods or below in periods of recession. After allowing for differences in the risk levels between durations of charters, a term structure relation between the time-charter equivalent and spot rates can be reached. This model uses the hypothesis of Elastic Expectation. After an empirical approximation, it was found that the Elastic Expectations of the participants are the driving force behind cyclical price movement. This for the first time represents a direct use of expectation in freight models. Zannetos (1966) observes that voyage charter rates follow a random walk model. Therefore, for Zannetos the analysis of freight rates should pay attention to the statistical process that governs the freight rate series only and no other variables.

1.19.2 Hawdon's (1978) model

Hawdon (1978) assumes that the demand for oil freight services is a function of total world trade in oil. His equation includes dry freight rate, new-build tanker prices, the ship's payroll, and an average ship size. Hawdon introduced an integrated model for the tanker shipping and tanker shipbuilding market and discussed the determinants of the freight rate of tanker shipping for both a short and a long period. The short-period freight rate was assumed to be the function of the inelastic supply of the tanker fleet. The size of fleet will, however, adjust in the long term to changes in market conditions. The data cover the period 1950–73. A regression equation with the freight rate of voyage charter of tankers (Frt) on the left hand side and the affected variable on the right was formulated, as follows:

$$Frt = a_1\left(\frac{1}{Bft}\right) + a_2\left(\frac{V_t}{Bft}\right) + a_3 Frd + a_4 Foi + a_5 Npt + a_6 Kp + a_7 Bgt + a_8 D1 + a_9 D2 + a_{10} D3 \tag{1.13}$$

Bft = tanker fleet
Vt = shipping trade volume of crude oil and mineral products
Frd = freight rate of trip charter for dry bulk
Foi = price of fuel
Npt = price of new tankers
Bgt = Average ship size of the tankers
$D1$ = dummy variable for Suez crisis 1957
$D2$ = dummy variable for the outbreak of the Korean war 1952
$D3$ = dummy variable for the closing of the Suez Canal 1967-1973

This equation is an expansion of an equation developed by Tinbergen. After econometric analysis, Hawdon (1978) concluded that the price of new tankers is unaffected by the average tanker size and the level of sailors' wages. In order to explain the long-term development of the freight rate of tankers, Hawdon examined the shipbuilding and second-hand market for tankers. He assumed that the ordering of new tankers (Nnt) was dependent on the price for new tankers (Npt), the sea transport volume of the crude oil and mineral oil product (Vt) and the voyage charter rate of tankers (Frt), as well as the change in the freight rate. This is shown in the following regression equation:

$$Nnt = a_1 pt + a_2 Vt + a_3 Frt + a_4 \Delta Frt \tag{1.14}$$

The most important affecting factors was specified to be the Vt. Through an empirical estimation the coefficient of freight rate and the coefficient of freight rate change consequently were assessed as ($a_3 = 0.04$) and ($a_4 = 0.05$). Elasticity of fleet volume to tanker volume orders for the year 1973 was assessed as 0.80. Contrary to the expectation of Hawdon, the coefficient of the price was positive for new tankers; therefore, voyage charter freight rate was assumed to be part of the new tankers' price determinant. Hawdon supposed that the price of new tankers (Npt_t) is in a linear relation to the present tanker freight rates, the voyage charter (Frt), the tanker freight rate of the previous period (Bft), the steel price (Hp), and average tanker size (Bgt) in the following equation:

$$Npt_t = a_1 Frt + a_2 Frt_{t-1} + a_3 Bft_{t-1} + a_4 Ps_t + a_5 Bgt_t \qquad (1.15)$$

The price per dwt of new tankers is assumed to be linearly related to rates, rates lagged, the size of the fleet, the average size of tankers and the steel price. Hawdon estimates a linear relationship employing both the Ordinary Least Squares (OLS) and the 2-Stage-Least Squares (2SLS) method.

1.20 The economy of time-charter rates

In the previous section, spot or voyage charter rates were explained. Time-charter (TC) rates, by contrast, are determined by the expectations of the market participants, somewhat similarly to the Fisher (1896) Expectation Hypothesis (EH) of the term structure of the interest rate. In general finance and according to the hypothesis of the term structure of the interest rate, long-term rates are determined by the expectations of the agents about future short-term rates. There are several studies which reject or confirm the hypothesis of the term structure of interest rate in different markets. This hypothesis states that the long-term interest rate is the weighted average of the current interest rate and the expected future short-term interest rate, plus a constant term premium. Long-term interest rates are usually higher than short-term rates because they require a risk compensation or term premium. This is similar to the situation in the shipping market, where long-term charter rates are higher than short-term charter rates or spot rates. Freight rate term charter rates should reflect expected future short-term rates. The term premium in shipping is time-varying according to Kavussanos and Alizadeh (2002a).

There are numerous papers in this area. Bohl and Sikols (2004) suggest that an upward-sloping term structure implies that inflation is expected to rise. Lekkos and Milas (2004) also conclude that downward-sloping term structure happens at a time of expected future recession. According to the non-arbitrage argument, a security should grow at the risk-free interest rate unless a risk is being taken. In the shipping market, the ship owner should not become better off by taking out a TC contract or a series of spot contracts.

In Chapter 2, we investigate the economic value of the forecast of the freight rate in the tanker shipping industry. The ship operator is assumed to allocate the ship utility between the TC and spot charter markets according to the forecast result, and we check if there is any economic value for this forecast. The economic benefit gained in excess of a fixed policy approach using either alternative, obtained by a ship operator who follows our forecasting rules, cannot be used to disprove the validity of the efficient market hypothesis. In shipping finance, Kavussanos and Alizadeh (2002a) have investigated the expectation hypothesis of term structure in the formation of term charter rates and have examined the validity of the expectation hypothesis. According to them, the discounted earnings from a n period TC contract should be equal to the discounted expected earnings from a series of m period spot contracts within the length of the TC plus a term premium $\emptyset$

$$TC_t^n = \theta \sum_{i=0}^{k=1} \delta^i \, E_t FR_{t+im}^m + \emptyset, k = n.m \qquad (1.16)$$

where TC_t^n is the n period earnings TC contract at time t, $E_t FR_{t+im}^m$ is the expected earnings of the spot charter contract at time t, which lasts over m period from $t + im$ to $t + (i+1)m,$ δ is the discounting factor and θ is the coefficient of proportionality. $k = n/m$ is the positive integer indicating the number of spot charter agreements during a TC contract and $\emptyset$ is the term premium. The term premium is included because TC contracts are relatively more secure than the spot contacts, and charters and shippers only go to the TC if the TC freight rate is discounted compared to the spot charter rates.

Alizadeh *et al.* (2007) have also investigated the predictive power of the implied forward TC rates as a forecast of future TC rates. They conclude that the implied TC rates outperform the forecast from competing time series models such as ARIMA models. They also found that the implied forward TC rates are unbiased predictors of TC rates. Several authors have formally tested the applicability of classic expectations theory in freight markets. For instance, Glen *et al.* (1981) investigate the risk premium in the tanker market for the period 1970–7 and find that the estimated risk premium is negative in most cases, although it is not significantly different from zero. Hale and Vanags (1989) test the expectation hypothesis in dry bulk markets. Their empirical tests either reject the hypothesis or are neutral. Veenstra (1999) also tests the expectations hypothesis in the dry bulk markets, using Campbell and Shiller's (1987) net present value model, Veenstra postulates that ship owners prefer voyage charters and require a constant positive risk premium to enter into period time-charters so as to offset the loss in liquidity. This liquidity premium hypothesis is rejected by Veenstra's empirical tests. Kavussanos and Alizadeh (2002a) also test the expectations hypothesis in dry bulk freight markets and statistically reject the theory. They attribute this failure to the existence of a time-varying risk premium and attempt to model this using an EGARCH-M approach. Their results suggest that the risk premium is negative and depends on the conditional volatility of the freight rate spread.

Figure 1.24 presents the TC rates for two classes of bulk carriers, Handysize 30,000 dwt and Capesize 150,000 dwt. It appears that the three-year TC is not always higher than the six-month time charter. The rates are moving together in the long term, but there are several short-term differences in movements. The correlation coefficients for all the TC returns are more than 87%; this is very similar to the bulk carrier spot returns.

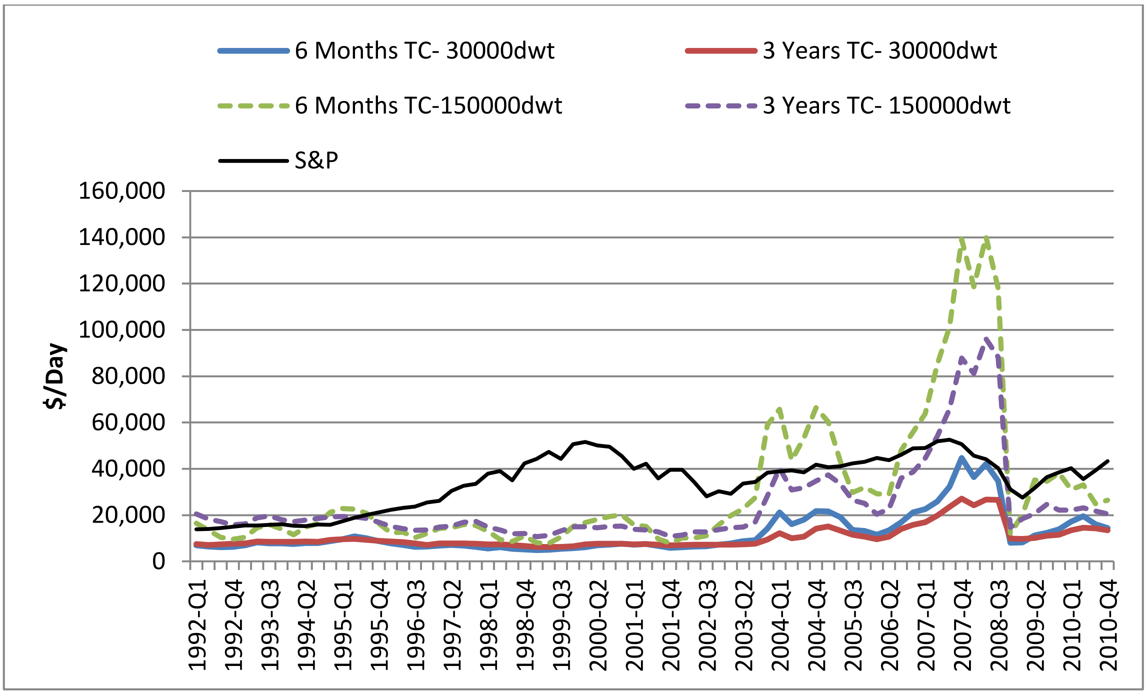


Figure 1.24 Time-charter rate, Handysize and Capesize dry bulk carrier

Table 1.10 Correlation panel of dry bulk time-charter rates

r	*Return*	*Price*
6 months–3 years, both 30dwt	93%	97%
6 months–3years, both 150dwt	91%	98%
150dwt–30 dwt both 6 months	87%	98%
150dwt–30 dwt both 3 years	91%	96%
S&P500 – 6 months 30dwt	35%	43%
S&P500 – 6 months 150dwt	37%	45%
S&P500 – 3 years 30dwt	34%	40%
S&P500 – 3 years 150dwt	33%	37%

The bulk carrier spot returns and S&P500 return were correlated to each other by around 14%; for TC rates the correlation averages around 34%. At the start of the super-boom in 2003 the three-year and six-month TC rates were very close to each other, but before the end of the super-boom in mid-2008 the six-month TC rates were almost 60% more than the three-year TC rates. Figure 1.25 presents the quarterly TC rates for the Panamax and VLCC tankers. Comparing the rates with S&P500, we observe that in 2008, when the S&P500 had already started a major crash, the TC rates were still increasing, but started to crash after a while.

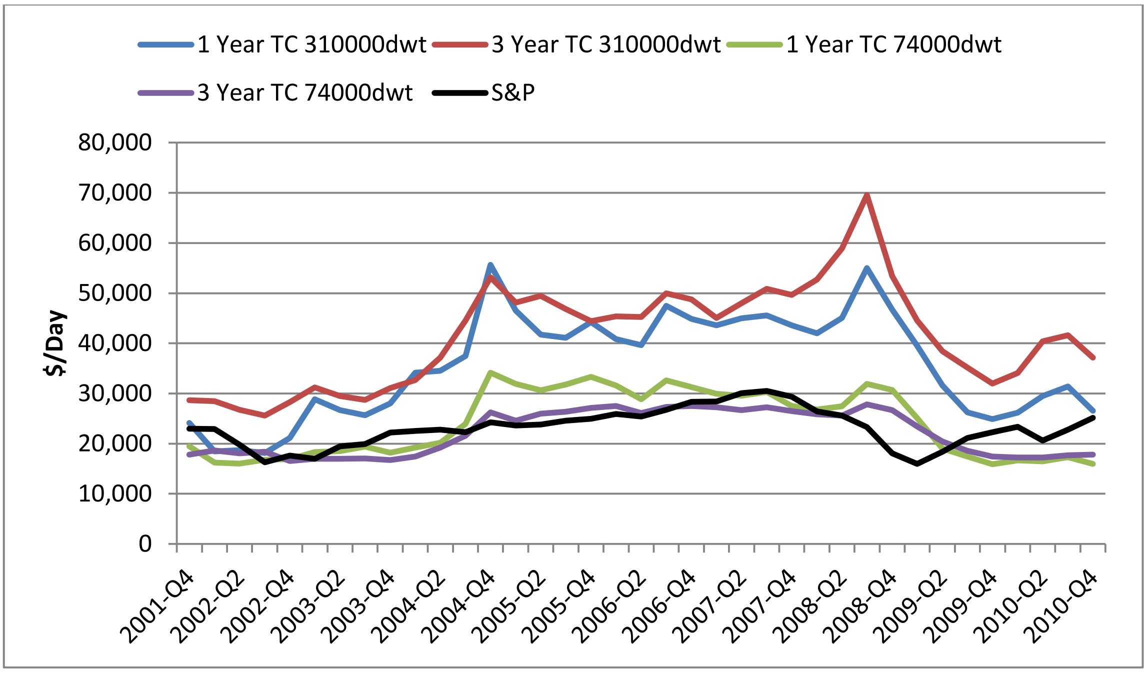


Figure 1.25 Time-charter tanker rate, Panamax and VLCC

Table 1.11 Correlation of time-charter tanker rates

r	*Returns*	*Prices*
Panamax – 1 year, 3 years	74%	92.8%
Panamax, VLCC – both 1 year	81%	96.6%
Panamax, VLCC – both 3 year	63%	85%
VLCC – 1 year, 3 years	80%	95%
S&P500 – Panamax 3 year	1%	52%
S&P500 – Panamax 1 year	2%	55%
S&P500 – VLCC 1 year	-2%	56%
S&P500 – VLCC 3 year	1%	62%

The tanker TC returns are strongly related to each other. There is no relation between S&P500 return and TC tanker return. In dry bulk TC returns there was a correlation of more than 30% with S&P500. Therefore it appears that the dry bulk TC rates are more closely related to the world economic climate. If we look at the prices, we see that they are more than 90% correlated to each other. Up until now we have compared TC and spot freight rates separately. Figure 1.26 compares the spot and TC rates taken together of two dry bulk classes, Capesize and Handymax.

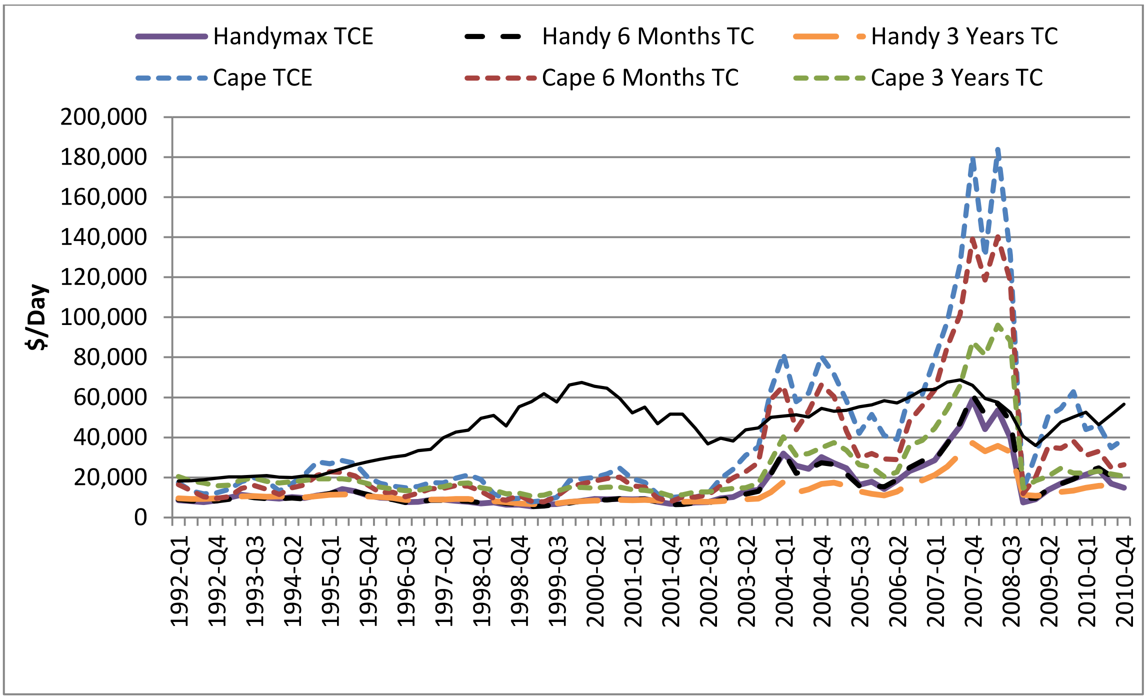


Figure 1.26 Comparison of TC and TCE spot freight rates, Capesize and Handymax

Table 1.12 Correlation of TC and TCE spot rates

r	*Returns*	*Prices*
Handy TCE–Handy 6 months TC	89%	99.2%
Handy TCE–Handy 3 years TC	87%	96.3%
Cape TCE–Cape 6 months TC	88%	99.1%
Cape TCE–Cape 3 years TC	82%	96.7%
Handy TCE–Cape 3 years TC	85%	95.1%
Cape TC–Handy 3 years TC	88%	96.2%

The spot or voyage rate is not of the same kind as the TC rate (Figure 1.21). Hence, the time-charter equivalent (TCE) of spot freight rates is considered instead of the spot rate itself. The expectation is that TCE rates are higher than TC rates; this was explained in section 1.18. In case of the Capesize rates, the TCE is greater than the six- and three-year TC rates. In the case of Handymax, which is a much smaller vessel than Capesize, the TCE looks identical to the six-month TC. Table 1.12 suggests that TC returns and TCE spot freight returns are 85–9% correlated to each other. Therefore, as might be expected, there is a high relation between them, though it is not 100%.

1.20.1 Classical time-charter models

Strandenes (1984) argues that ship owners are willing to let their vessel on long-duration TC at freight rates below the current spot freight rate, when the spot rates are high relative to the long-term equilibrium freight rate. When the current spot freight rate is low, ship owners let their vessel on long-term charters only at a freight rate above the current rate. Strandenes (1984) has modelled the relation between freight rate, time charter, voyage charter and expected long-term freight rate as:

$$Fz^{\tau} = \rho(\tau)(aZeg + bZek) \tag{1.17}$$

$\tau =$ *duration of time charter*
$Fz =$ *time charter rate*
$Zeg =$ *TCE-time charter equivalent of spot freight rate*
$Zek =$ *time charter equivalent of the expected long-term freight rate*

Strandenes also examined the sensitivity of the price for second-hand ships with regard to present and expected long-term freight rate and voyage charter. The relation between new-build price (P_n), second-hand price (P) and expected short- and long-term profit is formulated as follows:

$$P_n = Pk(uGwg + vGwk) \tag{1.18}$$

If: $u = \frac{a}{r} + d \qquad v = \frac{b}{r} + d$

Gwg = *monthly profit with voyage charter rate*
Gwk = *monthly profit with excepted voyage charter rate*
k = *constant disruptive effect k=11.5*
d = *trade*
r = *capital interest rate*
a, b = *coefficient with sum equal to 1*

Strandenes uses OLS to measure the short- and long-term expected TCE of the spot market. In assessing market cycles, however, because of long duration the relative effect of the freight rate decreases and the effect of equilibrium rate increases. The evidence for the term structure in the rates lies in the development of the estimates, with an increase in the duration of the TC contract. If duration increases, the relative effect of the current freight rate decreases and the effect of equilibrium rate increases. In addition, the sum of weights decreases with duration. This, according to Strandenes, indicates that ship owners are risk-averse. The positive difference between the TC rate and the combined influence of the voyage charter and equilibrium rate can be seen as a risk premium that increases with duration. The longer the TC contract, the more certain the ship owner is about the expected revenue. A risk-averse ship owner would therefore have a greater preference for a longer TC contract than a voyage charter ship owner would, and a greater preference for a short-term TC than for a voyage charter contract.

1.21 Baltic Exchange freight rate information

Chapter 3 analyses the volatility of Baltic Exchange indexes. For this reason, this section explains the nature of freight market information and the Baltic Exchange. The exposure to freight market risk is hedged by freight derivatives. This is done by trading a specific time or spot charter rate for a forward position; settlements are usually against one of the route assessments published by Baltic Exchange. The Baltic Exchange is the only source of maritime market information for trading and settlements of physical and derivative contracts. The Baltic Exchange publishes seven daily indexes: Baltic Dry

Index (BDI), Baltic Panamax Index (BPI), Baltic Capesize Index (BCI), Baltic Supermax Index (BSI), Baltic Handysize Index (BHSI), Baltic Dirty Tanker Index (BDTI) and Baltic Clean Tanker Index (BCTI). Chapter 3 analyses the volatility of BDI, BPI and BCI. BDI is the equally weighted average of the BCI, BPI, BHSE and BHI, and takes into account 26 routes on both voyage and TC contracts. Of all the indexes, it is BDI that is usually used as a standard indicator of shipping freight rate.

BPI is the specific indicator of Panamax class vessels; the calculation is based on four routes of the TC contract. BCI is the specific indicator of the Capesize class of vessels; the calculation is based on six voyage charters and four TC contracts. Figure 1.27 presents the daily movement of four Baltic Exchange indexes and S&P500. The calculation of the indexes is on a daily basis, itself based on the rates provided by selected ship brokers around the world, usually referred to as Baltic Exchange Panellists.

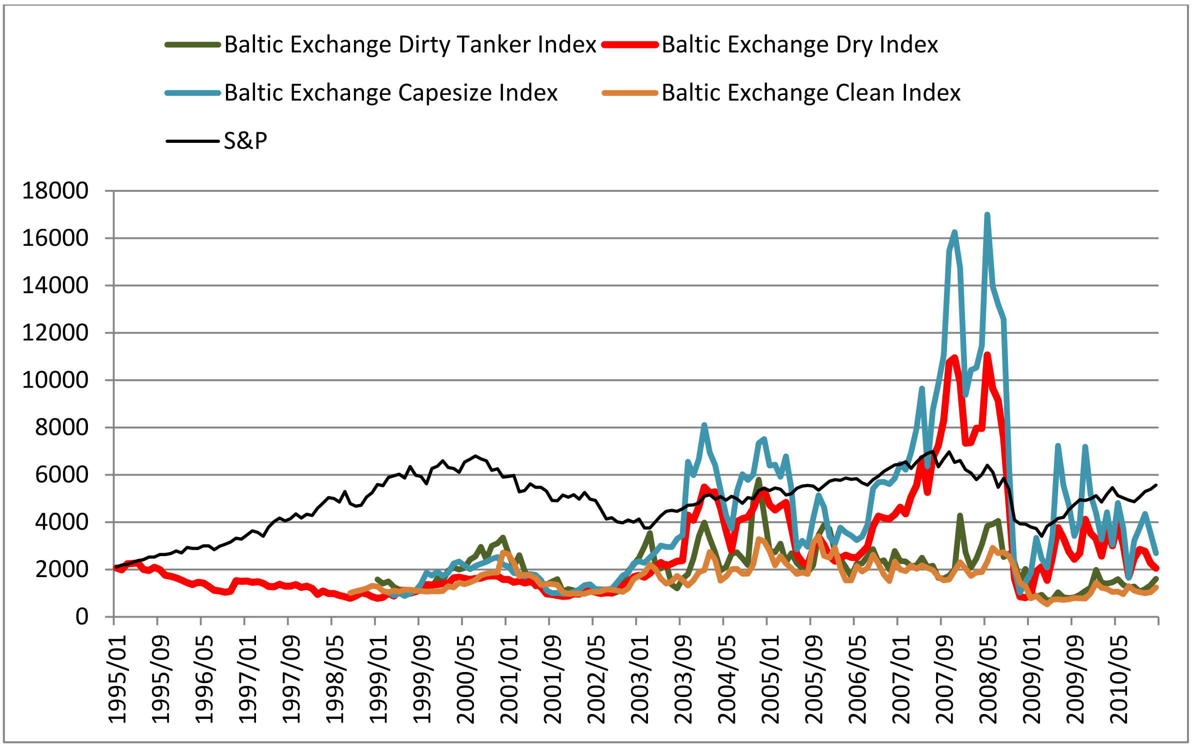


Figure 1.27 Baltic Exchange indexes

The Baltic Exchange also provides forward curves and settlement data. The freight derivatives are traded either outside any exchange, as an over-the-counter product in cash settlements, or as a cleared product through a clearing house. The cleared product or futures are settled on a daily basis. The clearing houses are the London Clearing House (LCH), the Norwegian Futures and Options Clearinghouse (NOS), the Singapore Exchange (SGX) and the Chicago Merchandise Exchange (CME).

1.22 Shipping companies' stock

In Chapter 4 we forecast shipping stock returns using macroeconomic and financial variables. We argue that because the macroeconomic variables capture risk premium, if the risk premium is time-varying and correlated with macroeconomic variables we should be able to find stock return forecasting power in macroeconomic variables. For this reason, in this section the shipping company stock market is briefly introduced. The prospects of shipping companies are followed by looking at their stocks. The extent of the shipping companies' exposure to individual events depends on individual stocks. Some companies operate in the TC market, which means that their exposure is strongly linked to the credibility of their charterer. Some other companies operate in the spot market and their income depends to the current economic situation; these companies may face more risk of vessel unemployment, and their income is more volatile.

Figures 1.30 and 1.31 present the monthly movements of two US-listed dry bulk and tanker companies, DryShips (NASDAQ: DRYS) and Frontline (OSE: FRO,NYSE: FRO). According to their websites they have market capital of 1,590 and 2,200 million dollars. Their stock prices are compared here to the Baltic Dirty Tanker Index (BDTI) and Baltic Dry Index (BDI). Frontline and DryShips are the biggest tanker and dry bulk companies listed in the USA. FRO stock return is 53% correlated to S&P500 return, 30% correlated to BDI, and only 15% correlated to BDTI. FRO is a tanker company and BDTI is the specific tanker index, so it is expected to have more relation with BDTI than BDI, but this is not the case here. DRYS stock return is 33% correlated to BDI, as against 55% for S&P500. Both companies have similar correlations with S&P500 and BDI. Generally speaking, during the years 2008–11 shipping companies were struggling because of the financial crisis. However, those companies which time-chartered their vessels before the crisis were able to stand strong during the recession.

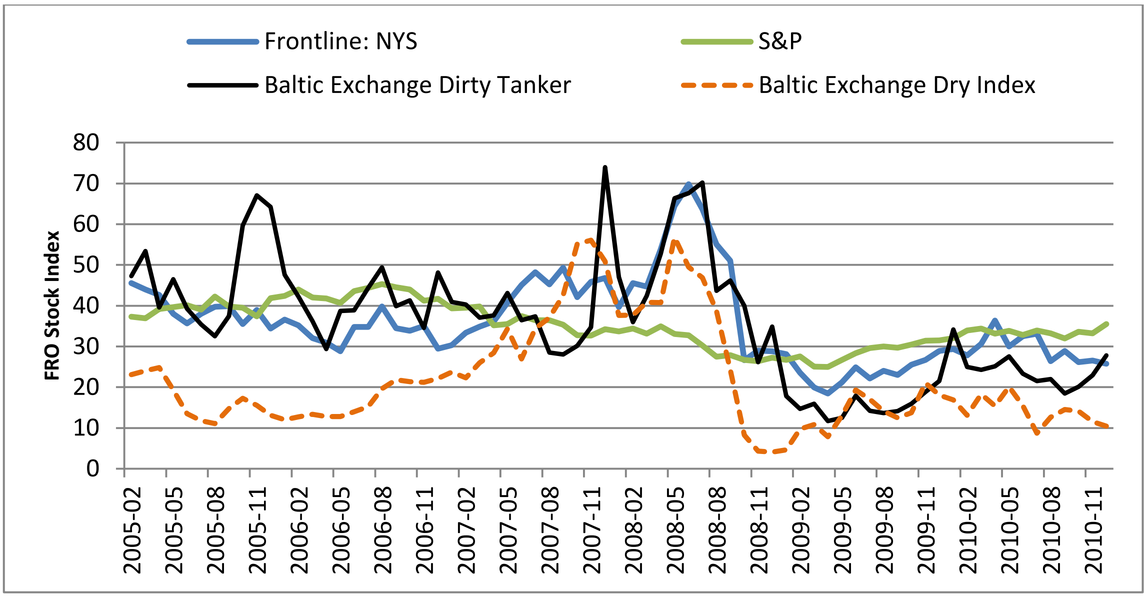


Figure 1.28 Tanker company stock

Table 1.13 Correlation of FRO with S&P and Baltic Exchange Indexes

r	*Returns*	*Prices*
FRO – S&P500	53%	62%
FRO – BDI	30%	78%
FRO – BDTI	15%	72%
S&P500 – BDI	32%	66%
S&P500 – BDTI	13%	54%

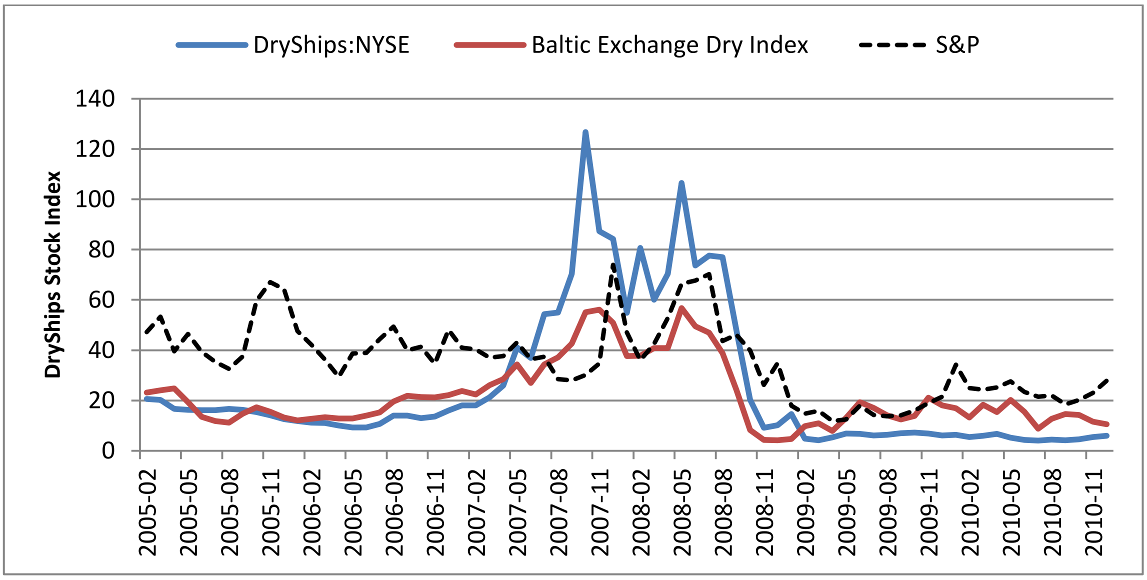


Figure 1. 29 Dry bulk company stock

Table 1.14 Correlation of DryShips with S&P500 and BDI

r	*Returns*	*Prices*
DryShips–S&P500	55%	57%
DryShips–BDI	33%	92%

1.23 Overview of S&P500 correlations

An overview of the S&P500 correlations reported in previous sections is presented in Table 1.15. In addition to the shipping companies stock returns, the dry bulk TC and second-hand returns show a strong relation with S&P500. Demolitions also have -26% relation with S&P500. New-build price returns and tanker spot returns have the lowest relation with S&P500. Dry bulk freight rates are correlated more than tanker freight rate to S&P500. This could be because demand for oil is less affected by the world economy than demand for dry bulk. The oil trade is currently relatively insensitive to the ups and downs of the general macroeconomic business cycle.

Table 1.15 S&P500 correlation panel with shipping variables

r	*Returns*	*Prices*
Average stock prices	54%	60%
Time-charter dry bulk	34%	34%
Second-hand dry bulk	25%	25%
Ship scrapping	-26%	0.04%
Fleet growth	18%	89%
Second-hand tanker	17%	78%
Second-hand container	16%	37%
Spot freight dry bulk	14%	46%
New-build order book	9.4%	30%
New-build bulk	6%	35%
Spot freight tanker	3%	20%
New-build price tanker container	1%	30%

Imports of industrial dry bulk are more closely linked to economic cycles. These raw material cargoes largely end up in investment goods or consumer durables, which are highly sensitive to the economic cycle. Consequently, whereas the predominant cause of variations in tonne–mile employment in the dry bulk sector has been economic and cargo demand cycles (the tonne component), in the tanker sector it has been shifts in regional oil production and refinery capacity (the mile component). Even in the energy sector, bulkers and tankers no longer compete in the same market-place and therefore they have different sensitivities to the overall state of the business cycle, which is itself far less sensitive to the cost and availability of energy. Hence there is no reason for their freight rates to be affected to the same extent by the same variables.

1.24 Structure of the thesis

This thesis is divided into five chapters. The three main chapters, Chapters 2, 3 and 4, are each devoted to a different area of applied econometrics with concentration on the shipping market. Chapter 2 forecasts the freight rate with macroeconomic and commodity variables and attempts to examine the validity of the EMH. Chapter 3 investigates the volatility and value at risk of the Baltic Exchange freight rate indexes. Chapter 4 predicts the shipping stock market. The freight rate and the shipping time series are taken from Clarkson's Shipping Intelligence Network (SIN). The economic, financial, commodity and Baltic Exchange time series have been obtained from Thomson Reuters Datastream. A variety of software is used, for different purposes. MATLAB is used for the calculations in Chapter 1 and EXCEL is employed for graphical features. In Chapter 2 a tailor-made MATLAB code is written, and PcGive was used for graphs. In Chapter 3, MATLAB, EVIEWS and PcGive have all been employed. In Chapter 4 a tailor-made MATLAB code is compiled, and PcGive is used to plot the data. All the statistical tests, through all the chapters, are considered with 5% levels of significance unless specified otherwise.

1.25 Summary

In this chapter we introduced the different aspects of the shipping industry. We also introduced different types of freight rate and discussed the way they are formed. We found that the freight rates of the different ship classes are highly correlated to each other. We found that US GDP grew by 8.6% between 1970 and 2009 and that the shipping fleet grew by 6.1% during the same period. However, only the dry bulk and tanker markets were included and it could be that adding the other types of ships would cause the 6.1% to increase. However, data for other types of ships are not available before 1970. We also found that time-charter and spot rates are highly correlated to each other. Dry bulk freight rates are more correlated to S&P500 than tanker freight rate. This could be because demand for oil is less affected by the world economy than demand for dry bulk. We found that shipping order book return is 52% and 49% correlated to time-charter rate and second-hand prices respectively, and that order book return is 9.4% correlated to S&P500. Figure 1.13 showed that ship demolition decreases during the economic boom and at times of high freight rates. Demolition return is -26% correlated to S&P500 and -62% correlated to LME index, which may indicate that there are more demolitions when metal prices are low. The bulk and tanker average new-build returns are 78% correlated to each other and 31% correlated to LME; they show no relation with S&P500. Second-hand bulk and tanker prices are 25% and 16% correlated to S&P500.

Chapter 2

The Economic Value of Freight Rate Forecast

2.1 Introduction

This chapter investigates the economic value of forecasts of the freight rate in the bulk shipping industry for ship operators. The ship operator is assumed to allocate the ship utility between a spot charter and time-charter (TC) market according to the forecasts of the quarterly excess freight rate. The forecasts are computed using a linear regression model with macroeconomic and commodity variables as regressors. The excess freight rate is the difference between the TC and the spot charter rates. The ship operator uses a recursive forecasting approach and switches the chartering strategy across the two positions. The economic benefit of this forecasting approach in excess of a fixed policy approach will be used to discuss the validity of the efficient market hypothesis (EMH) for the dry bulk freight rate industry.

The economics of the spot and TC freight rate and the way they are formed are discussed in sections 1.19 and 1.20 of Chapter 1. The TC freight rate depends on the market participants' expectations about future spot rates. There is a term-structure relationship between spot and TC rates. The term structure is derived from a no-arbitrage argument model. This means that a ship operator should not be able to make more money by contracting the ship in the TC market than by contracting it in the spot market for a series of voyage charters equal to the length of the term-charter. In this chapter econometric forecasting will be used to find out if the ship owner can make more money by choosing between the spot and TC market. The results of economic benefit gained in excess of gains from a fixed policy approach using either alternative, obtained by a ship operator who follows our forecasting rules, will be used to discuss the validity of the EMH.

Unlike the finance literature on stock returns, the use of regression models for forecasting has not yet been discussed in detail for shipping economics and there are no existing empirical results using regression models to optimize chartering strategies. Choosing the right policy is crucial for the well-being of ship operators so as to ensure a healthy stream of income. The research here employs regression models to determine optimal policies for chartering in the ocean transport services of bulk commodities.

The shipping market can be separated into two main markets: (1) the liner market, and (2) the bulk market. The liner market is the market for regular transportation services and transports manufactured cargo in containers. The bulk market is close to pure competition. The liner market is oligopolistic and is similar to the airline market. The operator of a ship faces three decisions in utilizing the ship:

1) Charter the ship in the spot market and receive the spot freight rate (for one voyage).
2) Charter the ship in the term charter market and receive the TC freight rate (for multiple voyages).
3) Lay up the vessel in order to wait for better market conditions. Laying up a ship incurs some ‘in’ and ‘out’ costs, but the amounts are usually quite small.

The alternatives discussed up until now are chartering strategies. From the investment point of view the strategies are:

1) Sell a vessel via the second-hand market.
2) Purchase a vessel in the second-hand market.
3) Order a new vessel (buy a new-build).
4) Scrap the vessel (sell for demolition).

Here we only consider the chartering strategies. The term ‘spot freight rate’ used in this chapter refers to time-charter equivalent (TCE) spot freight rate.

The process of decision-making and the efficiency and predictability of the freight rate market have previously been discussed in the literature on maritime finance (Adland and Strandenes, 2006). If a market is informationally efficient it is impossible to beat the market, as all the information is already incorporated in the freight price. Jensen (1978) gives a comprehensive definition of market efficiency in writing:

> A market is efficient with respect to information set Ω if it is impossible to make economic profits by trading on the basis of information set Ω.

The above definition suggests that analysing the economic profit generated on the basis of an information set provides information on market efficiency. Therefore, in this research the predictability of the bulk freight shipping market will be analysed in terms of the economic profit produced by the forecasts.

This chapter will use a recursive modelling and forecasting strategy with out-of-sample forecasting from regression models. An advantage of using a recursive modelling approach is that each forecast is computed using the most recent sample data. This approach has received a great deal of attention in the empirical finance literature (McMillan, 2001; Pesaran and Timmermann, 1995, 2000; Sollis, 2005). Recursive strategy decisions are made according to forecasts of the excess freight rate. If the ship operator is confident of the forecast, he switches across the spot and TC market. If the forecast is in favour of the spot market the ship-owner will allocate the ship to the spot market. Otherwise he prefers the term 'charter market'. To see whether the returns are predictable and generate economic profit, the final wealth based on choosing either of these options is compared to the final wealth calculated by the recursive forecasting strategy.

Most of the short-term shipping market is moved largely by factors other than the observable macroeconomic fundamentals; however it is widely believed that in the long-term the shipping market is dependent on macroeconomic factors and commodity prices. This, however, has not been investigated econometrically. In macroeconomics, it is typically assumed that macroeconomic agents are rational and markets are efficient. In other words, agents form rational expectations about the future, incorporating all their current knowledge and preferences into decision making. Moreover, because this paradigm also applies to pricing, the current price of the freight must embody all past information and can only be moved by news (EMH). Under the rational expectations hypothesis, economic agents use all available information about the future in a rational manner to determine the value of an asset. Assuming all economic agents to be risk neutral, the current market price x_t of an asset as a consequence fully reflects all past and current information relevant to the future value of that asset embodied in the information set Ω_t – the market for the asset is thus informationally efficient. Under the above-mentioned circumstances market efficiency implies that currently available information does not carry any predictive value about subsequent price changes, and so the best forecast (i.e. the forecast with the smallest mean squared error) of future prices is simply the current price:

$$E_t(x_{t+1}|\Omega_t) = x_t \tag{2.1}$$

Where x_t : price.

Hasbrouck (1996) states:

> … from an economist's perspective the actual security price in many microstructure models can be interpreted as an idealized 'informationally efficient' price, corrupted by perturbations attributed to the frictions of the trading process.

Assuming risk-neutrality, the EMH implies that asset prices follow a random walk[7]

$$x_t = x_{t-1} + \varepsilon_t \qquad (2.2)$$

where $\varepsilon_t \sim IID\ (0, \sigma^2)$. For the global shipping market, the empirical evidence from tests of the random walk hypothesis is mixed. Berg-Andreassen (1997), using the augmented Dickey Fuller (ADF) test, concludes that the Baltic Freight Index (BFI) and Baltic International Freight Futures Exchange (BIFFEX) follow a random walk. Kavussanos and Nomikos (1999) also argue that the BFI follows a random walk. Kavussanos and Alizadeh (2002a), using an EGARCH-M model, does not find support for the Expectation Hypothesis of the term structures of freight rates owing to the existence of a time-varying risk premium (the expectation hypothesis assumes a random walk). Tvedt (2003) uses ADF tests and concludes that the random walk can be rejected in most cases.

If, however, the rather unrealistic assumption of risk neutrality is relaxed, the random walk hypothesis is no longer implied by the EMH and a random walk is neither a necessary nor a sufficient condition for rationally determined asset prices (Lo, 1997, Ch. 2). Therefore a failure of the random walk hypothesis does not necessarily imply failure of the EMH. In addition, for other reasons the notion of the EMH cannot be always true in the shipping market. Sometimes the operator is forced to make a chartering deal because they are required to do so by the banks from which the mortgage used to buy their ship has been obtained. Alternatively the desired chartering contracts may not always be available. There are other reasons to suspect that the stochastic process of the freight rate will not be a Markov process, and that the future value of the series could be dependent on the random walk model.

It is hard to see how the phenomena of ship owners expecting more income and taking more risk could be fitted to the rational expectation framework in the freight market. A random walk requires $i.i.d$ increments. However, the occurrence of regime shifts over long stretches of time (due to changes in the economic, social, technological, institutional or regulatory environment) makes the assumption of $i.i.d$ increments unrealistic.

[7] See Cuthbertson and Nitzsche (2004) for further details on the EMH and random walk hypothesis.

2.2 Review of previous research on chartering strategies

One of the early studies using an economic model for ship chartering strategies is that by Mossin (1968). Mossin assumes that the freight rate follows a random walk and that the underlying stochastic process is stationary. Because of the stationary assumptions the optimal policies are given by a fixed threshold. If earnings fall to a level y_1 the ship should be laid up; if earnings rise to a level y_2 the ship should be put back into trading. This strategy only considers the possibility of trading with the ship or not trading with the ship, that is, when to start trading and when to lay up the ship. It argues that the system behaves as a 'discrete state Markov chain following a Bernoulli process without discounting' (see e.g. Mossin, 1968, p 7 for more information).

Devanney (1971) develops a model for ship chartering strategy. He considers the TC rate and compares it with multiple spot rates. His model maximizes the expected present value earnings until the end of the operational life of the ship. The earning is measured in terms of round trip voyages. On the basis of ship operator expectation about future freight rates, this model takes transition probabilities as exogenous variables, and the chartering alternatives are similar to those discussed in section 2.1. The ship operator's expectation about future freight rates is formed by the current spot freight rate prices, the rate of changes of spot rates and the capacity of shipping fleet on order. The major problem with the Devanney model is that the assumptions regarding the risk preferences of the agents can change the results of the model. The Devanney model is correct for a single ship policy, whereas the optimal fleet policy is the result of empirical observation. That is, for a newly mortgaged vessel the owner would always be forced to go to the time charter in order to assure a steady revenue to pay back the ship mortgage, while an older vessel operator with no unpaid mortgage is better able to apply the strategies given by algorithm. The Devanney model is only applicable to the individual cases and not to the aggregate data. However, the shipping market data are available in aggregate format and the hence the Devanney model is hard to test or to prescribe. In this chapter we do not consider these imperfections that exist in the ship chartering market.

Devanney (1971) assumes that each agent has different preferences and different responses towards risk and future shipping demand. Another chartering strategy is presented in Norman (1981). Norman also investigates optimal chartering, but his study does not really present an optimal chartering strategy as it claims, but rather tries to prove that chartering the ship in the TC market does not necessarily create a healthy cash flow to pay the ship mortgagee. According to Norman (1981), for the period 1963–79 the optimal strategy would have been to have fewer possible investments in buying vessels, but instead to charter the fleet in the spot market taking advantage of the substantially higher spot rates applying in that period. Norman's study was undertaken using the tanker market data. Norman proposes two approaches: portfolios of charters, which refers to an operator who has to manage a portfolio of ships, and chartering timing strategies. For the portfolio charters, Norman determines (on the basis of historical data) the ship operator price of risk against ship operator risk preferences; then, the optimal mix of ships on the spot and TC can be determined. In the case of charter timing, Norman considers a relation between spot charter and TC rates, $VC = \alpha + \beta TC$, where VC is the spot rate and TC the term charter rate. If $VC \geq \alpha + \beta TC$, the operator accepts the spot contracts; otherwise, he accepts the term charter contract.

Another study of chartering strategy is given by Taylor (1981). Taylor proposes a computer-driven simulation model to determine the optimal 'fleet mix'. The distinctive feature of Taylor's study is the possibility of including combined carriers (ships that carry both dry and liquid cargoes). Then, the ship owner can operate with added flexibility in both submarkets. Taylor's analysis assumes the existence of a so-called chartering preference function that shows the proportion of long-term charters ship owners are willing to take as a function of a freight index. Taylor's work, however, does not show how to determine those preferences functions, nor does his methodology guarantee optimality. Strandenes (1984) also argues that ship operators are willing to let their vessel on time charters of long duration at freight rates below the current spot freight rate when spot rates are high relative to the long-term equilibrium freight rate. When the current spot freight rate is low ship owners let their vessels on long-term charters only at a freight rate above the current rate. Strandenes constructs measurements of the short- and long-term expected TCE of the spot market by OLS. In assessing the market cycles, however, because of long duration the relative effect of the freight rate decreases and the effect of the equilibrium rate increases.

Alizadeh, Adland and Koekkebaker (2007) also investigated whether excess profit can be made by chartering strategies based on technical trading rules. They examined whether chartering a vessel for a long period and letting it for multiple periods during this time results in some economic gain. The trading strategy is based on the application of technical trading to the differential between short- and long-term charter rates. If the spread between the two rates exceeds the average of the spread, a ship operator can charter the ship for a long period and re-let it in multiple charters, so the simple Moving Average trading rule yields significant economic benefit.

As a general rule, the ship broker charges 1.25% commission, while longer TC may have a discounted commission of 1%. There is not much difference between a six-month time charter and the equivalent period of spot charters in terms of commission or transaction cost. Therefore, we do not consider the effect of transaction cost when the ship operator switches between the two alternatives.

2.3 Econometric characteristics of freight rate

In this section, some of the econometric characteristics of the freight rate are explained and compared in some instances to the S&P500. We find that the freight rate is non-stationary and has a tendency to persist in short-term (although, as is discussed above, other researchers have found that the freight rate is stationary).

2.3.1 Unit root and variance ratio test for the freight rate

Here we test for unit root in the freight rate indexes and also the freight series that will be analysed in more detail later in this chapter. We assess the null hypothesis of a unit root in the Baltic Dry Index (BDI), Baltic Panamax Index (BPI) and S&P500 indexes and their logged series using the augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) and variance ratio (VR) test (Lo and MacKinlay 1988). The daily series from 2000 until the end of 2010 has been used. The ADF test involves estimating the following model:

$$\Delta x_t = \mu + \gamma t + \emptyset_1 r_{x-1} + \sum_{i=1}^{k} \beta_i \Delta r_{x-i} + \varepsilon_i \tag{2.3}$$

The relevant test statistics are the *t*-statistics for testing $H_0\colon \emptyset_1 = 0$, which should be compared with the DF critical values.

If x_t is considered as a natural logarithm of price, then the variance ratio (VR) test is based on the characteristic that the variance of $\left(x_t - x_{t-q}\right)$ is q times the variance of

$(x_t - x_{t-1})$, and the random walk hypothesis can be evaluated by comparing $1/q$ times the variance of $\left(x_t - x_{t-q}\right)$ with the variance of $(x_t - x_{t-1})$. Then, VR is defined as follows:

$$VR(q) = \frac{\hat{\sigma}_q^2}{\hat{\sigma}_1^2} - 1 \tag{2.4}$$

The null hypothesis is that VR(q) is equal to 1. The VR test-statistics is given by:

$$Z(q) = \frac{\widehat{VR}(q)-1}{\sqrt{\hat{s}(q)}} \tag{2.5}$$

The results are given in Table 2.1, 2.2 and 2.3. These show that the null hypothesis is not rejected and the series are non-stationary. Since a unit root is a requirement for a random walk process, we also check the null hypothesis of random walk by the Variance Ratio test. This test is based on the fact that the variance of the random walk increased linearly with time. This test has a null hypothesis of a random walk. Table 2.3 presents the results from the ADF test for four freight series that have been specifically used in this chapter. Since the computed ADF test-statistics are all greater than the critical value, we cannot conclude by rejecting the null hypothesis, and this means that all the logged series have a unit root and are non-stationary. We use the excess of the TC rate over the spot freight rate (VC) for the forecasting models used in this chapter (see section 2.4.1 for more details). The results of the ADF test for these series are presented in Table 2.10. They confirm that the series do not have a unit root and hence they are stationary. All the results show the rejection of the random walk hypothesis.

Table 2.1 ADF test results for indexes

	BDI	*BPI*	*S&P500*	*log BDI*	*log BPI*	*log S&P500*
Test statistic	-0.467	-0.504	-0.516	-0.004	0.191	-0.180
p-value	0.480	0.467	0.462	0.650	0.722	0.586

5% cValue: -1.941

Table 2.2 Variance ratio test results for indexes

	BDI	*BPI*	*S&P500*	*log BDI*	*log BPI*	*log S&P500*
Test statistic	12.93	13.90	-3.13	15.84	14.45	-2.77
Ratio	1.78	1.80	0.91	1.82	1.83	0.91

5% cValue: $[-1.96,1.96]$, p-values: 0

Table 2.3 ADF test results for the logarithms of the spot and TC series

Log series	TC/HAN	VC/HAN	TC/CAP	VC/CAP
Test stat	0.119	0.020	-0.106	-0.101

5% cValue -2.87

These rejections could be due to heteroskedasticity or because of higher-order autocorrelation in the data. For a random walk, the ratio values in the last row should be equal to 1. The S&P500 ratios are both less than 1, which may suggest that these series are mean-reverting. The BDI and BPI series are all greater than 1, which may suggest that they are mean-averting.

2.3.2 Freight rate returns and autocorrelation

In the previous section there was a suggestion that there may be autocorrelation in the freight rate return series. Table 2.4 presents the autocorrelation function. The first lag of the BDI return has the correlation of 0.41, which diminishes to 0.14 in the 4th lag. S&P500 returns do not have any correlation. Therefore the freight rate series has correlation with itself and has a tendency to persist in the short term.

Table 2.4 Sample autocorrelation function for BDI and S&P500

Vector of lags	1	2	3	4
BDI	0.4147	0.2492	0.1559	0.1487
S&P500	-0.0598	-0.0152	0.0437	0.0015
Confidence bounds: 0.06 and -0.06				

Figures 2.1 and 2.2 presents the autocorrelation function for 20 lags. Weekly data from the first week of 2009 for 1,100 observations has been used to calculate the autocorrelation. In this chapter we do not use the BDI returns for forecasting, but rather the excess freight rate for two classes of dry bulk ships. The unit root tests for the excess freight rates are discussed in section 2.5.

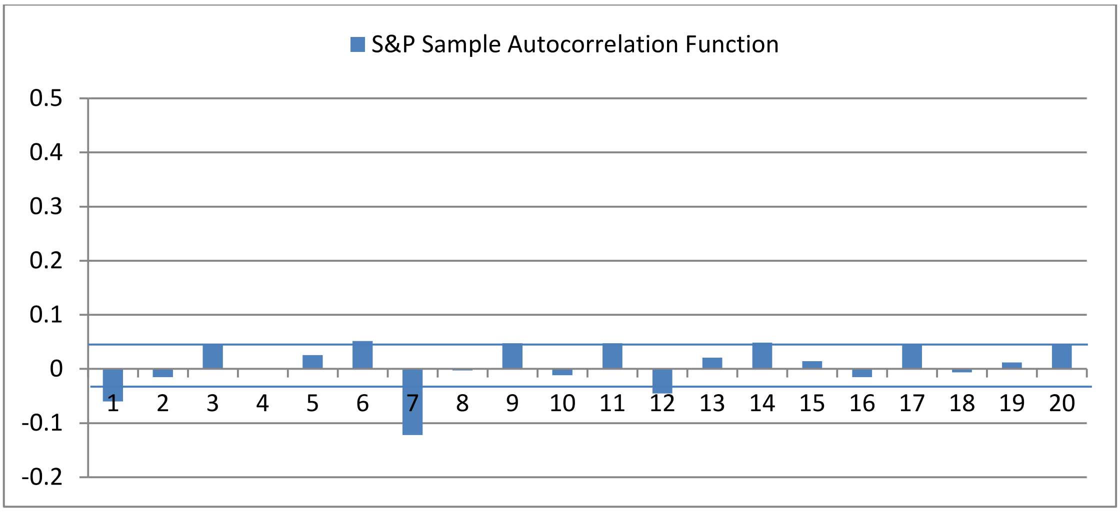


Figure 2.1 BDI autocorrelation

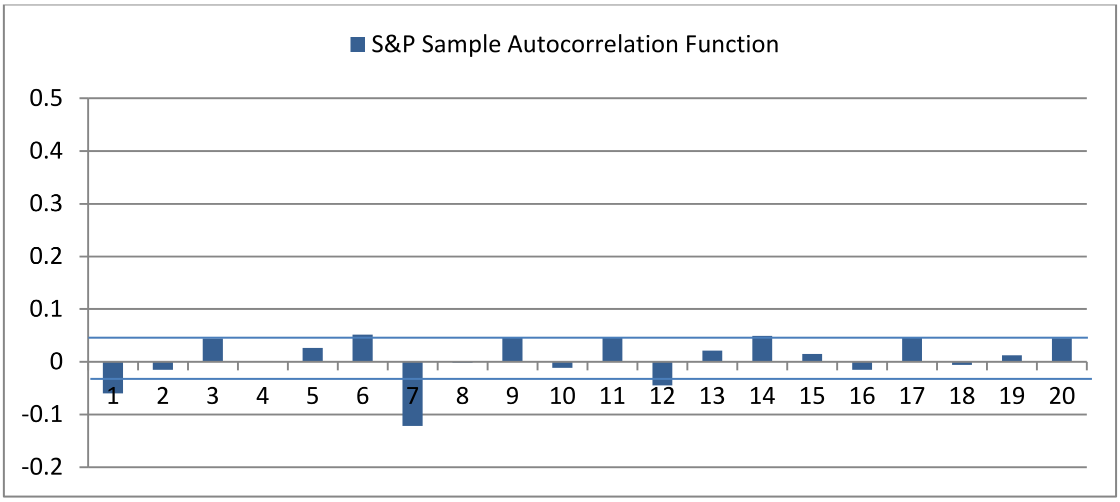


Figure 2.2 S&P500 autocorrelation

2.4 Methodology

The ship owner or the ship operating company in the bulk shipping market faces an important chartering decision in utilizing the ship: to charter the ship in the spot market multiple times, or to charter it in the TC market on a specified time scale. The term charter (TC) is also known as period charter. For chartering in the spot market the ship operator receives the spot freight rate, which could be different for each of the multiple voyages. For the TC market he receives the TC rates, which are fixed for the whole period of the charter.

We now describe an econometric strategy to decide between these two alternative chartering possibilities. This strategy can be used by the ship owner, but can also be by employed by the shipper (the firm that demands transportation services). The time-charter possibilities are quite wide; they vary from six months or one year to 2–3 years and 5–8 years. For our purpose, we assume six months' TC versus multiple spot charters. We forecast two steps ahead of quarterly excess freight prices regressed recursively on relevant explanatory variables. The model assumes that the excess freight rate follows a stationary process (our unit root tests revealed this to be the case: see Table 2.5). We assume that the explanatory variables reflect the freight dynamics and can signal the optimal policy. The forecast of excess freight is used by the ship operator to decide whether to charter the ship in the spot or the TC market. If the forecast is positive the ship operator chooses the spot market; if negative, the TC market. When the results have been computed, the proposed optimal policy will be compared with the following strategies:

1) Choosing the spot market for the entire period.
2) Choosing the TC market for the entire period.

Therefore, at the end of the forecasting period there would be three columns of results: two of them containing the earnings derived from the fixed policies of either the TC or the spot freight market, and one containing the earnings derived from the switching strategy.

2.4.1 Switching strategy

At time (t) the ship operator tries to forecast the excess freight rate, which is the difference between TC and spot charter rates in time $(t+2)$ of the quarterly date, and calculate whether the market will have positive excess at that time. The total of two steps' quarterly forecast is compared to the one-period six months' TC option. The same procedure will be undertaken when information has been updated in the next period. If the forecasts of excess are positive, the ship operator decides to choose the spot freight rate market, and if negative the TC market. Our strategy is a multiple period decision problems to maximize the ship operator utility over all decision periods. The model is

$$r_t = ln(vt_t) - ln(tc_t)$$
$$r_{t+1} = \hat{\alpha} + \hat{b}X_t$$

$$X_{t+1} = \hat{c} + \hat{b}X_t$$
$$r_{t+2} = \hat{a} + \hat{\beta}X_{t+1}$$
$$r_{t+2} > 0$$
$$r_{t+2} = vt$$
$$r_{t+2} \leq 0$$
$$r_{t+2} = tc \tag{2.6}$$

where the matrix of X is

$$X = \begin{bmatrix} 1\ x_{11} & \cdots & x_{51}y_{61} \\ \vdots & \ddots & \vdots \\ 1\ x_{1t} & \cdots & x_{5t}y_{6t} \end{bmatrix} \tag{2.7}$$

where r_t is the excess freight rate, vt_t spot freight rate and tc_t time-charter freight rate. The variables are described in Table 2.1. With the switching chartering strategy, the approach is to set up a predictive model of two-step-ahead excess by using quarterly information and calculate future excess with that fixed model. In general finance, Pesaran and Timmermann (1995) show that the predictability of S&P500 stock returns can guide an investor in switching the asset holdings between market portfolios and Treasury bill and exploit net profit over a buy-and-hold strategy. An extended version of this paper, with application to UK stock returns, has also been published by Pesaran and Timmermann (2000). The investors discussed in these papers commonly switch their portfolios between one stock market portfolio and a short-term Treasury bill in their markets according to one set of forecasts on excess stock returns in each period. Pesaran & Timmerman (2000) distinguish possible regressors by three types. Every model starts with all core variables in set A, allowing new variables introduced from set B & C into the predictive model. We simply assume that the investor chooses to predict variables from the same set of regressors in every period. This strategy has been modelled with MATLAB, and the main code for the forecasting engine is presented in section 2.4.2.

2.4.2 MATLAB code for the main forecast engine

We have written a Matlab code to forecast the two-steps-ahead of the excess freight. The main engine of the code is shown in Figure 2.3.

```
Copyright 2011 Kasra Pourkermani
while i<=N-1;
Lx1=x1(1:i-1);
Lx2=x2(1:i-1);
Lx3=x3(1:i-1);
Lx4=x4(1:i-1);
Lx5=x5(1:i-1);
Ly=y(1:i-1);
X = [ones(size(Lx1)) Lx1.^2 Lx2.^2 Lx3.^2 Lx4.^2 Lx5.^2 Ly.^2];
ny=y(2:i);
XX = [Lx1.^2 Lx2.^2 Lx3.^2 Lx4.^2 Lx5.^2 Ly.^2];
ststs1=regstats(ny,XX,'linear')
bata= inv(X'*X)*X'*ny
fc=bata(1,1)+bata(2,1)*x1(i)+bata(3,1)*x2(i)+bata(4,1)*x3(i)+bata(5,1)
*x4(i)+bata(6,1)*x5(i)+bata(7,1)*y(i)
tx1=x1(1:i-1);
tx2=x2(1:i-1);
tx3=x3(1:i-1);
tx4=x4(1:i-1);
tx5=x5(1:i-1);
g1 = [ones(size(tx1)) tx1.^2];
xd1=x1(2:i);
bo1=inv(g1'*g1)*g1'*xd1;
k1=zeros(i,1);
k1=bo1(1,1)+bo1(2,1)*x1(i)
g2 = [ones(size(tx2)) tx2.^2];
xd2=x2(2:i);
[b]=regress(xd2,g2,0.5);
k2=zeros(1,1);
k2=b(1,1)+b(2,1)*x2(i);
g3 = [ones(size(tx3)) tx3.^2];
xd3=x1(2:i);
bo3= inv(g3'*g3)*g3'*xd3;
k3=zeros(i,1);
k3=bo3(1,1)+bo3(2,1)*x3(i)
g4 = [ones(size(tx4)) tx4.^2];
xd4=x4(2:i);
bo4=inv(g4'*g4)*g4'*xd4;
k4=zeros(i,1);
k4=bo4(1,1)+bo4(2,1)*x4(i)
g5 = [ones(size(tx5)) tx5.^2];
xd5=x5(2:i);
bo5= inv(g5'*g5)*g5'*xd5;
k5=zeros(i,1);
k5=bo5(1,1)+bo5(2,1)*x5(i)
ty=y(1:i-1);
gy = [ones(size(tx1)) ty];
xyd=y(2:i);
byo= inv(gy'*gy)*gy'*xyd;
py=byo(1,1)+byo(2,1)*y(i);
fff=zeros(i,1);
fff(i,1)=bata(1,1)+bata(2,1)*k1+bata(3,1)*k2+bata(4,1)*k3+bata(5,1)*k4
+bata(6,1)*k5+bata(7,1)*py;
 if fff(i,1)>0;    str(i-(n-1),1)=oyy(i,1);
end;
if fff(i,1)<=0;   str(i-(n-1),1)=ozz(i,1);
end;
    i=i+2;
end;
```

Figure 2.3 Matlab code to forecast the two-steps-ahead.

2.5 Choice of regressors

In this section the choice of forecasting regressors considered by the ship operator is discussed. The operator chooses only candidate predictors that can be accessed, and makes his choice on the basis of prior belief as well as publicly available information. Before the chartering decision is made, the ship operator includes variables which he believes have a certain power to explain the variation in freight rate market. The ship operator has no uncertainty as regards the choice of predictors, the specifications of predictive models, or the best forecasts.

The level of seaborne trade derives from the world economic situation, and macroeconomic indicators are a direct reflection of the world economy. Seaborne trade to a great extent determines the demand for shipping services, which means that the higher the increases in seaborne trade from period to period, the higher the demand for shipping services, and as a result the higher the freight rate. Consequently, a positive role is expected from these variables.

Another indicator of economic activity is the price of the major commodities, since an increase in prices for commodities such as oil, iron ore, coal or grain will indicate a stronger demand for these commodities. Since most of them are produced or extracted in areas where their utility is lower than in the areas where they are consumed, they have to be transported by ships. Consequently an increase in demand for shipping services will occur, followed by an increase in freight rates. As a result, a positive role is also expected for commodity variables.

Table 2.5 ADF test results for all returns

	Explanatory variables										*Dependent variables*	
	Commodity variables					Macro variables						
	X_{C1}	X_{C2}	X_{C3}	X_{C4}	X_{C5}	X_{M1}	X_{M2}	X_{M3}	X_{M4}	X_{M5}	r_{tCAP}	r_{tHAN}
Test stat	-9.37	-8.78	-7.28	-6.98	-7.35	-7.27	-4.27	-3.90	-3.34	-7.26	-6.15	-5.06

pValue 0.001- cValue -1.944 - 5% significance

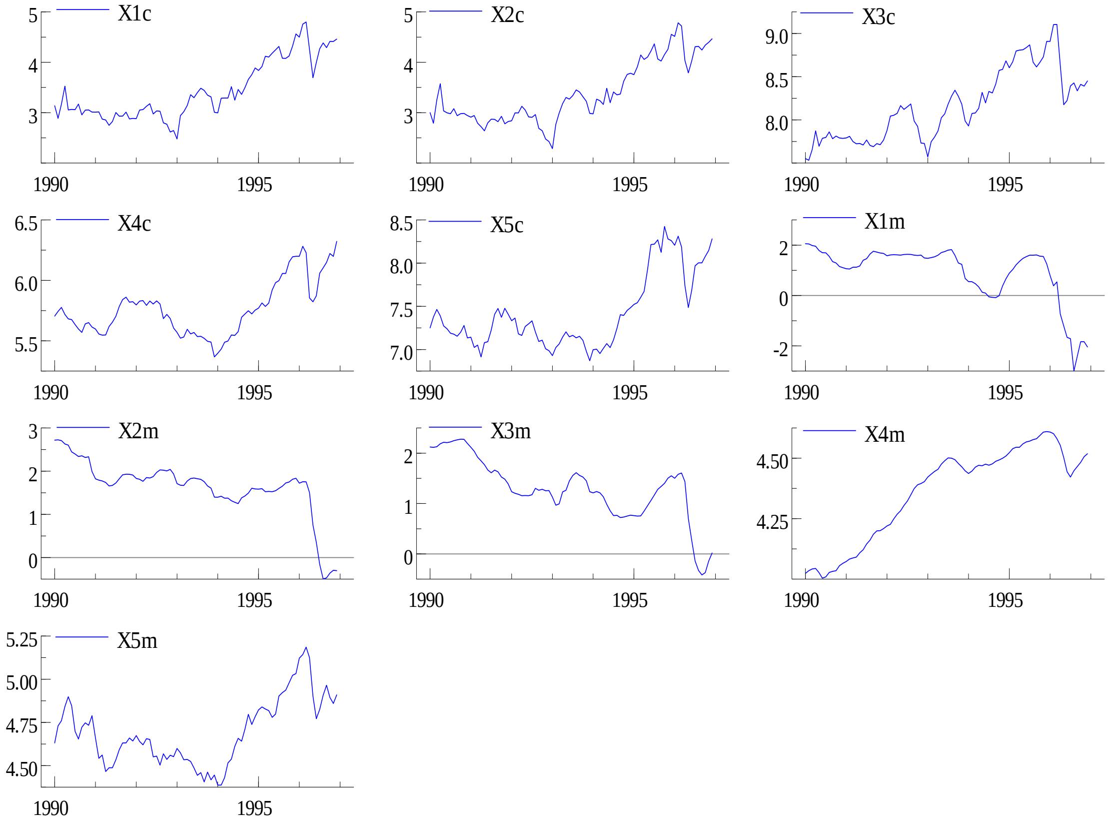


Figure 2.4 Plot of the variables natural logarithms

Table 2.6   Overview of the variables

Commodity group explanatory variables	
$x1$	Crude Oil WTI Cushing U$/BBL
$x2$	Crude Oil-Brent Dated FOB U$/BBL
$x3$	S&P500 GSCI Commodity
$x4$	CRB Commodity Index Raw Industrials
$x5$	LME-LMEX Index
r_t	Excess freight rate (spot charter $-$ TC)
Macroeconomic group explanatory variables	
$x1$	USA Treasury Bill 2ND Market 3 month
$x2$	UK Inetrbank3 Month (LDN:BBA)
$x3$	Germany FIBOR – 3 month
$x4$	USA Consumer Confidence Index
$x5$	USA Industrial Production
r_t	Excess freight rate (spot charter $-$ TC)

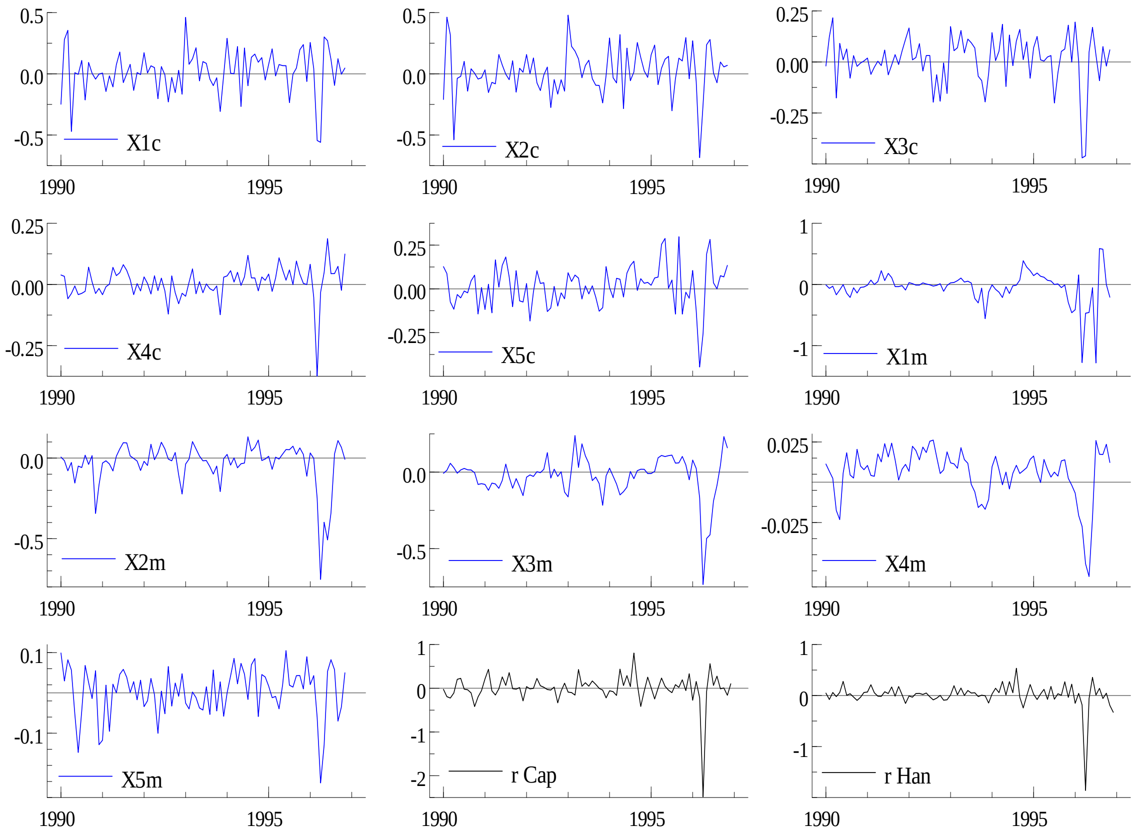


Figure 2.5 Plot of the variables returns

The selected variables are series of 5 quarterly macroeconomic variable returns and 5 quarterly commodity variable returns, which are regressed separately in two sets. Table 2.6 presents the overview of variables. Among the macroeconomic variables, industrial production and interest rate are believed to be important. Industrial production is sensitive to changes in demand, and is important for shipping because the materials it consumes and its products are vital cargoes for the shipping industry. In the tanker market there is also a close relationship between OPEC oil production and VLCC (Very Large Crude Carriers) earnings. Interest rate is also highly correlated with oil prices. The oil price specifically is an important regressor because it is a real indicator of a high standard of living, and is also a hedge and trading instrument; in this it is in fact similar to some other commodities such as aluminium, which is not included in this set of variables. Table 2.5 presents the ADF test of all variables. The computed ADF test-statistics are all smaller than the critical values at 5% significant level and hence the null hypothesis of the test is rejected. This means that the inputs do not have a unit root problem and are stationary.

The predictability of the excess freight rate market can be identified on the basis of models constructed with lagged macroeconomic variables and commodity price returns. The investor, who is collecting available information from both markets at each time, will use a one-month lag for financial and macroeconomic indicators. Figure 2.5 is the plot of all the input variables and Figure 2.4 demonstrate the natural logarithms of these variables.

2.6 Empirical results

2.6.1 Handymax results

The shipping data are provided by Clarksons Research Company, and the rest of the data are taken from Thompson DataStream. The full regression sample is from 1990-Q1 to 2010-Q4. The forecast period is from 2000-Q3 to 2010-Q4. Each set of Handymax and Capesize excess freight rates is regressed separately by the two groups of explanatory variables. In general the results are mixed, but three out of four cases suggest that by using the given strategy the ship operator will be financially better off.

The switching series for Handymax and Capesize are shown in Tables 2.7 and 2.10 respectively. According to these tables, the switching strategy does not create more economic value in the Handymax series, but can produce around 20% more daily earnings in the Capesize series. None of the series is significantly different from the others from a statistical point of view. Table 2.7 compares the Handymax strategies where VC (voyage charter) is the spot freights, TC the time-charter rates, and SW the switching strategy. In this table ECO and COM are, respectively, the macroeconomic and the commodity group of variables.

Following the switching strategy with commodity variables, a Handymax tanker operator can slightly improve cash flow, by 640 USD/day compared to the spot chartering option and by 10 USD/day compared to the term-charter option. The descriptive statistics for Handymax series are shown in Table 2.8. The fourth and sixth columns in Tables 2.7 and 2.10 represent the accuracy of forecast: if the forecast for a period is correct it is demonstrated by 1, and if false by 0. The tables indicate that 50%

of forecasts are correct by macroeconomic variables forecasts and 59% by commodity prices forecasts. If we consider the one-step-ahead forecast we find that 42% of the signs are correct with commodity regressors and 47% with macroeconomic regressors. There is a 50% difference in forecast signs between the two regressor series.

Table 2.7 Comparison of Handymax chartering strategies[8]

Date	*\$/day TC/HAN.*	*\$/day VC/HAN.*	*\$/day SW/COM.*	*1/0*	*\$/day SW/ECO.*	*1/0*
2000-Q3	8688	9134	9134	1	9134	1
2000-Q4	8688	9173	9173		9173	
2001-Q1	9177	9007	9007	0	9007	0
2001-Q2	9177	9241	9241		9241	
2001-Q3	7838	7800	7800	0	7800	0
2001-Q4	7838	6775	6775		6775	
2002-Q1	6508	6714	6508	0	6508	0
2002-Q2	6508	7504	6508		6508	
2002-Q3	7227	7650	7227	0	7650	1
2002-Q4	7227	9538	7227		9538	
2003-Q1	10062	10181	10062	0	10181	1
2003-Q2	10062	13213	10062		13213	
2003-Q3	13023	13762	13023	0	13023	0
2003-Q4	13023	22255	13023		13023	
2004-Q1	33077	31983	31983	0	33077	1
2004-Q2	33077	25918	25918		33077	
2004-Q3	24346	24279	24279	0	24346	1
2004-Q4	24346	30191	30191		24346	
2005-Q1	26563	27220	27220	1	26563	0
2005-Q2	26563	24581	24581		26563	
2005-Q3	15786	16271	16271	1	15786	0
2005-Q4	15786	17837	17837		15786	
2006-Q1	15335	14242	15335	1	15335	1
2006-Q2	15335	18334	15335		15335	
2006-Q3	24869	23140	24869	1	24869	1
2006-Q4	24869	25775	24869		24869	

[8] 1 = correct forecast sign, 0 = false forecast sign, TC/HAN = Time-charter Handymax, VC/HAN = spot Charter Handymax, SW/COM = switching between the spot charter and time charter with commodity regressors forecast, SW/ECO = switching with macroeconomic regressors.

2007-Q1	28431	28602	28602	1	28431	0
2007-Q2	28431	37279	37279		28431	
2007-Q3	47192	45538	45538	1	45538	1
2007-Q4	47192	58913	58913		58913	
2008-Q1	51385	44135	44135	0	44135	0
2008-Q2	51385	53606	53606		53606	
2008-Q3	47962	39784	47962	1	47962	1
2008-Q4	47962	7456	47962		47962	
2009-Q1	9615	9053	9615	1	9615	1
2009-Q2	9615	13741	9615		9615	
2009-Q3	16731	16883	16883	0	16883	0
2009-Q4	16731	19288	19288		19288	
2010-Q1	22750	21471	21471	0	21471	0
2010-Q2	22750	23809	23809		23809	
2010-Q3	20577	16947	16947	0	16947	0
2010-Q4	20577	9615	9615		9615	
Sum	*894284*	*867838*	*894698*		*892947*	
Average	*21292*	*20662*	*21302*	*50%*	*21260*	*59%*
Forecast sign difference between ECO & COM: 38%. Correct signs: ECO>COM. Economic value: COM>ECO						

Table 2.8 Descriptive statistics[9]

	TC/HAN.	*VC/HAN.*	*SW/COM.*	*SW/ECO.*
Average	21292.48	20662.81	21302.33	21260.64
Median	16731.00	17392.00	16915.00	16334.50
Maximum	51385.00	58913.00	58913.00	58913.00
Minimum	6508.00	6714.00	6508.00	6508.00
Std. Dev.	13705.19	13189.60	14082.77	14082.60
Skewness	0.95	1.15	1.04	1.09
Kurtosis	2.84	3.78	3.14	3.29
Jarque-	6.36	10.46	7.69	8.59

9 TC/HAN = time-charter Handymax, VC/HAN = spot charter Handymax, SW/COM = switching between the spot charter and time charter with commodity regressors forecast, SW/ECO = switching with macroeconomic regressors.

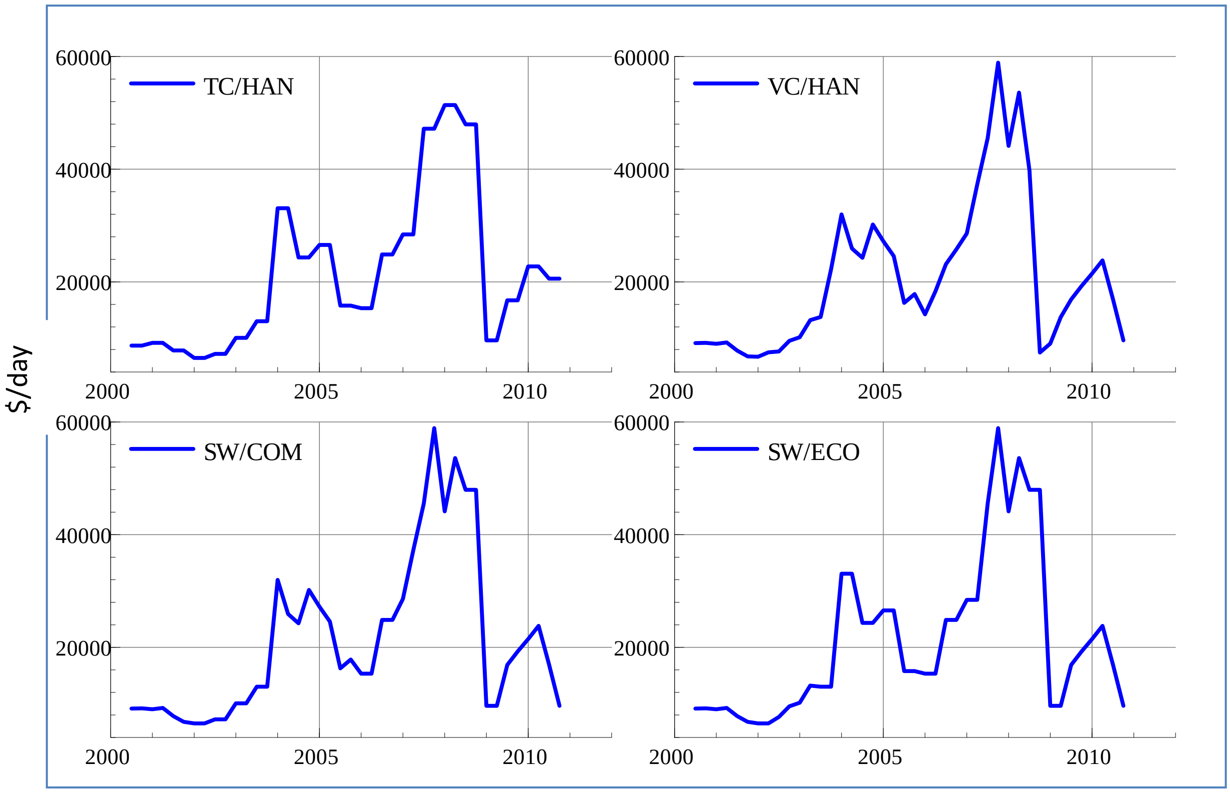


Figure 2.6 Handymax series (x axis is $/day)

Between the four series, SW/COM and TC/HAN, which are the forecasts by commodity variables and by TC-only strategy, have the highest values. This means that by following SW/COM the ship operator can earn $21,302.33 by every day, which is only 3% higher than the spot charter rate (VC/HAN). All the four options in the Handymax series produce virtually the same result. None of these series is statistically different from the others.

Figure 2.6 shows that from the switching series, both SW/COM and SW/ECO are able to take the highest spikes from VC/HAN. Figure 2.7 presents the tabulation of Handymax series divided into classes; according to the visual illustration VC/CAP and SW/ECO are taller and fatter. SW/COM distribution is taller than the others, as expected, but all four are similar. Figure 2.8 compares the accuracy of the forecast between macroeconomic and commodity variables. The lines equal to 1 are the sign of the correct forecast; during the years 2001, 2002, 2010 and 2011 the forecasts are similar.

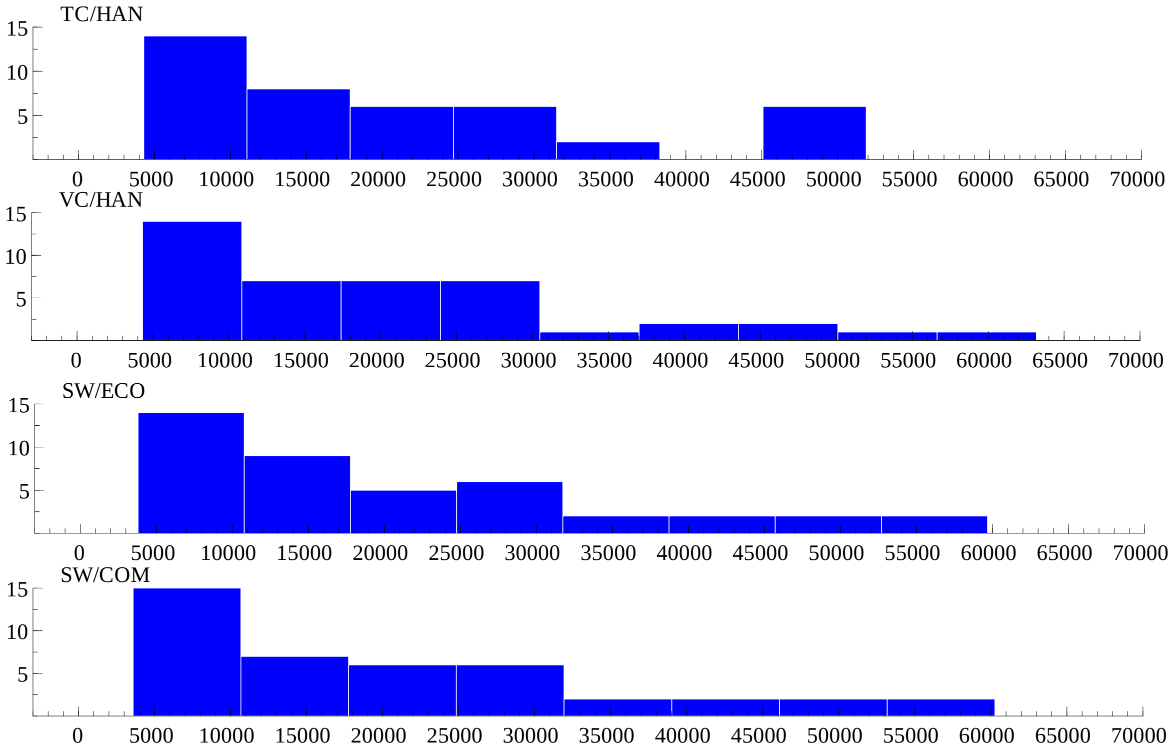


Figure 2.7 Distribution of series

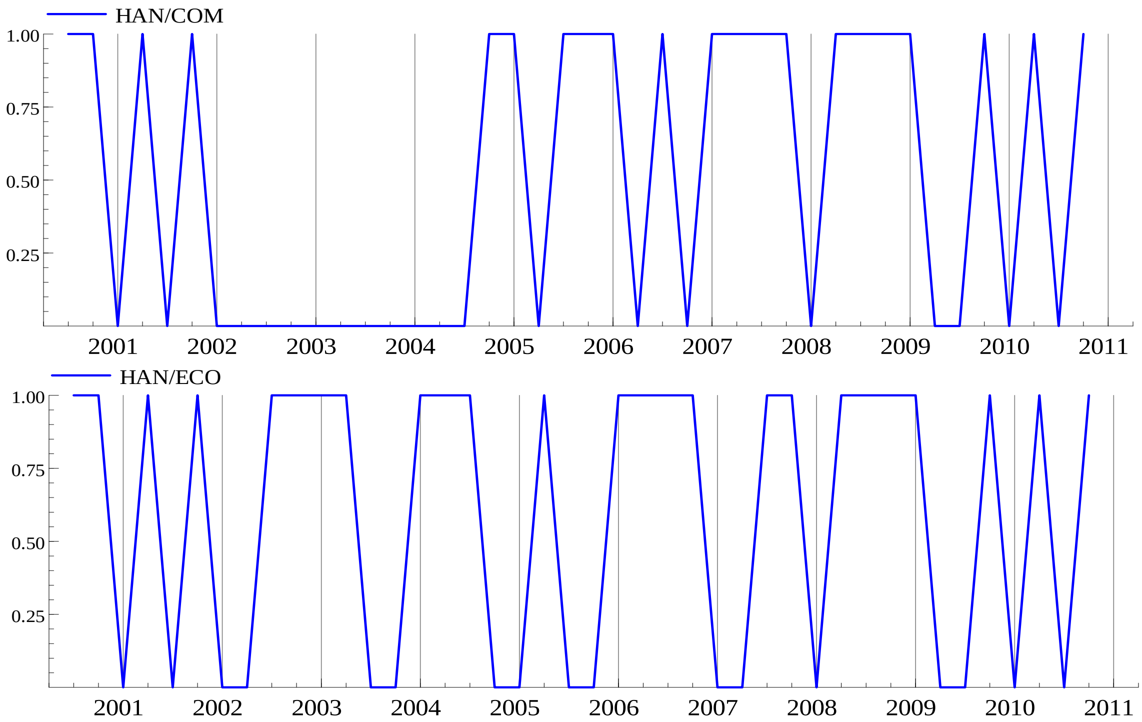


Figure 2.8 Comparison of Handymax prediction

Table 2.9 present the properties of the explanatory variables regressions for Handymax excess freight. The bottom section of Table 2.9 presents the properties of the regression coefficient of commodity variables.

Table 2.9 Handymax macroeconomic variables regression properties

Handymax/Macroeconomic					
Variables	*beta*	*se*	*t-stat*	*p-val*	
Constant	0.103	0.027	3.847	0.000	
$x1$ US TB	-0.374	0.101	-3.714	0.000	
$x2$ UK Intra	0.521	1.013	0.514	0.609	
$x3$ Ger. FIBOR	2.094	1.375	1.523	0.132	
$x4$ Conf.	-0.240	0.693	-0.347	0.730	
$x5$ Indus.	-533.478	135.032	-3.951	0.000	
y	-0.081	0.139	-0.581	0.563	
Adjusted R2	*F statistic*	*sse*	*dfe*	*p-val*	
0.416		2.621	75.000	0.000	
Mean squared error	*DW statistic*	*dw*		*p-val*	
0.035		2.284		0.290	
Handymax/ Commodity					
Variables	*beta*	*se*	*t-stat*	*p-val*	
Constant	0.053	0.020	2.704	0.008	
$x1$ Oil WTI	1.818	0.848	2.145	0.035	
$x2$ Oil Brent	-0.605	0.668	-0.907	0.368	
$x3$ S&P500	-3.868	1.666	-2.322	0.023	
$x4$ CRB	-10.987	3.026	-3.631	0.001	
$x5$ LME	1.752	1.079	1.623	0.109	
y	0.018	0.117	0.151	0.880	
Adjusted R2	*F statistic*	*sse*	*dfe*	*p-val*	
0.691		1.388	75.000	0.000	
Mean squared error	*DW statistic*	*dw*		*p-val*	
0.019		2.185		0.465	

From the five regressors, only US Treasury Bill and US Industrial Production have statistical significance according to their *p*-values. 'sse' is the sum of squares due to error of the fit. The 'sse' value of closer to zero indicates a fit that is more useful for forecast. For macroeconomic variables this value is 2.2 but for commodity variables it is 1.3: therefore, commodity variables are more useful for the forecast. R-square is the square of the correlation between the response values and the predicted response values. A value closer to 1 indicates that a greater proportion of variance is accounted for by the model. Again, the value of the commodity variables is 0.71 and is closer to zero. 'dfe' is the degree of freedom in the error. Adjusted R-square is the degree of freedom adjusted R-square. A value closer to 1 indicates a better fit.

The Crude Oil WTI Cushing, S&P500 GSCI Commodity and CRB Commodity Index Raw Industrials are statistically significant; the other two regressors, Crude Oil-Brent and LMEX (London Metal Exchange) Index, are not.

2.6.2 Capesize results

Now we report the results of the Capesize series. By following the switching strategy a Capesize tanker operator can slightly improve cash flow, by 1,449 USD/day compared to the voyage chartering option and by 13,383 USD/Day compared to the TC market. The full series are set out in Table 2.10 and the descriptive statistics of the series in Table 2.11. The column of 1/0 in Table 2.10 represents the accuracy of forecast. If the forecast for a period is correct it is 1 and if false 0. This shows that 76% of forecasts are correct by macroeconomic variables and 66% by commodity variables.

Table 2.10 Capesize comparison of chartering strategies[10]

Date	*\$/day TC/CAP.*	*\$/day VC/CAP.*	*\$/day SW/COM.*	*1/0*	*\$/day SW/ECO.*	*1/0*
2000-Q3	19427	21689	19427	0	19427	0
2000-Q4	19427	24668	19427		19427	
2001-Q1	15788	19276	15788	0	15788	0
2001-Q2	15788	17566	15788		15788	
2001-Q3	9731	11601	9731	0	9731	0
2001-Q4	9731	9849	9731		9731	
2002-Q1	10135	10539	10539	1	10539	1
2002-Q2	10135	10136	10135		10135	
2002-Q3	11096	11835	11835	1	11096	1
2002-Q4	11096	19489	19489		11096	
2003-Q1	19827	24166	19827	0	19827	0
2003-Q2	19827	30916	19827		19827	
2003-Q3	27490	35279	35279	1	35279	1
2003-Q4	27490	63534	63534		63534	
2004-Q1	65692	81692	81692	1	81692	1
2004-Q2	65692	57775	57775		57775	
2004-Q3	53231	62199	62199	1	62199	1
2004-Q4	53231	80342	80342		80342	

[10] 1 = correct forecast sign, 0 = false forecast sign, TC/HAN = time-charter Capesize, VC/HAN = voyage Charter Capesize, SW/COM = switching between the voyage charter and time charter with commodity regressors forecast, SW/ECO = switching with macroeconomic regressors.

2005-Q1	60375	71579	71579	1	71579	1
2005-Q2	60375	58279	58279		58279	
2005-Q3	29714	42020	42020	1	42020	1
2005-Q4	29714	51397	51397		51397	
2006-Q1	29269	40848	40848	1	40848	1
2006-Q2	29269	39013	39013		39013	
2006-Q3	48027	61727	61727	1	61727	1
2006-Q4	48027	61505	61505		61505	
2007-Q1	63769	79564	79564	1	79564	1
2007-Q2	63769	97805	97805		97805	
2007-Q3	101269	126396	126396	1	101269	0
2007-Q4	101269	180196	180196		101269	
2008-Q1	118615	130507	130507	1	118615	0
2008-Q2	118615	183856	183856		118615	
2008-Q3	117942	131068	117942	0	131068	1
2008-Q4	117942	13767	117942		13767	
2009-Q1	20192	31287	31287	1	20192	0
2009-Q2	20192	50568	50568		20192	
2009-Q3	34558	54509	54509	1	54509	1
2009-Q4	34558	62819	62819		62819	
2010-Q1	31000	43942	43942	1	43942	1
2010-Q2	31000	46124	46124		46124	
2010-Q3	24962	34860	34860	1	34860	1
2010-Q4	24962	39362	39362		39362	
Sum	*1824218*	*2325549*	*2386412*		*2063573*	
Average	*43433*	*55370*	*56819*	*57%*	*50331*	*71%*

Forecast sign difference between ECO & COM: 9%.
Correct signs: ECO>COM.
Economic value: COM>ECO.

Table 2.11 Descriptive statistics

	TC/CAP.	*VC/CAP.*	*SW/COM.*	*SW/ECO.*
Average	43433.76	55370.21	56819.33	49132.69
Median	29714.00	45033.00	48346.00	42981.00
Maximum	118615.00	183856.00	183856.00	131068.00
Minimum	9731.00	9849.00	9731.00	9731.00
Std. Dev.	33355.29	42669.42	43328.14	33892.80
Skewness	1.16	1.46	1.30	0.70
Kurtosis	3.22	4.84	4.37	2.60
Jarque-Bera	9.45	20.84	15.09	3.74

Table 2.11 presents the descriptive statistics of the final switching and fixed strategy. Between the four series, SW/COM, which is the forecast by commodity variables, has the highest value; this means that the ship operator can earn $56,819 every day, which is 23% higher than the TC rate (TC/CAP). The spot charter stands second, at $55,370 every day, which is only 2% different from the best strategy. Considering the possible abnormalities of data these two series are not really different, nor are they statistically different. None of the series is statistically diffident from the others at 5% significance level.

We now compare the obtained series by plotting the actual and frequency distributions presented in Tables 2.10. From the switching series, SW/COM is able to take the highest spikes from VC/CAP, but the SW/ECO fails to make an accurate forecast. Macroeconomic variables were shown to have predicted more correct signs, but the timing of these correct forecasts and their magnitude is different from the commodity regressors'. Figure 2.11 shows the tabulation of the Capesize series divided into classes; by the visual illustration VC/CAP and SW/ECO are taller and fatter.

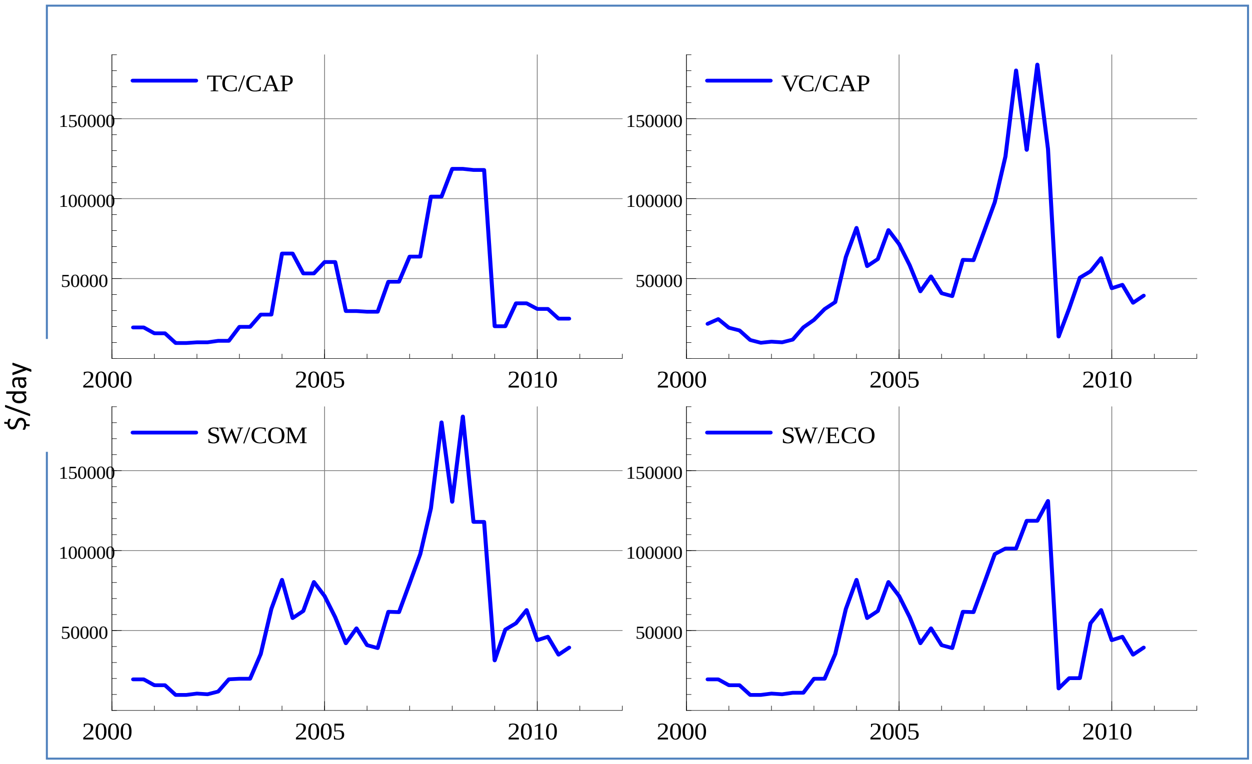


Figure 2.9 Capesize series (x axis is $/day)

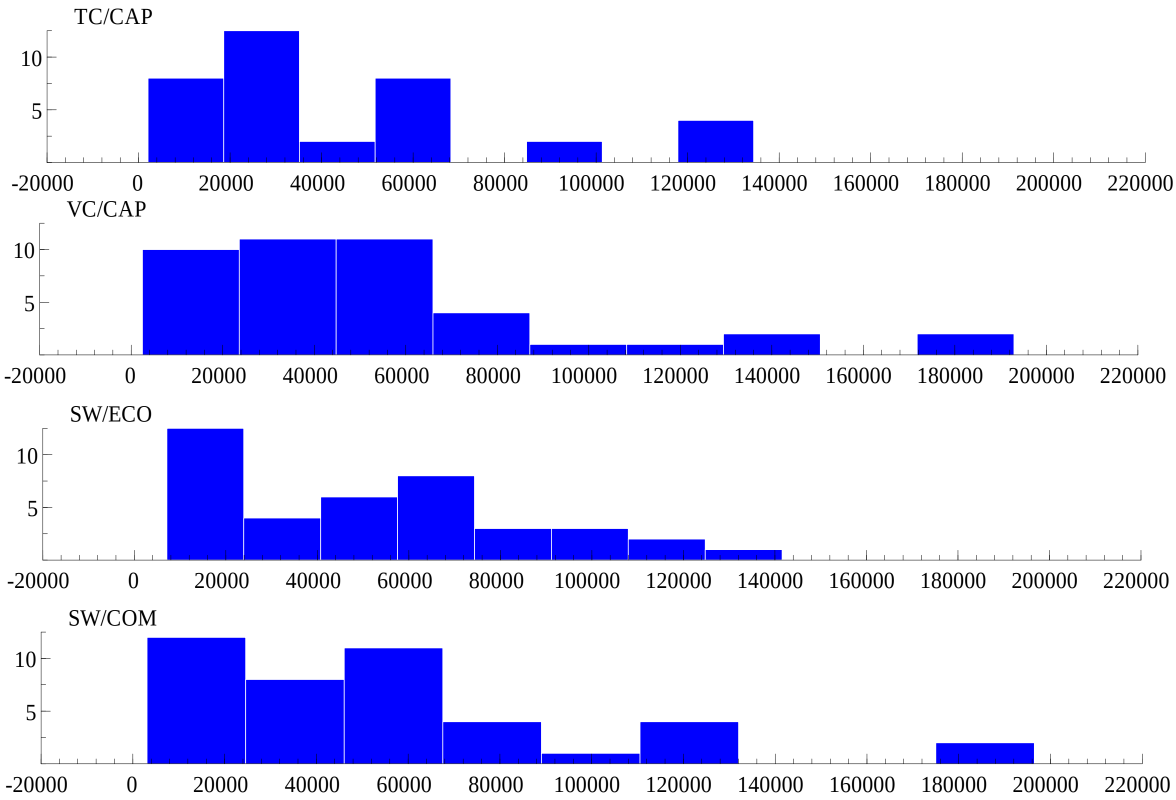


Figure 2.10 Frequency distribution of Capesize series

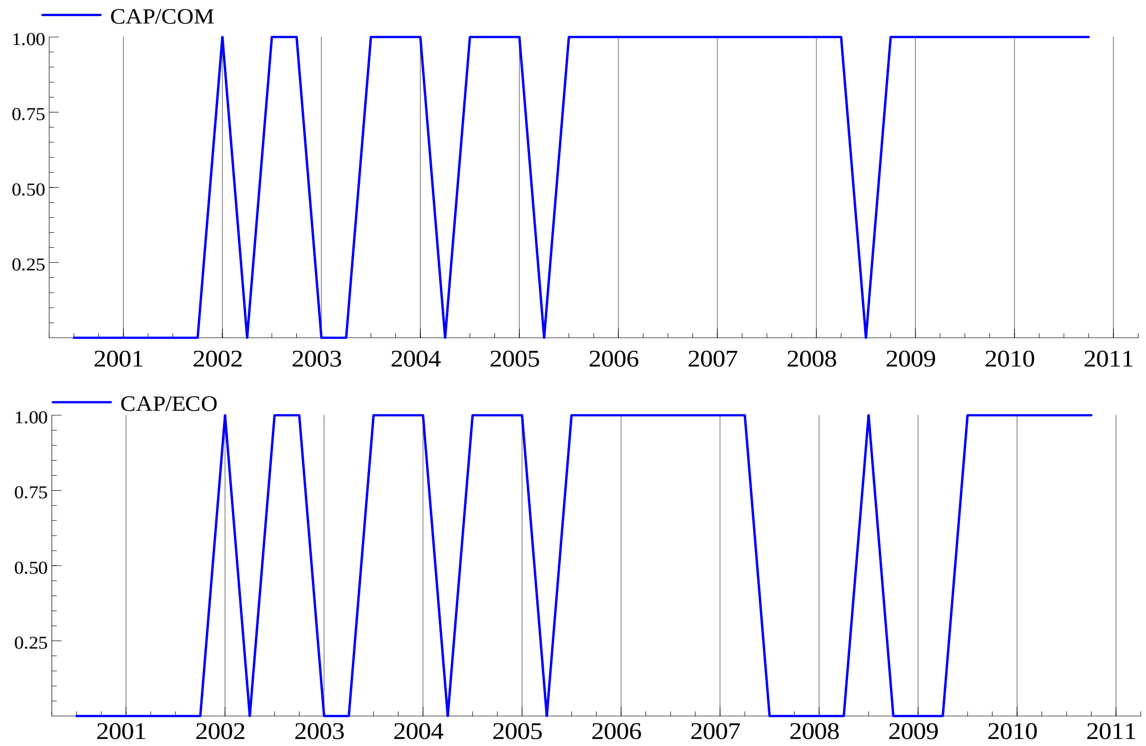


Figure 2.11 Comparison of Capesize prediction

Table 2.12 Capesize macroeconomic regression properties

Capesize /Macroeconomic				
Variables	*beta*	*se*	*t-stat*	*p-val*
Constant	0.310	0.040	7.759	0.000
$x1$ US TB	-0.364	0.152	-2.391	0.019
$x2$ UK Intra	-0.139	1.550	-0.089	0.929
$x3$ Ger. FIBOR	4.554	2.095	2.174	0.033
$x4$ Conf.	-0.927	1.085	-0.854	0.396
$x5$ Indus.	-584.178	200.562	-2.913	0.005
y	-0.140	0.171	-0.815	0.418
Adjusted R2	*F statistic*	*sse*	*dfe*	*p-val*
0.273		6.023	75.000	0.000
Mean squared	*DW statistic*	*dw*		*p-val*
0.080		1.752		0.172
Capesize / Commodity				
Variables	*beta*	*se*	*t-stat*	*p-val*
Constant	0.256	0.030	8.475	0.000
$x1$ Oil WTI	1.866	1.374	1.358	0.179
$x2$ Oil Brent	-0.745	1.070	-0.697	0.488
$x3$ S&P500	-6.339	2.284	-2.775	0.007
$x4$ CRB	-9.973	4.436	-2.248	0.027
$x5$ LME	1.987	1.732	1.147	0.255
y	0.198	0.117	1.693	0.095
Adjusted R2	*F statistic*	*sse*	*dfe*	*p-val*
0.568		3.582	75.000	0.000
Mean squared	*DW*	*dw*		*p-val*
0.048		1.960		0.754

Figure 2.11 illustrates the similarities in forecast of the two commodity and macroeconomic series for the Capesize series. The horizontal lines at 1 and 0 are the sign of correct and false forecasts. The forecasts are very similar, except during 2007, 2008 and 2009.

Table 2.12 presents the regression properties of the excess Capesize freight forecast by macroeconomic variables. It suggests that, very similarly to the Handymax series, three of the five regressors, US Treasury bill, US Industrial Production and Germany FIBOR interest rate, are statistically significant. The bottom section of Table 2.12 presents the commodity variables of the excess Capesize freight forecast: again similarly to the Handymax series, Crude Oil WTI Cushing, S&P500 GSCI Commodity, CRB Index Raw Industrials and LMEX index are statistically significant. Only Crude Oil-Brent is not statistically significant.

2.7 Conclusion

From Table 2.7 and 2.10 it is clear that there is 38% difference in the forecast signs of two explanatory variables for Handymax, and only a 9% difference for Capesize. Figure 2.12 suggest that the 9% difference occurs mainly during the 2008–9 periods; during the other years the forecasts are similar. For the Handymax series the story is very different, and unlike with the Capesize series during 2008–9 the forecasts are similar. Most of the differences for Handymax are during 2003–6.

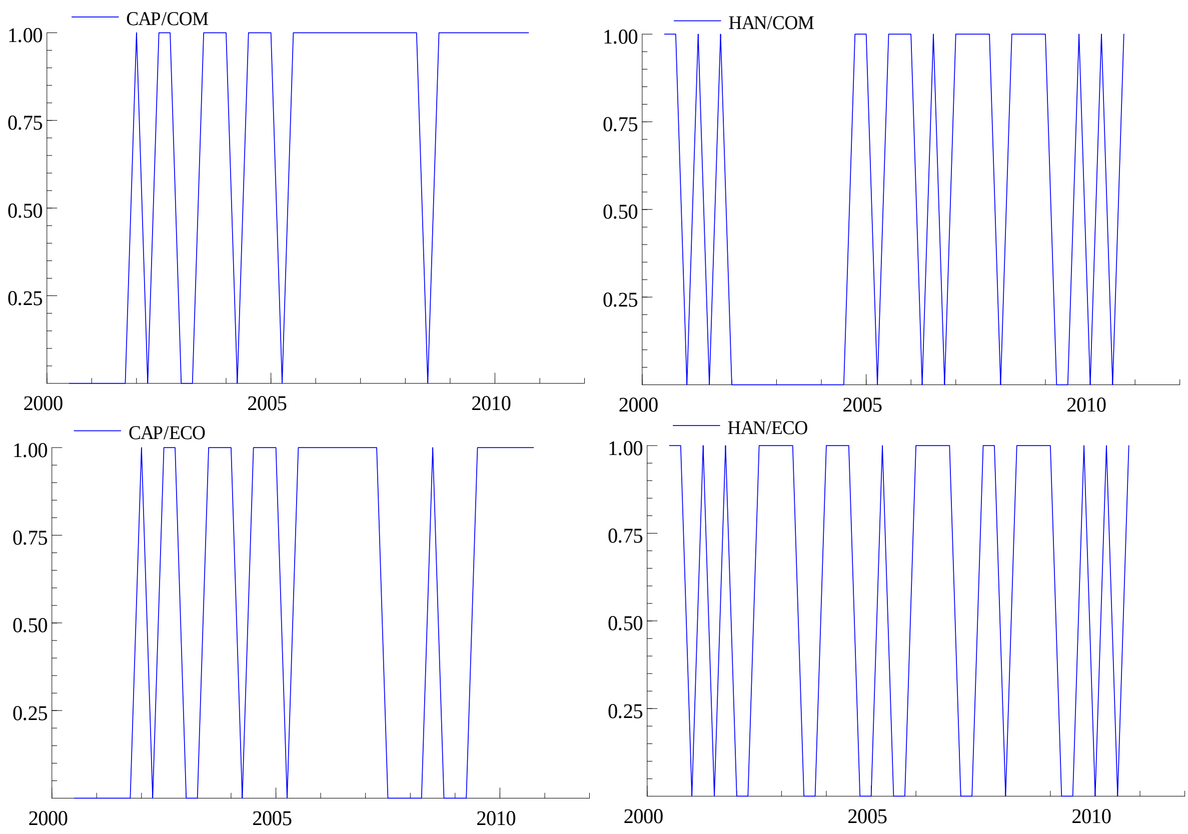


Figure 2.12 Similarities of forecast between Handymax and Capesize

We explained earlier in this chapter that time charters are formed by the market participants' expectations about future spot rates. There is a term-structure relationship between spot and time-charter rates. The term structure is derived from the no-arbitrage argument model, which means that a ship operator should not be able to make more money by contracting the ship in the time-charter market than by contracting it in the spot market for a series of voyage charters equal to the length of the time charter. Table 2.13 presents an overview of the earning differences. In the Capesize class the ship operator can make 23% more if the excess freight is forecasted with commodity variables. In the Handymax class the ship operator cannot make any extra money. Therefore, the results of the forecasts are mixed and cannot be used to disprove the EMH. The fact that in one case there is a possibility of making significantly more money is not enough to challenge EMH. This is because the freight rate estimate is based on the ship broker's reports rather than market data and there always can be the potential of mistakes and inaccurate quotes thus the evidence to challenge the EMH should be must stronger.

Table 2.13 Overview of the percentage of the earning differences

	Capesize		*Handymax*	
	Commodity	Macro economic	Commodity	Macro economic
Percentage of correct forecast signs	57%	71%	50%	59%
Percentage of extra earnings compared to time charter	23%	11%	0%	0%

2.8 Summary

In this chapter we have investigated the economic value of the freight rate forecast in the bulk shipping industry. The full regression sample is from 1990-Q1 to 2010-Q4. The forecast period is from 2000-Q3 to 2010-Q4. The ship operator forecasts the quarterly excess freight rate and will allocate the ship utility between a spot charter and time charter. The results of the economic benefit in excess of the fixed policy approach of using either spot charter or time charter for the entire period is used to discuss the validity of the EMH.

The assumption of rational expectations underlying the EMH is based on the idea that unlimited economic profit would be generated if an agent could predict the market constantly, and hence if the market were efficient it would be impossible to beat the market. Time charters are formed by the market participants' expectations about the future spot rates. There is a term-structure relationship between spot and time-charter rates. The term structure is derived from a no-arbitrage argument model: this means that a ship operator should not be able to make more money by contracting the ship in the time-charter market than by contracting it in the spot market for a series of voyage charters equal to the length of the term-charter.

This chapter has predicted the market by OLS in advance to find out if the ship owner can make more money by choosing between spot and time charter. In shipping, Alizadeh, Adland and Koekkebaker (2007) also investigated whether excess profit can be made by chartering strategies based on technical trading rules. They examined whether chartering a vessel for a long period and letting it for multiple periods during this time result in some economic gain. The trading strategy is based on application of technical trading to the difference between short- and long-term charter rates. If the spread between the two rates exceeds the average of the spread, the ship operator can charter the ship for a long period and re-let it in multiple charters, so the simple Moving Average trading rule yields significant economic benefit. In our case, at time t the ship operator tries to forecast the excess freight rate (which is the difference between time-charter and spot charter rates) for time $t + 2$, then this is compared to the six-month time-charter option. The same procedure will be undertaken when information has been updated in the next period.

If the forecasts of the excess are positive, the ship operator will choose the spot freight rate market, and if negative the time-charter market. Following this, the switching strategy does not create more economic value in Handymax classes, but can produce around 11% to 23% more earnings in Capesize classes. We us two groups of regressors, macroeconomic and commodity indicators. There is a 38% difference in forecast signs in Handymax series and 9% difference in Capesize series. The 9% difference is Capesize occurs during the 2008–9 period, while at other times the forecasts are similar. For the Handymax series, during 2008–9 the forecasts are similar, most of the difference occurring during 2003–6. The reason we only investigate the dry bulk market and not the tanker market is that such a time charter hardly exists in the tanker market and therefore adequate time series are not available. There is also another negative aspect in the data, namely that they are based on the ship broker's best estimate, which sometimes may not be particularly accurate. In addition, in some periods of very high or very low freight rates the appropriate time charter simply may not exist, so the ship operator does not have any chance of pursuing this strategy.

Chapter 3

Forecasting Volatility in the Shipping Freight Rate Market

3.1 Introduction

One of the issues in shipping risk management and freight trading is the measurement and quantification of freight risk and the volatility of the freight rate. Freight rate in the bulk shipping market was in in a state of growth from 2003 up until mid-2008 when it collapsed at a time of global financial crisis. Freight rate volatility is a major source of risk for freight traders and other market participants. This chapter investigates the characteristics of this volatility in bulk shipping by analysing three freight rate indexes of the Baltic Exchange. These indexes are published on a daily basis and provide the daily freight market prices which are used to settle freight futures. We analyse and predict the volatility of daily return freight with GARCH models for Dry, Panamax and Capesize Baltic Exchange freight rates indexes (hereafter BDI, BPI and BCI). These indexes represent different vessel sizes from 14 January 2000 to 14 January 2010.

The aim of the volatility analysis is to forecast and analyse the amount by which the freight rate is expected to fluctuate in given periods. The volatile nature of freight rates offers the opportunity for large profits, and can also lead to large losses. For this reason, monitoring the volatility and assessing the magnitude of risk exposure is an important part of shipping risk management. Successful trading positions and strategy in the freight futures market require successful forecasting of freight rate volatility. In addition, estimating volatility will help ship owners and charterers to make better decisions regarding hedging policies. The importance of volatility forecasting may also stretch to the ship-financing banks and other traditional market players, by giving them ideas about risk measurement in the area of extreme freight rate movements. Volatility is actually the dispersion of the variable, which can simply be measured by variance, and which is represented in Table 3.3. Variance gives a good indication of volatility over a defined period, but because the shape of the interaction and elasticity between demand and supply my differ over time, volatility estimates by variance cannot be accurate. In some periods, the over-supply of ships resulting from massive ordering (see section 1.8) can be absorbed by demand, with no significant effect on freight rate. At other times, the market interactions could be different and any over-supply can have a massive effect on freight rate.

The ARCH model introduced by Engle (1982) offers a solution to these problems and captures the time-varying dynamics of volatility. Several academic papers have attempted to investigate the characteristics of freight rate volatility. Cullinane (1992) provides a model of speculation by applying the Box-Jenkins approach; owing to data limitations it arrives at an ARIMA (3,1,0) model. Veenstra and Franses (1997) studied monthly freight rates for three Capesizes and three Panamax routes by using the Augmented Dickey-Fuller test and concluded that the specification of long-term relationships does not improve the accuracy of short- or long-term forecasts, which can be interpreted as a validation of the EMH. Adland and Cullinane (2005) present a simple argument rejecting the applicability of expectations theory in bulk shipping freight markets, by showing that the risk premium must be time-varying and must depend in a systematic way upon freight market conditions and the duration of a period time-charter. Kavussanos and Nomikos (2000) made estimations on time-varying and constant hedge ratios in the BIFFEX (Baltic International Freight Futures Exchange) market by using a GARCH error structure model and a GARCH-X model, and found that the GARCH-X specification is better than a simple GARCH model in estimating risk. Owing to the heterogeneous composition of the BIFFEX index it failed to reduce spot position risk, which led to the reconstruction of the BFI (Baltic Freight Index) and BPI (Baltic Panamax Index).

Kavussanos (1996) applied ARCH and GARCH models in order to analyse time-varying behaviour in the freight rates (spot and time-charter rates) for dry bulk vessels of different size. The results suggest the significance of ARCH and GARCH parameters and a better fit when a better comparison was made on the two alternative approaches of modelling freight, the classical linear model and the GARCH model. Kavusannos concludes that the pattern and magnitude of time-varying volatility in dry bulk freight markets are different across different vessel sizes; the freight rates volatility in larger vessels are larger than smaller ones. Kavussanos (1997) has also examined the dynamics of volatilities in second-hand prices. He explains that price volatilities in different dry bulk classes have an asymmetric response to outside shocks but are positively related to the size of the vessel. This is because larger vessels are less flexible than smaller ones in finding trading routes and in choice of cargo, and hence smaller vessels can adapt more easily to unexpected changes.

Chen and Wang (2004) applied Nelson’s EGARCH model to investigate the leverage effect in the international bulk shipping market. They concluded that the phenomenon of asymmetric impact between past innovations and current volatility seems to be an inherent attribute of this market. Jing *et al*. (2008) have investigated volatility in the dry bulk daily freight rates return of Capesize, Panamax and Handysize vessels. They divided the sample period into two, and their GARCH results show that the shocks will not decrease, but have a tendency to strengthen for all the series, while further external shocks to the market have a different magnitude of influence on volatility in different types of vessels owing to their distinct flexibility. Their EGARCH results show that the asymmetric characters are distinct for different vessel size segments and different market conditions.

3.2 Volatility models

3.2.1 Historical Volatility

Let us assume that ε_t is the innovation in mean for the relevant index log price changes. To estimate the volatility at time t over the last N days where N is the forecast period we have:

$$V_{H,t} = \left[\left(\frac{1}{N}\right)\sum_{i=0}^{N-1}\varepsilon_{t-i}^2\right]^{1/2} \tag{3.1}$$

This is actually an N day simple moving average (MA) volatility where the historical volatility is assumed to be constant over the estimation and the forecast periods. To involve long run or unconditional volatility using all previous returns available at time t we have many variations on the simple MA volatility model (Fama, 1970).

3.2.2 ARCH (q)

ARCH modelling is the dominant statistical technique employed in the analysis of time-varying volatility. In ARCH models volatility is a deterministic function of historical returns. The original ARCH (q) formulation proposed by Engle (1982) models conditional variance as a linear function of first q past squared innovations:

$$\sigma_t^2 = c + \sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2 \tag{3.2}$$

This model allows today's conditional variance to be substantially affected by the large square error term associated with a major market move in any of the previous q periods. It thus captures the conditional heteroskedasticity of financial returns and offers an explanation of the persistence of volatility.

3.2.3 GARCH (p, q)

GARCH (p, q) specification generalizes the model by allowing the current conditional variance to depend on first p past conditional variance as well as on q past squared innovations. That is,

$$\sigma_t^2 = K + \sum_{i=1}^{p} \alpha_i \sigma_{t-i}^2 + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2 \qquad (3.3)$$

where K denotes long-run volatility.

GARCH	*Generalized Autoregressive Conditional Heteroskedasticity*
Autoregressive	Mechanism that incorporates past innovations into present.
Conditional	Means variance has dependence on the past.
Heteroskedasticity	Means time-varying variance or volatility.

The key insight of GARCH models lies in the distinction they make between the conditional and unconditional variances of the innovations process ε_t. By accounting for the information in the lags of the conditional variance in addition to the information in the lagged ($t - i$) terms, the GARCH model reduces the number of parameters required. In most cases, one lag for each variable is sufficient. The GARCH (1,1) model is given by:

$$\sigma_t^2 = k + \alpha_1 \sigma_{t-1}^2 + \beta_1 \varepsilon_{t-1}^2 \qquad (3.4)$$

It can successfully capture thick tailed returns and volatility clustering, which are characteristics of freight rates.

3.2.4 EGARCH $(\boldsymbol{p},\boldsymbol{q})$

The EGARCH model introduced by Nelson (1991) builds in a directional effect of price moves on conditional variance. Large price declines, for instance, may have a larger impact on volatility than large price increases. The EGARCH (p,q) model – with student's-t distribution with the degree of freedom more than 2 – for the conditional variance of innovations with leverage terms and an explicit probability distribution assumption is:

$$\sigma_t^2 = K + \sum_{j=1}^{p} \beta_i \, log\, \sigma_{t-i}^2 + \sum_{j=1}^{q} \alpha_j \left[\frac{|\varepsilon_{t-j}|}{\sigma_{t-j}} - E\left\{\frac{|\varepsilon_{t-j}|}{|\sigma_{t-j}|}\right\}\right] + \sum_{j=1}^{q} L_j \left(\frac{\varepsilon_{t-j}}{\sigma_{t-j}}\right) \qquad (3.5)$$

$$E\{|z_{t-j}|\} = E\left\{\frac{|\varepsilon_{t-j}|}{\sigma_{t-j}}\right\} = \sqrt{\frac{\nu-2}{2}} \frac{\Gamma\left(\frac{\nu-1}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)} \qquad (3.6)$$

The key insight of GARCH models lies in the distinction they make between the conditional and unconditional variances of the innovations process ε_t.

3.2.5 GJR $(\boldsymbol{p},\boldsymbol{q})$

Glosten *et al.* (1993) aim to capture the possible asymmetric impact of shocks with different signs on volatility. The GJR (p,q) model for conditional variance is an extension of an equivalent GARCH (p,q) model with zero leverage terms. Thus, the initial parameters for the GJR model should be identical to those for the GARCH models. The difference is the additional assumption with all leverage terms being zero:

$$\sigma_t^2 = K + \sum_{i=1}^{p} \alpha_i \sigma_{t-i}^2 + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} L_j S_{t-j} \varepsilon_{t-j}^2 \qquad (3.7)$$

EGARCH and GJR models are asymmetric models that capture the leverage effect, or negative correlation, between asset returns and volatility. Different news, shocks or innovations have a different effect on the pattern of the volatility; the impact of positive shocks is always different from that of negative shocks. This concept is referred to as leverage and is discussed in section 3.11. The reason for applying EGARCH and GJR is that the GARCH models allow the lagged innovations to have a asymmetric effect on the time-varying variance, and when leverage exists the GARCH models do not make a correct estimation of the model. Both models include leverage terms that explicitly take into account the sign and magnitude of the innovation noise term. Although both models are designed to capture the leverage effect, they differ in their approach. Alizadeh and Nomikos (2007a) apply an augmented EGARCH model to test the relationship between the shape of the term structure and the volatility of freight rates; they conclude that a non-linear relation exists between volatility of freight rates and the slope of the forward curve in the form of cubic function.

3.2.6 Regime switching models

Markov's switching model has been applied in various fields, the most important being the analysis of business cycles. This type of GARCH model shows during which periods the behaviour of the market could be different owing to the shape of supply and demand (see section 1.9 for more information). Also, the switching model, as its name suggests, adapts the volatility model by switching the mean and variance between different models. In shipping literature this approach is employed by Alizadeh and Nomikos (2004) and by Alizadeh *et al.* (2008).

3.3 Data and descriptive statistics

We use three different freight rate indexes to analyse the fluctuations in dry bulk shipping sub-markets. Figure 3.1 presents the pattern of prices for the three indexes. The data contain the daily observation series from 14 January 2000 to 14 January 2010. The three indexes are the Baltic Dry Index (BDI), the Baltic Panamax Index (BPI) and the Baltic Capesize Index (BCI). The BDI is widely accepted as a leading economic indicator because it predicts future economic activity (Willie, 2008). It is not a specific measure of a size, but a weighted average of the several freight rates (see Table 3.2 for more information). The Capesize index reflects the Capesize vessel market and is calculated from the weighted average weights on major routes (7 spot charter and 4 time charter routes) as assessed by a panel of ship brokers. The Panamax index, also a daily index, reflects the Panamax market and is calculated from the weighted average on major routes: three spot charter routes and four time charter routes. The plotting of the data does not show any seasonality effect or any specific trend. We are interested in return series, and GARCH models assume return series; we differentiate the series once to get the return. The return series in Figure 3.2 shows some extreme volatility clustering after the year 2008.

Table 3.1 Description of BPI and BCI ship classes

Freight Indexes	*Baltic Panamax Index (BPI)*	*Baltic Capesize Index (BCI)*
Dead weight tonne	60,000–80,000	100,000+
% of world fleet	19%	10%

Table 3.2 Description of the BDI calculation

Ship classification	*Capesize*	*Panamax*	*Supermax*	*Handysize*
Dead weight tonne	100,000+	60000–80000	45000–59000	15000–35000
% of world fleet	10%	19%	37%	34%
% of BDI	62%	20%	18%	18%

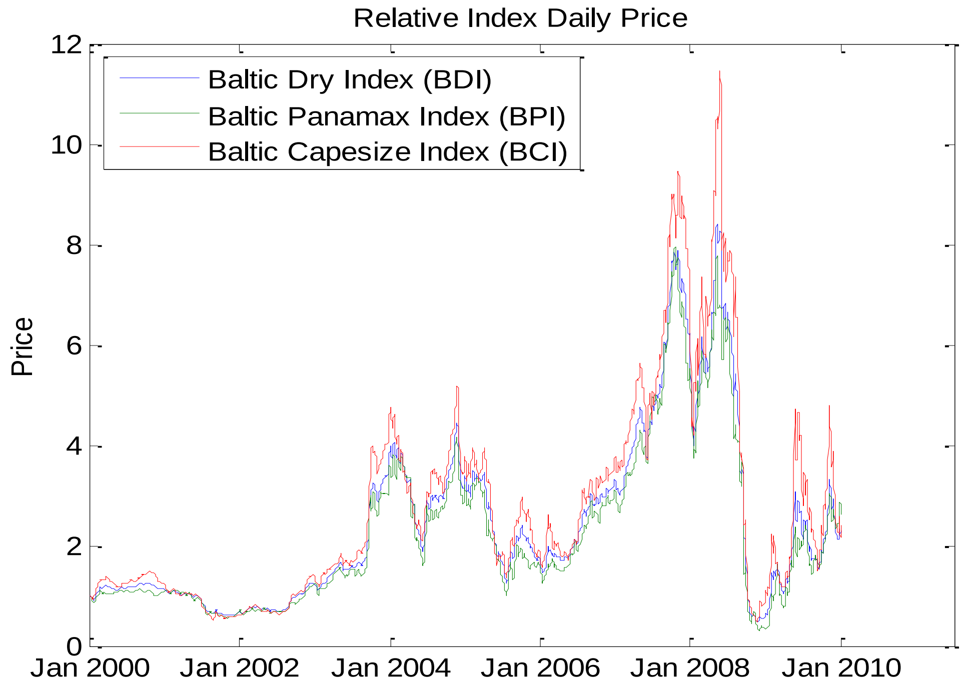


Figure 3.1 Freight rates indexes

Figure 3.2 is the logarithmic return and shows that the BCI has the highest positive daily spikes and negative daily spikes. The business and operation of Capesize vessels, because of their bigger size, are relatively more limited than those of Panamax vessels and the cost of running these vessels is greater than that of running Panamaxes. The demand for shipping is determined by supply and demand and is tight and inelastic; therefore, a small marginal increase in demand can raise the index very rapidly and a marginal decrease can lead to the rapid fall of the index. Because Capesizes have fewer options in choosing routes and cargoes they are more vulnerable, and this could be the reason for the higher spikes.

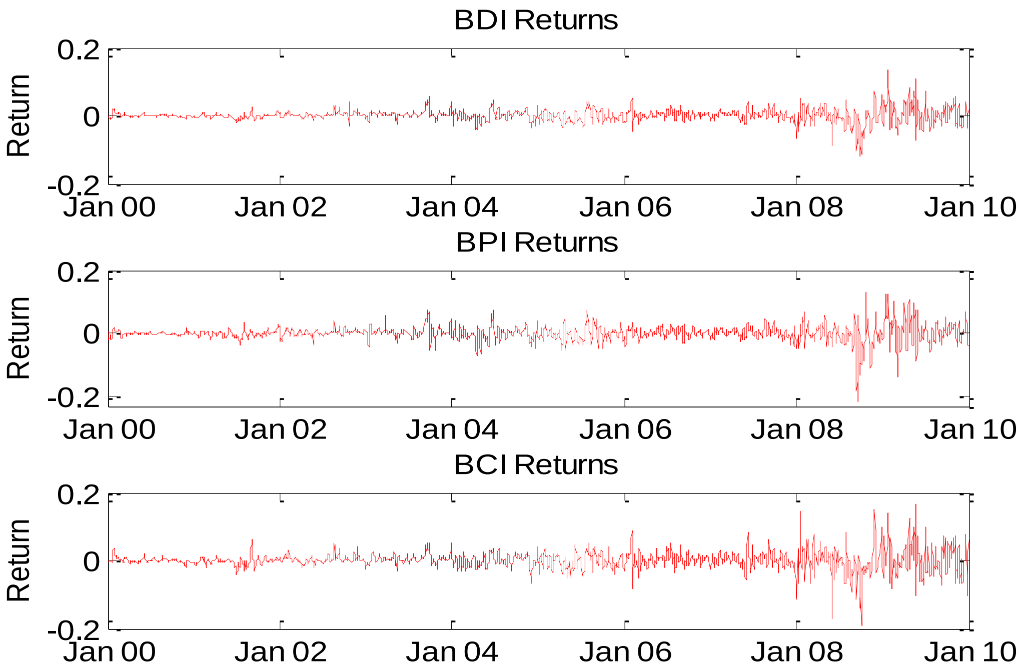


Figure 3.2 BDI, BPI (Panamax) and BCI (Capesize) returns

The descriptive statistics of returns are shown in Table 3.3. The data look highly non-normal, with a very high kurtosis. A normal distribution, which is the basis of many econometric models, has a symmetrical bell shape with a coefficient of kurtosis of 3. The descriptive statistics show that the greatest gain and loss in BDI is 13% and -11%. In BPI it is 12% and -2%, and in BCI 16% and -19%. The median of BPI and BCI is zero, which suggests that the volatility of these indexes is usually steady. The median of BDI is 0.00025, which signifies a high probability of the BDI being steady. The 99%, 95% and 90% daily Value at Risk (VaR) is the 1st, 5th and 10th percentage level of the returns. Value at Risk is mathematically the quantile of the distribution of a given portfolio or a single return series during a specific holding period. This holding period and the confidence interval may, however, vary according to the applications, but mostly it means a one-day holding period and a confidence level of 95%. Here, there is a 10% chance that the BDI will drop by 1.6% or more in one day. But there is a 1% chance that the BDI will drop by 5% in one day or more. There is a 1% chance that the BCI will drop by 6.9% or more in one day. The VaR will be discussed in section 3.12.

Table 3.3 Panel of descriptive statistics

	BDI	BPI	BCI
Max	0.1366	0.1283	0.1650
Min	-0.1195	-0.2162	-0.1921
Mean	0.000319	0.000368	0.000336
Mean Annual	0.07975	0.092	0.084
Standard Deviation	0.01735	0.0227	0.0240
Stan. Dev. Annual	4.3375	5.675	6
Variance	0.000301	0.000517	0.000580
Variance Annual	0.075	0.129	0.145
Median	0.000255	0	0
Skewness	-0.07066	-0.60090	-0.09242
Kurtosis	12.4676	14.4282	11.7605
VaR 90%[11]	-1.6741%	-2.1393%	-2.3211%
VaR 95%	-2.5605%	-3.3020%	-3.6557%
VaR 99%	-5.0183%	-6.1046%	-6.8998%
Maximum Loss	11.95%	21.62%	19.21%
Maximum gain	13.65%	12.83%	16.50%

The Maximum Loss is the percentage of the minimum return and the Maximum Gain is the percentage of the maximum return. These two refer to the maximum percentage that the investor may have lost or gained on his investment during the one-day period. The standard deviation is higher in Capesize vessels. The most important problem in the descriptive statistics is the very high positive kurtosis. Kurtosis describes trends in charts. Kurtosis risk is commonly referred to as fat-tail risk. The fat tail describes how there are more observations at the extremes than the tails of the normal distribution suggest: thus the tails are fatter. A high kurtosis presents a chart with fat tails and a low, even distribution, whereas a low kurtosis presents a chart with skinny tails and a

[11] The MATLAB code for VaR = 100 * quantile (series, [0.10 0.05 0.01]').

distribution concentrated towards the mean. High kurtosis means that some of the VaR models, such as delta normal, cannot be applied to these data. Although GARCH models have been widely used to model the volatility and VaR, they suffer from a serious limitation. GARCH models often fail to capture fully the fat tails observed in freight rate return series. Heteroskedasticity explains some, but not all, the fat-tail behaviour. Kurtosis and skewness are both higher in BPI. The three indexes are all negatively skewed. To compensate for this limitation, fat-tailed distributions such as student's t are applied to GARCH modelling. The negative values of skewness suggest that the left tails are highly extreme. Freight rate, like the other time series, exhibits volatility clustering or persistence; large changes tend to follow large changes and small changes tend to follow small. Volatility clustering suggests a time series in which successive disturbances are uncorrelated but serially dependent. Volatility clustering, which is a type of heteroskedasticity, accounts for some of the excess kurtosis.

3.3.1 MATLAB code related to Figure 3.3

We have written a MATLAB code in order to assess the distribution of data. Figure 3.3 presents the distribution of sample means together with the fitted normal distribution. The black line represents the probability density function for the normal distribution and the blue line the probability density function of the t distribution fitted to the data.

```
Copyright 2011 Kasra Pourkermani
Figure
subplot(3,1,1)
delta = 0.007;
bins = [-0.2:delta:0.15];
h = bar(bins,histc(dryret,bins)/(2609 * delta),'histc');
title ('BDI Returns')
means=dryret
[muhat,sigmahat,muci,sigmaci] = normfit(dryret)
numbins = 50;
hold on
[bincounts,binpositions] = hist(means,numbins);
binwidth = binpositions(2) - binpositions(1);
histarea = binwidth*sum(bincounts);
x = binpositions(1):0.001:binpositions(end);
y = normpdf(x,muhat,sigmahat);
z = tpdf(x*100,10)*97
plot(x,z,'-',x,y,'k','LineWidth',2)
h = findobj(gca,'Type','patch');
set(h,'FaceColor','r','EdgeColor','k')
legend('Density','t','Gaussian',...'Location','NorthEast')
```

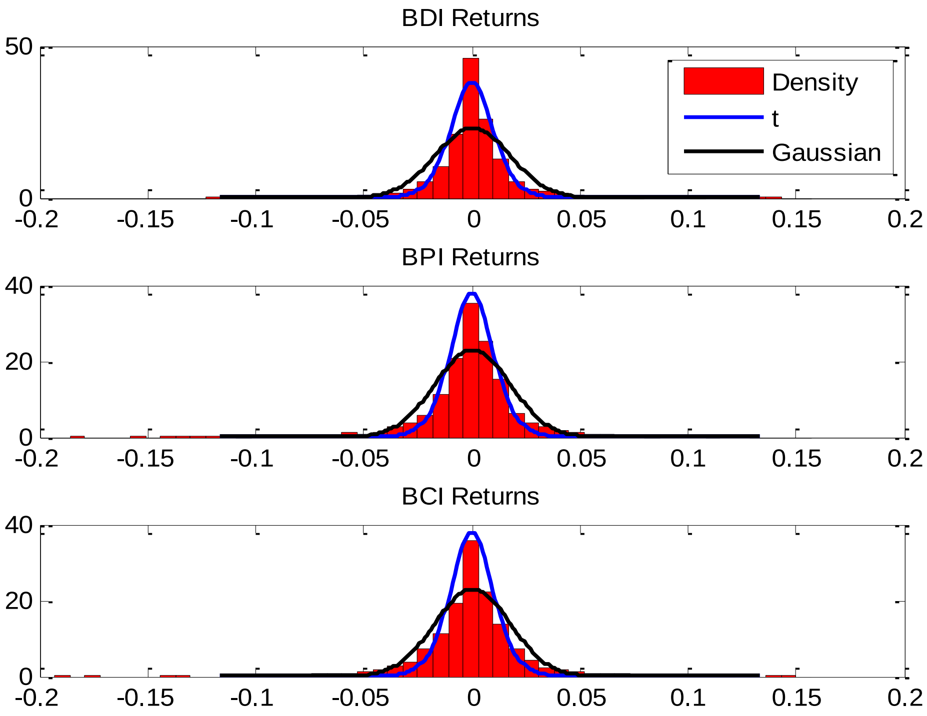


Figure 3.3 Indexes density and distribution type

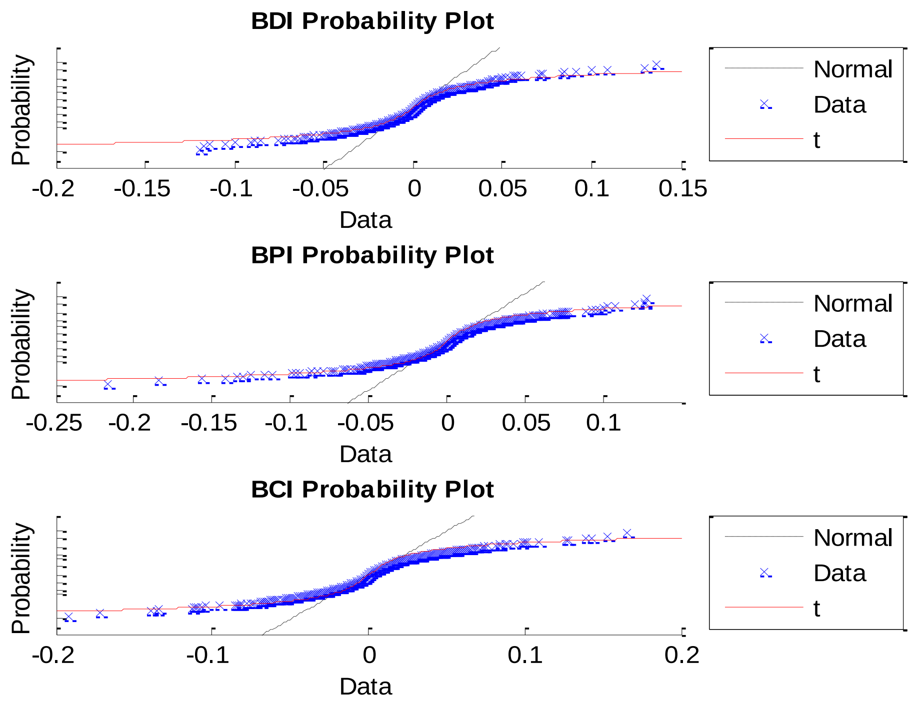


Figure 3.4 Paretotails function

From Figure 3.3 it is clear that the data fit more to the student's-t distribution, we also use the Paretotails function to further test the distribution type. Usually there is less data available to fit the tail of the distribution, and using this function we can better see how well the data can be fitted to the t-distribution. The horizontal line in Figure 3.4 represents the data. The Paretotails function fits normal and student's-t distributions by piecing together the empirical distribution in the centre of the sample with smooth generalized Pareto distributions (GPDs) in the tails. The output is an object of the Paretotails class; it creates an object defining a distribution consisting of the empirical distribution of X in the centre, and Pareto distributions in the tails. X is a real-valued vector of data values whose extreme observations are fitted to generalized Pareto distributions (GPD). We can now conclude that the indexes are fitted to student's-t distribution.

3.4 Sample autocorrelation of returns

The GARCH method assumes the observations to be approximately independent and identically distributed. However, this assumption does not hold with real data and most financial return series exhibit some degree of autocorrelation and, more importantly, heteroskedasticity. We use the sample autocorrelation function (ACF) to reveal serial correlation. The ACF of squared returns illustrates the degree of persistence in variance and implies that GARCH modelling may significantly condition the data. The ACF plays an important role in modelling the dependencies among observations. It describes the evolution of r_t over time. ACF indicates how long and how strongly a shock ε_t impacts the values of r_t. We now examine the ACF of the returns and squared returns, assuming all autocorrelations are zero beyond lag zero.

Figure 3.5 shows the ACF of the returns and the upper and lower standard deviation confidence bounds. As preliminary identification tools, the ACF and PACF provide some indication of the broad correlation characteristics of the returns and squared returns. There is a strong indication that we need to use correlation structure in the conditional mean. The ACF shows significant correlation and persistence in the return series. The BPI has a lower degree of persistence, which means that after a shock it takes less time for it to return to its mean. The ACF of the squared returns also indicates significant correlation and persistence in the second-order moments, so not only are the returns significantly correlated but the variance process is also significantly correlated and persistent. The correlation in variance process may suggest that the data are fit for ARCH modelling. The ACF shown in this figure appears to die out slowly, indicating the possibility that the variance process is close to being non-stationary, and may suggest that the mixed autoregressive and moving average (ARMA) model with order greater than one is a fit model to choose. The BPI and BCI returns both follow the same ACF format.

The Partial Auto-Correlation Function (PACF) is a tool for identifying the properties of an ARMA process, and can be useful is identifying the AR process. In all cases the PACF becomes zero after the second lag; therefore, the AR (2) model might be more appropriate. However, in practice the sample autocorrelation and partial autocorrelation functions are random variables and developing the model on the basis of these plots is not possible. Therefore, we use information-based criteria to find the best model.

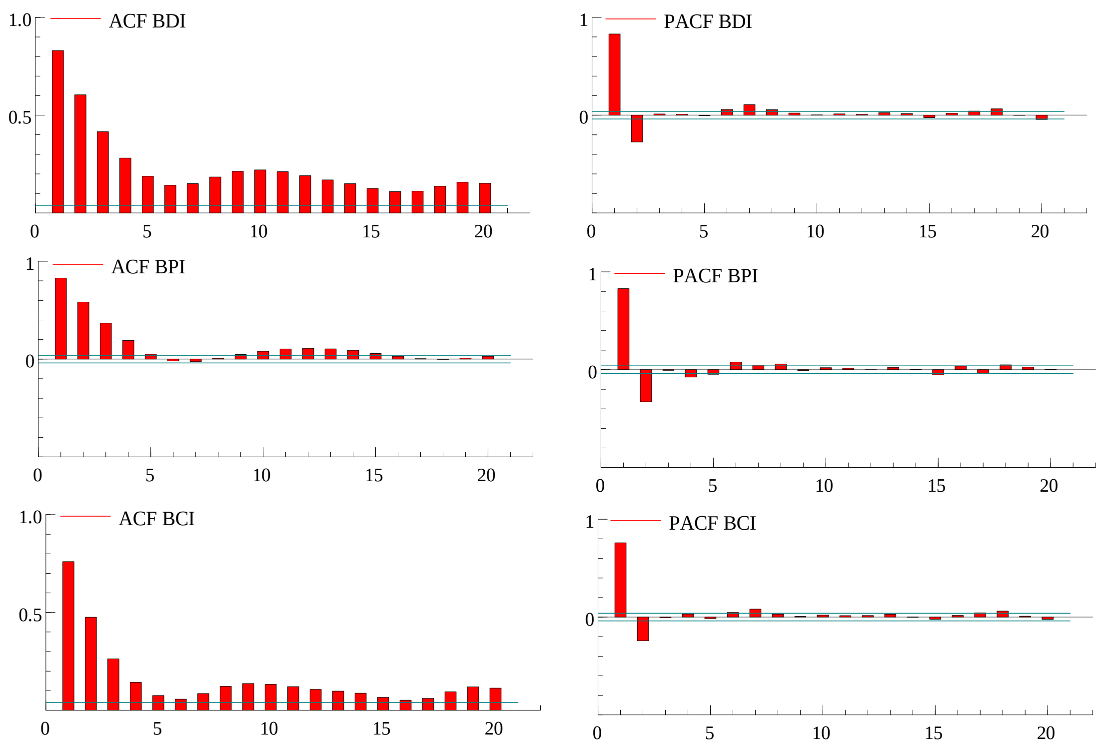


Figure 3.5 Plots of ACF and PACF for returns

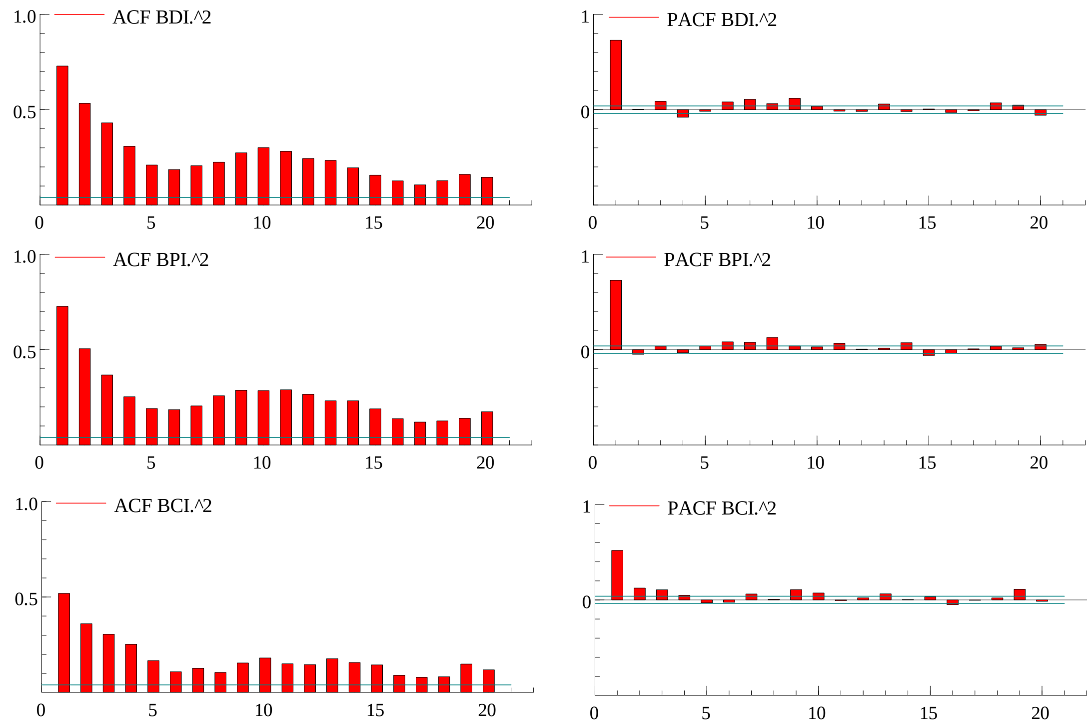


Figure 3.6 Plots of ACF and PACF for squared returns

3.5 Quantifying the correlation

A common assumption when modelling time series is that the forecast errors (innovations) are zero means random disturbances that are uncorrelated from one period to the next. Although successive innovations are uncorrelated, they are not independent. In fact, an explicit generating mechanism for an innovations process is

$$\varepsilon_t = \sigma_t z_t \tag{3.8}$$

where σ_t is the conditional deviation and z_t is a standardized, independent, identically distributed (*i.i.d*) random draw from a specified probability distribution. In this section we examine the indexes for the Engle ARCH test for the autocorrelated errors. These tests are most often used as a post-estimation test applied to fitted innovations. Here, we use it as part of the pre-fit analysis. The null hypothesis is that time series is a random sequence of normal disturbances since there is no ARCH effect. For the ARCH test input we have specified a 5% significance level and it fits up to 10, 15, 20 lags for the autocorrelation function. The test shows significant evidence in support of heteroskedasticity. It confirms the persistence characterises in the variance of the innovations and the presence of autocorrelated conditional heteroskedasticity in the innovations of all series. Hence the models of the ARCH family can be used to investigate volatility characteristics. The panels of results are presented in Table 3.4. The autocorrelation test with Ljung-Box-Pierce Q-test indicates that the p-value of every LBQ of each step is (0), which rejects the null hypothesis of non-correlation, and the series all demonstrate great autocorrelation. The Jarque-Bera test rejects the hypothesis of normality (skewness = 0 or kurtosis = 3), so these time series have the typical features (fat tail and spiked peak) of stock returns. These features show that the volatility of the indexes is concentrated around the median. All these features are almost similar to the stock price returns.

We also check whether the data are stationary by applying the ADF unit root test, finding that it rejects the null hypothesis of the unit root and that all the series are stationary.

Table 3.4 Panel of results

Ljung-Box-Pierce Q-test, null hypothesis of no serial correlation Test statistics			
Lags	10	15	20
BDI	3952.1	4339.9	4579.6
BDI. ^2	3772.2	4459.5	4698.9
BPI	3164.1	3164.1	3164.1
BPI. ^2	3476.0	3476.0	3476.0
BCI	2509.6	2509.6	2509.6
BCI. ^2	1776.7	1776.7	1776.7
Engle's ARCH test, null hypothesis of no ARCH effects exist Test statistics			
BDI	1445.2	1447.6	1458.2
BPI	1421.8	1435.5	1439.8
BCI	797.94	806.67	833.90
Jarque-Bera test H=1 p-Value=0			
BDI	3952.1	4339.95	4579.6
BDI. ^2	3772.2	4459.5	4698.9
BPI	3164.1	3282.4	3287.3
BPI. ^2	3476.0	4269.0	4531.4
BCI	2509.6	2633.6	2744.7
BCI. ^2	1776.7	2097.1	2247.3
ADF test H=1 , critical value = -1.941, p-values of test stat= 0.001, significance level=0.05			
	BDI	BPI	BCI
Test statistics	-15.51	-15.55	-18.67

3.6 Basic GARCH modelling

For modelling and investigating the persistence characteristics of the variance of the innovations we define a GARCH (1,1)–ARMA (1,1) model and estimate the parameters by fitting it to the data. GARCH models are consistent with various forms of efficient market theory, which states that observed past returns cannot improve the forecasts of future returns, and that GARCH innovations are serially uncorrelated. Equation 3.9 is the general ARMA for conditional mean and applies to all variance models with autoregressive coefficients θ, moving average coefficients $\emptyset$, innovations ε_t and returns y_t. The ARMA (p, q) consists of an AR part of order p and an MA part of order q:

$$y_t = \theta_1 y_{t-i} + \cdots + \theta_p y_{t-p} + \varepsilon_t + \emptyset_1 \varepsilon_{t-1} + \cdots + \emptyset_q \varepsilon_{t-q} \qquad (3.9)$$

GARCH models generalized the earlier ARCH models of Engle (1982) to include autoregressive (AR) as well as moving average (MA) terms. GARCH models are successful in equity markets since we can find significant GARCH effects in these markets. The limitation of GARCH models is that they operate best under relatively stable market conditions. Equation 3.10 is the GARCH (1,1) with normally distributed innovations. The next-period forecast of variance is a mixture of last-period forecast and last-period square return:

$$\sigma_t^2 = k + \alpha_1 \sigma_{t-1}^2 + \beta_1 \varepsilon_{t-1}^2 \qquad (3.10)$$

This an extension of the ARCH (1) model, $\sigma_t^2 = k + \alpha_1 \varepsilon_{t-1}^2$, developed by Engle (1982). This is called ARCH because it is autoregressive in squared returns. Next-period volatility is also conditional on information for this period; heteroskedasticity means non-constant volatility. To compensate for the fat tails in the indexes, the student's-t distribution is applied.

The results of applying the GARCH model are shown in Table 3.5. The GARCH or (α) value shows the intensity of outside shocks on market volatilities. A higher value indicates a more intense response to changes in the market and an inclination to disperse even more. The ARCH value which we call (β) indicates the character of the memory of self-volatility. When this value is $(0 < \beta < 1)$, the greater value indicates that the volatility decreases slowly and lasts longer. The persistence of volatility is measured by the sum of $\beta + \alpha$. In the initial model (the results are different in the amended model discussed in section 3.7) this value is equal to unity (= 1) so there is a unit root in conditional variance. The more this sum approaches unity, the greater is the persistence of shocks to volatility; if this value becomes more than unity, the GARCH process is non-stationary and the shocks will not decrease but have a tendency to strengthen. The value of (α) is 0.8336, 0.8782, 0.8169 for BDI, BPI and BCI respectively, which means that the BPI response to the outside shock is more intense between the three indexes. However, in the amended model in section 3.7 the (α) for BCI is higher than BPI. If we compare the BPI and BCI, which represent two specific size classes of Panamax and Capesize vessels, we can argue that Capesize vessels are less flexible in terms of their trade patterns and that their business is limited by their waterlines, routes and cargoes, whereas Panamax vessels can change their route and cargo more easily than Capesizes. Therefore, the value of (α) should be smaller in Panamax vessels but in fact it is bigger than in Capesize. Panamax has the smallest (β) value, so after a shock it comes back to its mean more quickly than other series. The model for the three indexes with a simple constant mean model with normally distributed GARCH (1,1) innovations is:

$$y(BDI)_t = 0.000044137 + 0.82563\, y_{t-1} + 0.18827\, \varepsilon_{t-1} \tag{3.11}$$
$$\sigma(BDI)_t^2 = 0.0000006 + 0.83363\, \sigma_{t-1}^2 + 0.16637\, \varepsilon_{t-1}^2 \tag{3.12}$$

$$y(BPI)_t = 0.00021454 + 0.77309 y_{t-1} + 0.23741 \varepsilon_{t-1} \tag{3.13}$$
$$\sigma(BPI)_t^2 = 0.00000004 + 0.87824\, \sigma_{t-1}^2 + 0.1217\, \varepsilon_{t-1}^2 \tag{3.14}$$

$$y(BCI)_t = 0.00012265 + 0.78813\, y_{t-1} + 0.16965\, \varepsilon_{t-1} \tag{3.15}$$
$$\sigma(BCI)_t^2 = 0.0000009 + 0.81965\, \sigma_{t-1}^2 + 0.18304\, \varepsilon_{t-1}^2 \tag{3.16}$$

The returns y_t consist of a constant, the last-period autoregressive coefficient, an uncorrelated white noise disturbance ε_t, and the last-period moving average coefficient. The variance σ_t^2 is a constant plus a weighted average of last-period forecast and last-period squared disturbance. Also, the sum of the $\beta + \alpha = 0.83363 + 0.16637 = 1$.

Table 3.5 GARCH results related to the initial model

	Parameters	*Value*	*Standard Error*	*t-statistics*
BDI	C	0.0000	0.0001	0.4175
	AR(1)	0.8256	0.0123	66.858
ARMA (1,1)	MA(1)	0.1882	0.0173	10.882
GARCH (1,1)	K	0.0000	0.0000	13.604
	GARCH(1)	0.8336	0.0030	276.875
	ARCH(1)	0.1663	0.0046	35.8983
BPI	C	0.0002	0.0001	1.2613
	AR(1)	0.7730	0.0142	54.372
ARMA (1,1)	MA(1)	0.2301	0.0213	10.775
GARCH (1,1)	K	0.0000	0.0000	16.089
	GARCH(1)	0.8782	0.0025	350.97
	ARCH(1)	0.1217	0.0054	22.425
BCI	C	0.0001	0.0001	0.9007
	AR(1)	0.7881	0.0128	61.111
ARMA (1,1)	MA(1)	0.1696	0.0220	7.6784
GARCH(2,1)	K	0.0000	0.0000	13.874
	GARCH(1)	0.8169	0.0037	217.97
	ARCH(1)	0.1830	0.0052	34.559

Table 3.6 Comparison of max and min volatility date

	Date	*No*	*Max return*	*Innovations*	*Volatility*
BDI Max	04/02/2009	2362	0.0436	0.0219	0.0123
	05/02/2009	**2363**	**0.1366**	**0.0963**	0.0144
	06/02/2009	2364	0.1295	-0.0014	**0.0414**
BDI Min	09/10/2008	2279	-0.0991	-0.0472	0.0244
	10/10/2008	**2280**	**-0.1195**	**-0.0287**	0.0294
	13/10/2008	2281	-0.1168	-0.0128	**0.0293**
BPI Mac	04/11/2008	2297	0.0253	0.0429	0.0234
	05/11/2008	**2298**	**0.1283**	**0.0986**	0.0266
	06/11/2008	2299	0.0736	-0.0485	**0.0425**
BPI Min	29/9/2008	2271	-0.1565	-0.0006	0.0384
	30/9/2008	**2272**	**-0.2162**	**-0.0953**	0.0360
	01/10/2008	2273	-0.1251	0.0638	**0.0474**
BCI Max	29/5/2009	2446	0.0669	-0.0122	0.0506
	01/06/2009	**2447**	**0.1650**	**0.1142**	0.0460
	02/06/2009	2448	0.0533	-0.0962	**0.0642**
BCI Min	14/10/2008	2282	-0.1104	-0.00005	0.0394
	15/10/2008	**2283**	**-0.1921**	**-0.1315**	0.0356
	16/10/2008	2284	-0.0782	0.0909	**0.0553**

Table 3.6 illustrates the corresponding maximum and minimum return rows in the three indexes. The aim is to ascertain whether maximum and minimum volatility occurs at similar times across the all three indexes. The comparisons show that they do not happen together. However, all the min and max occur between October 2008 and June 2009. We can see that volatility increases after any extreme change in return. Under the ARCH model, if the innovation return α_1 is large the next-period conditional volatility σ_{t-1}^2 will also be large.

3.7 The amended GARCH model

To produce a series of $i.i.d$ observations, we fit a second-order AR and first-order MA model to the conditional mean of the returns. We also fit a more appropriate GARCH model to the conditional variance. The second-order autoregressive model compensates for autocorrelation while the GARCH model compensates for heteroskedasticity. Additionally, the standardized innovations of each index are modelled as a standardized student's-t distribution to compensate for the fat tails often associated with equity returns. The ARMA (R, M) model for the conditional mean is

$$y_t = \theta_1 y_{t-i} + \cdots + \theta_R y_{t-R} + \varepsilon_t + \emptyset_1 \varepsilon_{t-1} + \cdots + \emptyset_M \varepsilon_{t-M} \qquad (3.11)$$

To choose the best model that fits the data, we use the Akaike Information Criterion (AIC). This makes adjustments to the likelihood function to account for the number of parameters, because the models we are comparing do not have the same number of parameters and we cannot compare the maximum value of their likelihood function. If the number of parameters is N, the AIC becomes

$$AIC(N) = 2\,ln(maximum\ likelihood) - 2N \qquad (3.12)$$

In addition to AIC we also use the BIC criterion. This is a more advanced criterion than AIC, which may choose models with too many parameters. In equation 3.14, n is the number of observations. The AIC gives 2 penalty for an extra parameter but BIC gives ln (number of observations) for an extra parameter:

$$BIC(N) = 2\,ln(maximum\ likelihood) - N ln(n) \qquad (3.13)$$

The results are shown in Tables 3.7. The first row lists the parameters of every possible model. For BDI, BPI and BCI, the best models are GARCH(4,1), GARCH(3,1) and GARCH (1,1).

Table 3.7 *Results of the model selection criteria*

parameters		C AR(1) MA(1) K GARCH(1) ARCH(1)	C AR(1) AR(2) MA(1) K GARCH(1) ARCH(1)	C AR(1) AR(2) MA(1) K GARCH(1) GARCH(2) ARCH(1)	C AR(1) AR(2) MA(1) K GARCH(1) GARCH(2) GARCH(3) ARCH(1)	C AR(1) AR(2) MA(1) K GARCH(1) GARCH(2) GARCH(3) GARCH(4) ARCH(1)	C AR(1) AR(2) MA(1) K GARCH(1) GARCH(2) GARCH(3) GARCH(4) GARCH(5) ARCH(1)
series	criterion	ARMA (1,1), GARCH (1,1)	ARMA (2,1), GARCH (1,1)	ARMA (2,1), GARCH (2,1)	ARMA (2,1), GARCH (3,1)	ARMA (2,1), GARCH (4,1)	ARMA (2,1), GARCH (5,1)
BDI	AIC	-19571.794	-19625.736	-19640.784	-19647.700	-19655.999	-19654.426
	BIC	-19530.727	-19578.803	-19587.984	-19589.032	-19591.465	-19584.026
BPI	AIC	-17858.970	-17922.130	-17928.198	-17941.487	-17939.832	-17940.056
	BIC	-17817.903	-17875.196	-17875.397	-17882.820	-17875.298	-17869.655
BCI	AIC	-17338.119	-17376.230	-17374.805	-17374.588	-16099.419	-17396.315
	BIC	-17297.052	-17329.297	-17322.005	-17315.921	-16034.885	-17325.914

The lower part of Table 3.7 shows the results of both model selection criteria. These results are associated with the middle blue line models, and the section above the blue section lists the parameters of every model. For BDI, both model selection criteria select ARMA (2,1)-GARCH (4,1); for BPI, again both criteria select ARMA (2,)-GARCH (3,1). For BCI, AIC selects ARMA (2,1)-GARCH (5,1) and BIC selects ARMA (2,1)- GARCH (1,1). We select the model with the fewest parameters, which is the BIC's selection.

Table 3.8 Results of the selected GARCH model

	Parameters	*Value*	*Standard Error*	*t-statistics*
BDI	C	0.0000	0.0000	0.9517
	AR(1)	1.2905	0.0568	22.719
ARMA (2,1),	AR(2)	-0.4414	0.0483	-9.1248
GARCH(4,1)	MA(1)	-0.2225	0.0642	-3.4619
	K	0.0000	0.0000	5.4150
	GARCH(1)	0.3042	0.0795	3.8264
	GARCH(2)	0.0322	0.0756	0.4261
	GARCH(3)	0.0597	0.0646	0.9231
	GARCH(4)	0.1998	0.0490	4.0784
	ARCH(1)	0.4039	0.0414	9.7417
	DoF	4.2721	0.3050	13.998
BPI	C	0.0000	0.0000	1.0788
	AR(1)	1.3476	0.0497	27.082
ARMA (2,1),	AR(2)	-0.514	0.0407	-12.615
GARCH(3,1)	MA(1)	-0.312	0.0575	-5.4240
	K	0.0000	0.0000	4.3422
	GARCH(1)	0.3929	0.1056	3.7192
	GARCH(2)	0.0000	0.1105	0.0000
	GARCH(3)	0.3131	0.0689	4.5393
	ARCH(1)	0.2938	0.0338	8.6850
	DoF	4.5588	0.30577	14.909
BCI	C	0.0000	0.0000	0.2543
	AR(1)	1.2208	0.0648	18.820
ARMA (2,1),	AR(2)	-0.4060	0.0528	-7.6775
GARCH (1,1)	MA(1)	-0.2081	0.0714	-2.9145
	K	0.00000	0.0000	6.2997
	GARCH(1)	0.7108	0.0165	42.987
	ARCH(1)	0.2891	0.0273	10.566
	DoF	3.9332	0.2665	14.755

Table 3.8 shows the value of the parameters for the selected models. The GARCH coefficient for BDI, BPI and BCI is 0.596, 0.706 and 0.710. The greatest value is for BCI; the larger values of this suggest that volatility decreases slowly and lasts longer. The sum of the ARCH and GARCH coefficients for BDI is 1.000009, and 1 for both BPI and BCI. The sum value of 1 indicate unit root in conditional variance. The more this number approaches unity, the greater is the persistence of the shocks to volatility. A number bigger than unity means the shocks does not decrease and have a tendency to strengthen.

In Figure 3.7 we compare the model innovations and the corresponding conditional standard deviations filtered from the raw returns. The lower graph clearly illustrates the variation in volatility (heteroskedasticity) present in the filtered innovations. These innovations represent the underlying zero-mean, unit-variance, *i.i.d* series.

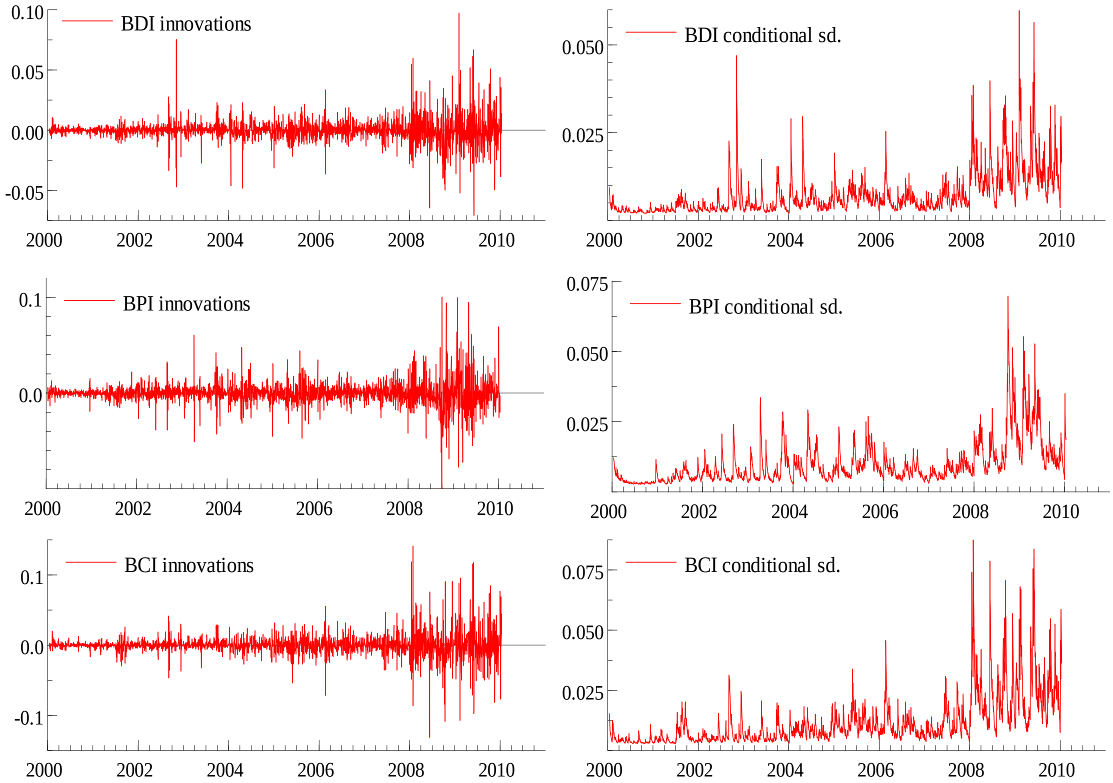
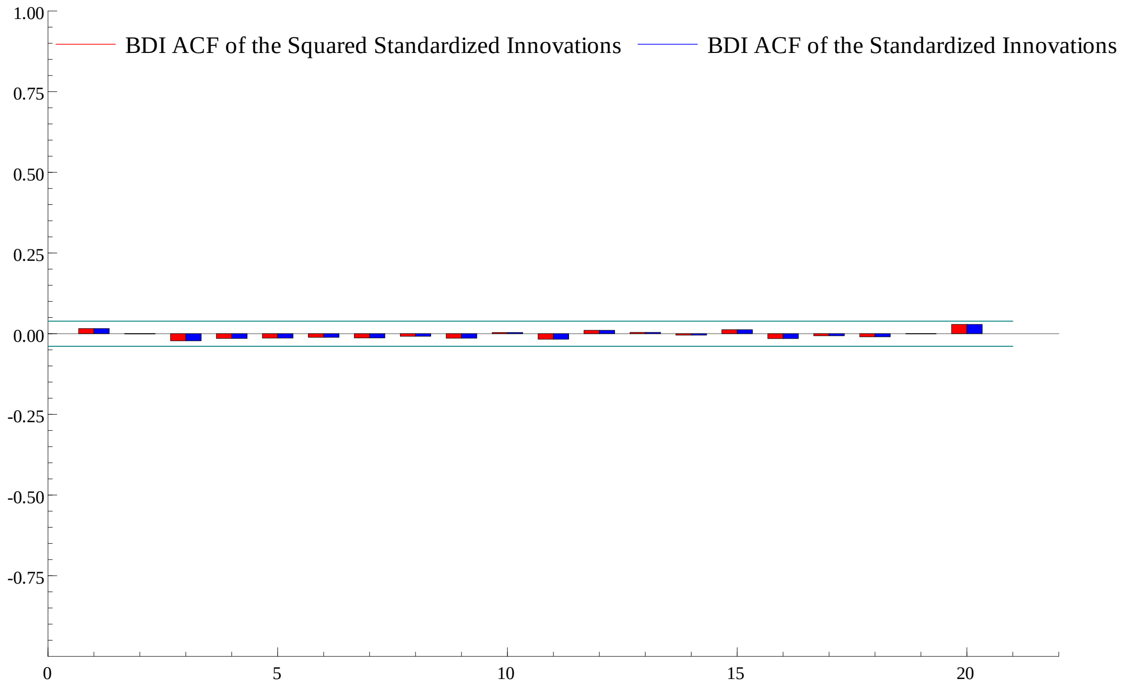
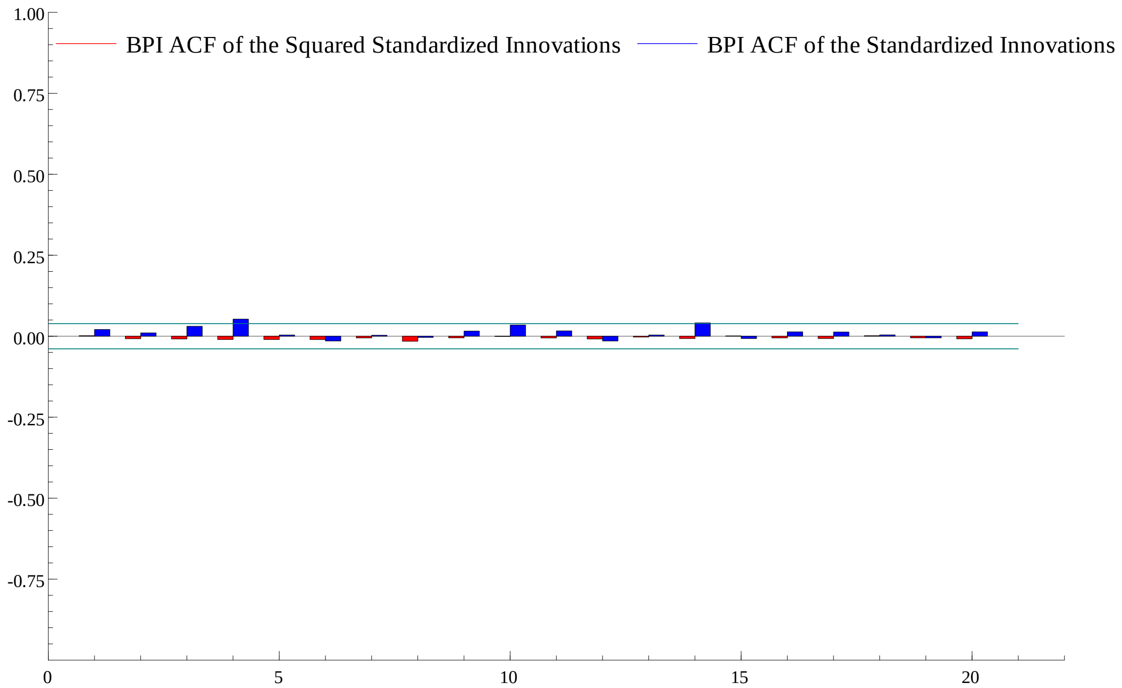


Figure 3.7 Comparison of innovations and conditional standard deviation

3.8 Correlation of the innovations

When a time series is said to have GARCH effect the series is heteroskedastic, meaning that its variance varies with time. We now check whether the variance remains constant.





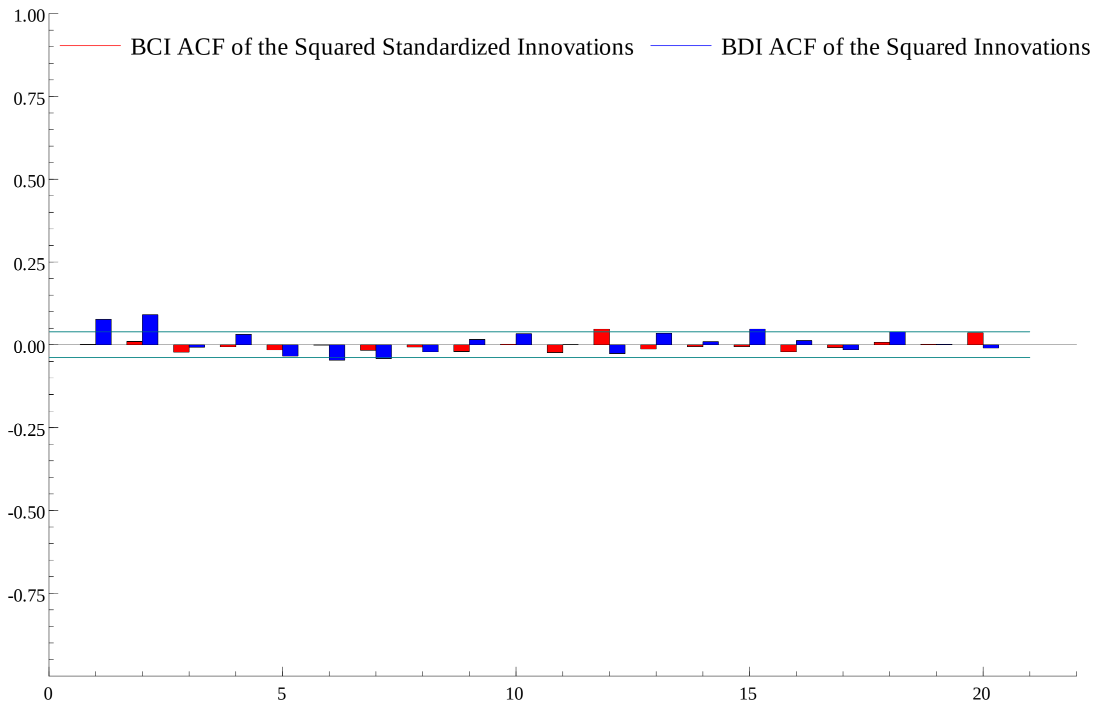


Figure 3.8 ACF of the standardized innovations

Figure 3.8 compares the standardized innovations or volatility-adjusted returns, which is the innovations divided by their conditional standard deviation. All three standardized innovations look similar, with some clustering. They also show no correlation.

3.9 Forecasting with GARCH models

We consider a simple GARCH (1,1) model similar to equation (3.3). The conditional variance is modelled by the past shock ε_{t-1}^2 and its own lagged value σ_{t-1}^2. The GARCH models in essence describe the evolution of the conditional variance of ε_t of the y_t, the volatility of which we are trying to model. This can be described as

$$\sigma^2\left(y_t \middle| y_{t-1}, y_{t-2,\dots}\right) = \sigma^2(\varepsilon_t|\varepsilon_{t-1}, \varepsilon_{t-2}, \dots) \qquad (3.20)$$

GARCH forecasting could be different from that of other forecasting models because the one-step-ahead forecast of σ_t^2 is given by the model itself. σ_{t+1}^2 is the true but unobservable value of the conditional variance at time $t+1$, so we obtain the estimate $\hat{\sigma}^2_{t+1}$of σ^2_{t+1} on the basis of the information that is available until time (t). The one-step-ahead GARCH (p, q) would be

$$\sigma^2_{t+1|t} = \hat{k}^{(t)} + \hat{\alpha}_1^{(t)} \sigma^2_{t-1+1|t} + \hat{\beta}_1^{(t)} \varepsilon^2_{t-1+1|t} \qquad (3.21)$$

where the estimated parameters $\hat{k}, \hat{\alpha}, \hat{\beta}$ and the values of $\sigma^2_{t-1+1|t}$ and $\varepsilon^2_{t-1+1|t}$ are known. To obtain a multi-step-ahead forecast, the previous one-step-ahead equation will be updated by recursive substitution for σ^2_t. According to Rachev *et al.* (2007), the multi-step-ahead forecast for the GARCH (p, q) model can be written as:

$$\sigma^2_{t+m|t} = \hat{k}^{(t)} \left(1 + \sum_{i=1}^{m-2} \left(\hat{\alpha}_1^{(t)} + \hat{\beta}_1^{(t)}\right)^i\right) + \hat{k}^{(t)} + \varepsilon^2_{t-m+m|t} + \hat{\alpha}_1^{(t)} \sigma^2_{t-m+m|t} \qquad (3.22)$$

Multiple steps ahead can be performed by repeated substitution. In practice the steps towards achieving the volatility forecast are: (1) estimating the model and calculating the next *n* period; (2) moving forward by recursive substitution and re-estimating the parameters and generating a new volatility forecast, and repeating this until the end of the sample; and (3) averaging the calculated volatility over each of the prediction dates. The accuracy of the forecast can be measured by appropriate forecast error statistics. Usual statistics are based on the deviation between forecasts and actual values (realizations) such as root mean squared error (RMSE). This is a scale-dependent measure although it is widely used to compare the volatility forecasts of different models.

Evaluating the conditional volatility forecast is more difficult because the true conditional volatility σ_t is unobserved. One possible approach is to find a proxy for the true conditional volatility over the backtesting period. The conditional volatility forecast can then be compared with this proxy to compute forecast errors, which can be evaluated in the usual way (e.g. by using RMSEF). We evaluate the forecast using root mean square forecast error (RMSFE), which is the square root of the average square distance of the average square distance. Where $\sigma^2_{t+1|t}$ is the one-step-ahead forecast given by (3.15) to measure the forecast error, we use the deviation between forecast and realizations (actual values) such as RMSEF. If the $\sigma^2_{t+1|t}$ and $\hat{\sigma}^2_{t+1|t}$ are the forecast volatility at time $t+1$ with the forecast period going from $t+1$ to $t+n$, the RMSEF is[12]

$$RMSEF = \sqrt{\frac{1}{n}\sum_{t+1}^{t+n}\left(\sigma^2_{t+1|t} - \hat{\sigma}^2_{t+1|t}\right)^2} \qquad (3.14)$$

3.9.1 One step ahead forecast with a variety of models

We now forecast the volatility in terms of eight different ARCH specifications for BDI index. The data cover the period 14 January 2000–14 January 2010, and the one-step-ahead forecasting starts from 16 March 2006. We generate 1,000 one-step-ahead forecasts of volatility. The conditional mean is $y_t = C + \varepsilon_t$. The model will be re-estimated every day in a recursive system.

Figure 3.9 illustrates one-step-ahead conditional variance forecast. The ARCH type forecast has a larger magnitude than the other three forecasts; therefore, the scale of the vertical axis, which is the value of volatility, is different from the scales of other forecasts. Between the models EGARCH (1,2) yield the least BIC value at -5.548. The ARCH (1) has the highest BIC value at -5.4535. The model selection criterion values are not completely reported because the different models forecast are evaluated by RMSF.

Table 3.9 One-step-ahead RMSEF for the eight models

ARCH (1)	ARCH (2)	GARCH (1,1)	GARCH (1,2)	EGARCH (1,1)	EGARCH (1,2)	GJR (1,1)	GJR (1,2)
1.260	1.154	1.074	1.089	0.986	0.920	1.054	1.183

[12] The MATLAB code for RMSE = sqrt (sum((data(:)-estimate(:)).^2)/numel(data));

Table 3.19 presents the RMSEF value for all the models. EGARCH (1,2) yields the lowest value between all models and hence is the best forecasting model. Figure 3.10 shows the 60-days, one-day-ahead forecast. We can see that, except for the ARCH models, there is not much visual difference between the other forecasts.

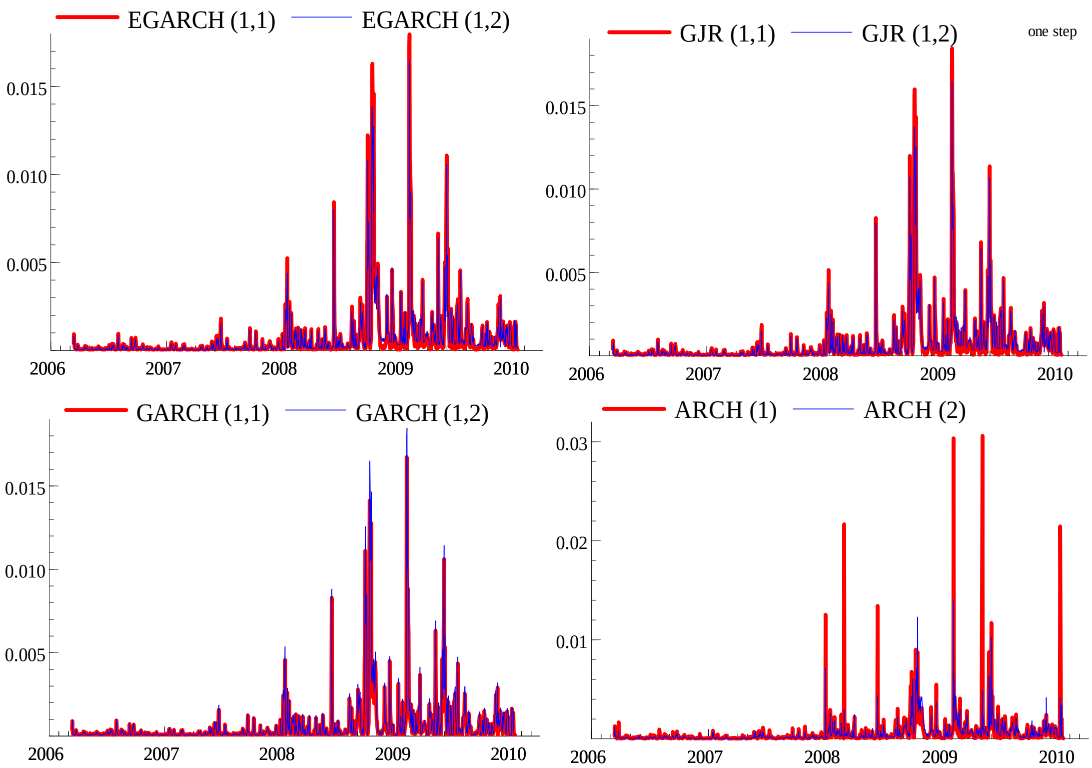


Figure 3.9 One-step-ahead forecast of BDI for 1,000 days

3.9.2 Ten step ahead forecast with a variety of models

We now perform a ten-step-ahead forecast instead of a one-step-ahead forecast with the same models. Figure 3.11 presents this forecast with a 1,000 period forecast. Each value in this figure is the 10th day conditional volatility forecast although this does not present the 1-to-9-step-ahead forecast. The period of forecast is similar to that shown in Figure 3.9. Visually, the EGARCH series forecasts come with much less value and look different from the other models. There is a significant difference between ARCH (1) and (2) forecasts.

Figure 3.12 shows a similar ten-days-ahead forecast over a 30-day period starting from 12 February 2009. For this forecast, GRACH (1,1) yields the lowest BIC at -4.438509, and EGARCH (1,1) has the highest BIC at -4.31631. Therefore, according to the BIC criterion the best model is GARCH (1,1). Table 3.10 presents the RMSEF value for all the models. GARCH (1,1) yields the lowest value of all the models and hence is the best forecasting model.

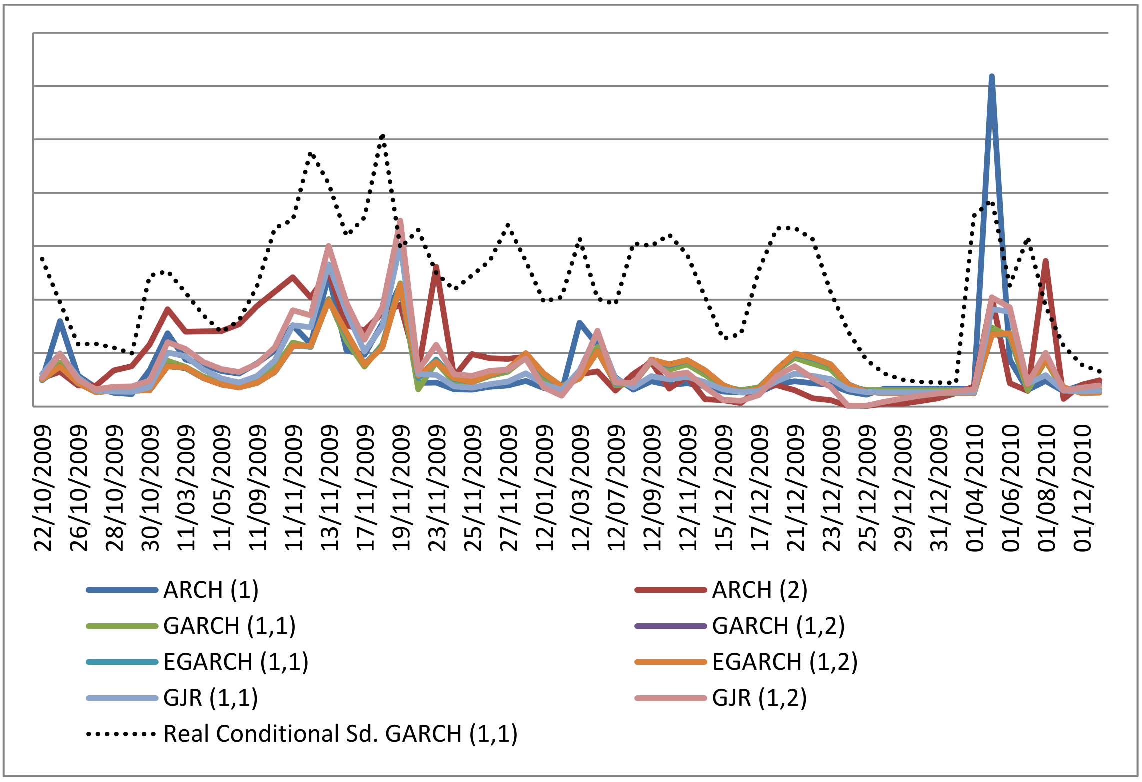


Figure 3.10 One-step-ahead forecast of BDI for 60 days

Table 3.10 Ten-step-ahead RMSEF for the eight models

ARCH (1)	ARCH (2)	GARCH (1,1)	GARCH (1,2)	EGARCH (1,1)	EGARCH (1,2)	GJR (1,1)	GJR (1,2)
3.261	3.128	2.823	3.121	2.969	2.964	3.752	3.433

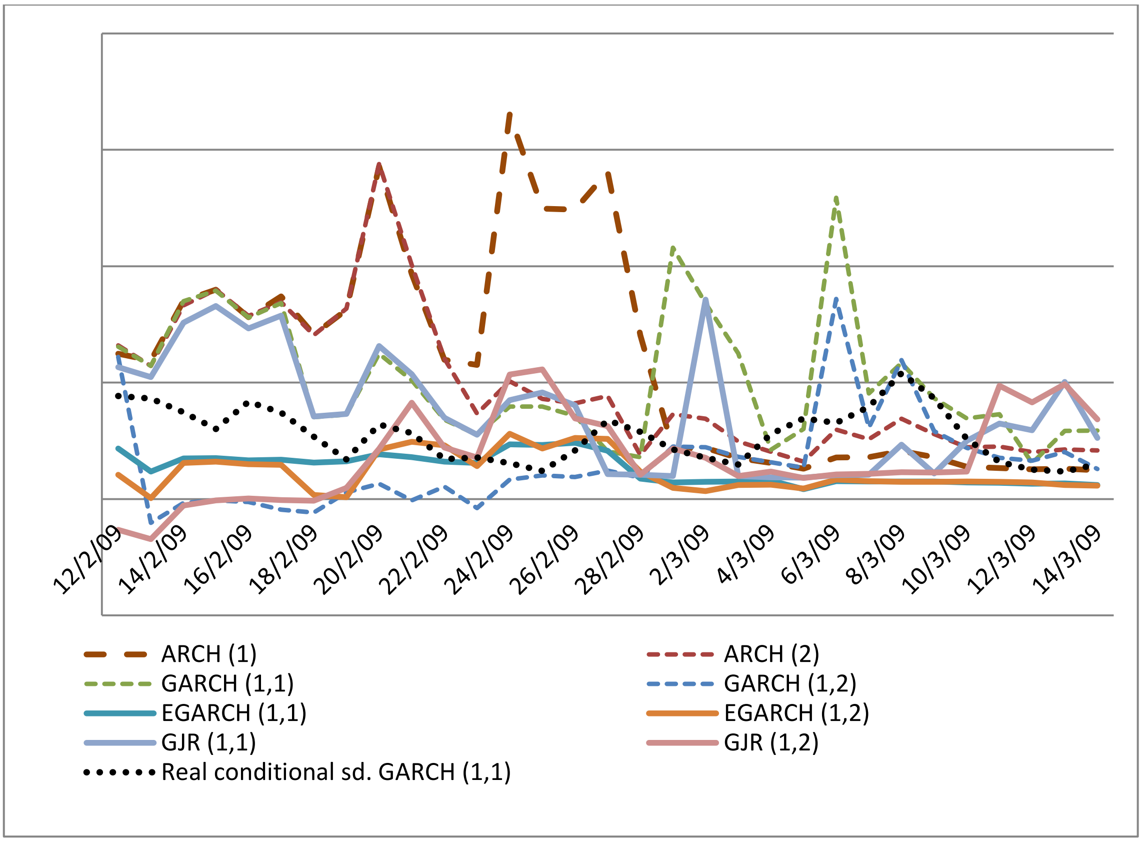


Figure 3.11 Ten-step-ahead forecast of BDI for 60 days

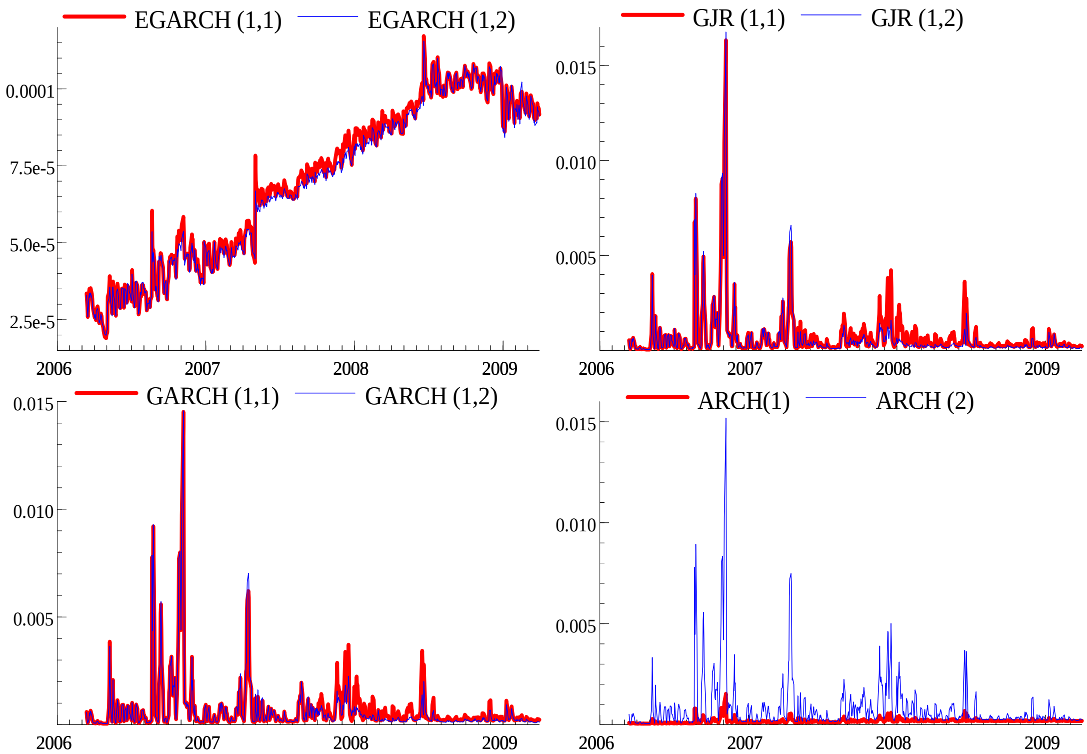


Figure 3.12 Ten-step-ahead forecast of BDI for 1,000 days

3.9.3 Thirty days forecast with amended GARCH

This section's forecast is based on the GARCH specification models for all three indexes selected in section 3.7. The specifications are GARCH(4,1), GARCH(3,1) and GARCH (1,1) respectively for BDI, BPI and BCI, all with conditional mean ARMA (2,1). We will use Monte Carlo simulation in estimating volatility by simulating 3,000 realization or sample pad for the same 30-day period. We then compare the simulated series in Figure 3.13 with the forecast series. The averages for the different simulation realizations are calculated and compared to the results of the forecasting function. Monte Carlo simulation is based on the assumption that prices follow a certain stochastic process. Once the stochastic mathematical process for the underlying asset is determined it can be used to generate many possible paths for the evolution of the asset price via the Monte Carlo simulation. The advantage of this method is that it allows for certain properties of the underlying asset price, such as seasonality and mean reversion, to be considered and incorporated into the simulation exercise. This is quite important, because such dynamics in asset price have a direct impact on the accuracy of the estimated volatility.

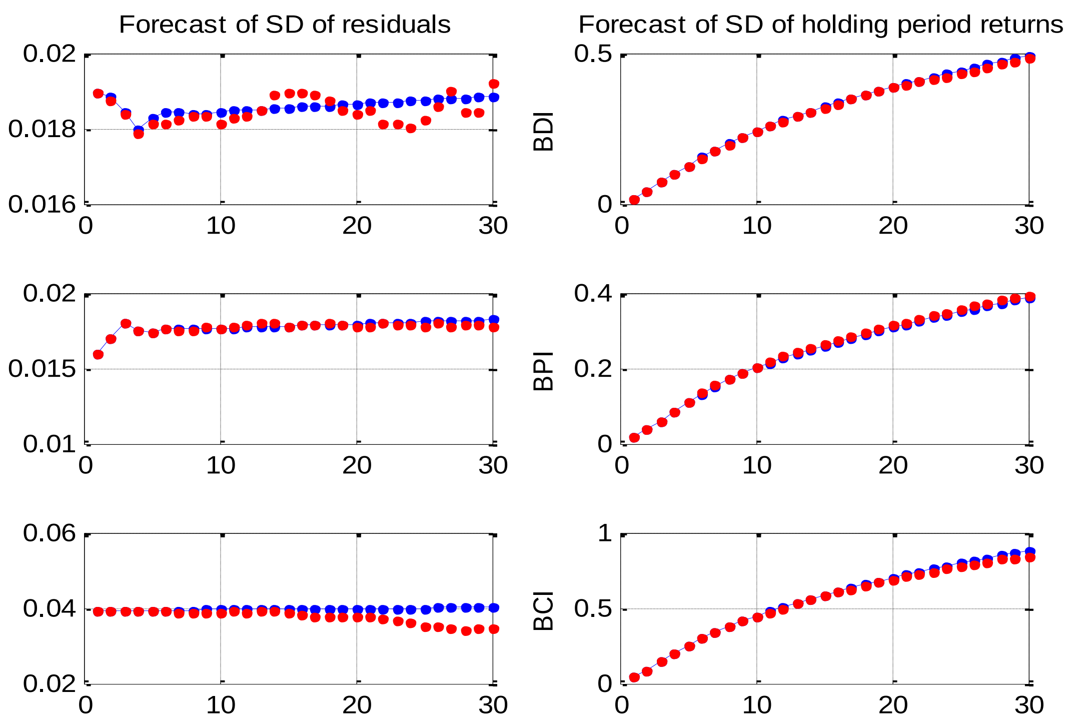


Figure 3.13 Panel of forecasts (blue dots: forecast; red dots: simulation)

The left-hand graphs show the recursive volatility forecast; blue coloured dots represent the forecast results and the red dots the Monte Carlo simulation results. The BCI forecast is steady at 0.04 and is much higher than the others; BDI volatility decreases for the first four days and then increases. The right-hand graphs show the matrix of volatility forecasts of each series over 30-day holding intervals.

3.10 Test of exponential GARCH

EGARCH and GJR models are asymmetric models that capture the leverage effect, or negative correlation, between returns and volatility (see section 3.2 for more explanation). Both models include leverage terms that explicitly take into account the sign and magnitude of the innovation noise term. Although both models are designed to capture the leverage effect, they differ in their approach. The leverage effect results in observed asset returns being negatively correlated with changes in volatility. In certain classes of time series, volatility tends to rise in response to lower than expected returns and fall in response to higher than expected returns; such an effect suggests GARCH models that include an asymmetric response to positive and negative impulses.

To capture the presence of the leverage effect in the freight indexes, we test with simple exponential EGARCH (1,1) and GJR (1,1). In order to choose the better specification we perform AIC and BIC and choose the lowest value. According to Table 3.11, for BDI the EGARCH (1,1) and for BPI and BCI the GJR (1,1) are the best models.

Table 3.11 Comparison of initial model selection criteria

	BDI	*AIC*	*BIC*
BDI	EGARCH(1,1)	-16722.22	-16687.02
	GJR(1,1)	-16715.50	-16680.29
BPI	EGARCH(1,1)	-15147.24	-15112.04
	GJR(1,1)	-15190.95	-15155.75
BCI	EGARCH(1,1)	-15112.04	-15147.24
	GJR(1,1)	-15190.95	-15155.75

Table 3.12 Specifications of the initial models

	Parameters	*Value*	*Standard Error*	*t-statistics*
BDI	C	0.0011	0.0000	12.524
	K	-1.9671	0.1318	-14.914
ARMA (0,0),	GARCH(1)	0.7901	0.0141	55.912
EGARCH(1,1)	ARCH(1)	1.2822	0.0491	26.112
	Leverage(1)	-0.0217	0.0329	-0.660
	DoF	7.5424	0.5562	13.560
BPI	C	0.0010	0.0001	5.8743
	K	0.0000	0.0000	10.275
ARMA (0,0),	GARCH(1)	0.3016	0.0207	14.546
GJR(1,1)	ARCH(1)	0.6710	0.0583	11.505
	Leverage(1)	0.0545	0.0727	0.7498
	DoF	8.4547	0.5967	14.169
BCI	C	0.0003	0.0001	1.8433
	K	0.0000	0.0000	11.396
ARMA (0,0),	GARCH(1)	0.2913	0.0184	15.793
GJR(1,1)	ARCH(1)	0.6911	0.0514	13.441
	Leverage(1)	0.0350	0.0652	0.5377
	DoF	8.1907	0.5479	14.948

Table 3.13 Comparison of model selection criteria

	BDI	*AIC*	*BIC*
BDI	ARMA (2,1), EGARCH(1,1)	-17945.81	-19607.66
	ARMA (2,1), EGARCH(2,1)	-19689.56	-19630.90
BPI	ARMA (2,1), EGARCH(1,1)	-17945.81	-17898.88
	ARMA (2,1), EGARCH(2,1)	-17959.22	-17906.42
BCI	ARMA (2,1), EGARCH(1,1)	-17428.40	-17375.60
	ARMA (2,1), EGARCH(2,1)	-17442.98	-17384.31

The results are shown in Table 3.12. The leverage is positive for BPI and BCI and negative for BDI, but none is statistically significant, which means the non-existence of asymmetric volatility. In the context of asymmetric function the link between current volatility and past innovation shocks is statistically significant for all the three indexes. This means that the effect of the unexpected shocks is distinguished in all three indexes. The persistence of shocks to volatility is statistically significant for all indexes; the BCI has the smallest value, which suggests that the persistence of shocks lasts less than in other series.

We now check the above results with other variations of EGARCH shown in Table 3.13. Table 3.14 presents the specification of the new models. The leverage is positive for BDI and negative for BPI and BCI, but again none is statistically significant, which means there is no evidence of asymmetric volatility.

Table 3.14 Specifications of the amended models

	Parameters	*Value*	*Standard Error*	*t-statistics*
BDI	C	0.0000	0.0000	1.1501
	AR(1)	1.3101	0.0547	23.941
ARMA (2,1),	AR(2)	-0.4624	0.0466	-9.9216
EGARCH(2,1)	MA(1)	-0.2323	0.0622	-3.7336
	K	-0.4145	0.0810	-5.1121
	GARCH(1)	0.6045	0.0771	7.8355
	GARCH(2)	0.3539	0.0759	4.6634
	ARCH(1)	0.6516	0.0503	12.931
	Leverage(1)	0.0222	0.0272	0.8186
	DoF	3.4002	0.2550	13.333
BPI	C	0.0000	0.0000	1.1069
	AR(1)	1.3477	0.0507	26.541
ARMA (2,1),	AR(2)	-0.5156	0.0415	-12.407
EGARCH(2,1)	MA(1)	-0.3127	0.0585	-5.3399
	K	-0.2489	0.0588	-4.2279
	GARCH(1)	0.6565	0.1082	6.0639
	GARCH(2)	0.3172	0.1067	2.9721
	ARCH(1)	0.4405	0.0435	10.114
	Leverage(1)	-0.0247	0.0227	-1.0878
	DoF	3.8888	0.2804	13.868
BCI	C	0.0000	0.0000	0.1882
	AR(1)	1.2212	0.0638	19.135
ARMA (2,1),	AR(2)	-0.4075	0.0522	-7.8017
EGARCH (2,1)	MA(1)	-0.2049	0.0711	-2.8803
	K	-0.3835	0.0729	-5.2567
	GARCH(1)	0.6754	0.0784	8.6141
	GARCH(2)	0.2814	0.0767	3.6661
	ARCH(1)	0.7282	0.0686	10.600
	Leverage(1)	-0.0049	0.0297	-0.1655
	DoF	2.9814	0.2209	13.492

3.11 Value at Risk of individual indexes

Value at Risk (VaR) is a method that calculates the possible losses relating to trading financial and commodity assets over a defined period of time. VaR is very comprehensible, and hence, owing to the growth in trading activities and the volatility of the financial markets, has become a standard risk management tool. It is relevant for investors in the global shipping market because the freight rate can be invested in for making profits and the investor needs to make a correct measurement of the expected risk. VaR predicts the financial loss over a given period with a given probability. The VaR at θ level for a return series is the quantile at $(1-\theta)\times 100\%$. The quantiles are the direct function of variance and hence the ARCH models converts into conditional VaR models. Econometric models of volatility dynamics such as GARCH models yield the VaR estimate, which reflects the current volatility background. However, these methods are based the assumption of conditional normality, which does not hold for our data.

We now assess the VaR of each of the three indexes over a 12-month holding period and compare the simulation-based VaR results of the two models. We use Monte Carlo simulation to estimate the VaR of the returns.

Table 3.15 VaR percentage losses of the two simulation models, 12 months

BDI confidence level	Constant volatility	EGARCH volatility
90%	27.3%	-05%
95%	37.1%	62.0%
98%	48.4%	17.9%
99%	55.8%	30.1%
99.5%	62.8%	47.1%
BPI confidence level	Constant volatility	GJR volatility
90%	36.9%	05.3%
95%	50.2%	18.2%
98%	65.1%	40.0%
99%	74.8%	63.0%
99.5%	83.9%	95.1%
BCI confidence level	Constant volatility	GJR volatility
90%	40.3%	24.5%
95%	54.3%	38.3%
98%	70.4%	62.4%
99%	80.7%	88.6%
99.5%	90.6%	97.8%

The first model simply assumes a constant mean and constant volatility process with conditional student's-t returns. The second model also assumes a constant mean, but allows for time-varying volatility by fitting the series to a GARCH model with conditionally t-distributed returns. Thus, the latter model compensates for asymmetries, or leverage effects, in the equity portfolio as well as the fat tails, or excess kurtosis, often observed in financial data. The choice of GARCH, EGAECH or GJR is purely based on the information criterion, but with constant mean (no ARMA). However, practically speaking, using any EGARCH or other similar models does not make much difference.

For each daily return model we simulate $100{,}000$ paths or trials over a one-year VaR horizon, assuming 252 trading days per annum. The two models are:

$$\sigma_t^2 = k + \alpha_1 \sigma_{t-1}^2 + \beta_1 \varepsilon_{t-1}^2 \qquad (3.15)$$

$$\sigma_t^2 = k \qquad (3.16)$$

Probability distributions are typically defined in terms of the probability density function. However, a number of other probability functions are used in applications. The cumulative distribution function (cdf), or just the distribution function, is the probability that the variable takes a value of less than or equal to *x*. We graph the cumulative distribution function in Figures 3.15, 3.16 and 3.17.

We examine the cumulative distribution function of each simulated model and compare the VaR at various probabilities. Two plots are shown. The first illustrates the entire cdf. The second highlights the lower tail of the distributions, corresponding to the simulated trading losses, and allows a more detailed comparison of the two models. However, at high confidence levels (i.e. low probabilities) the GJR model predicts a significantly higher VaR.

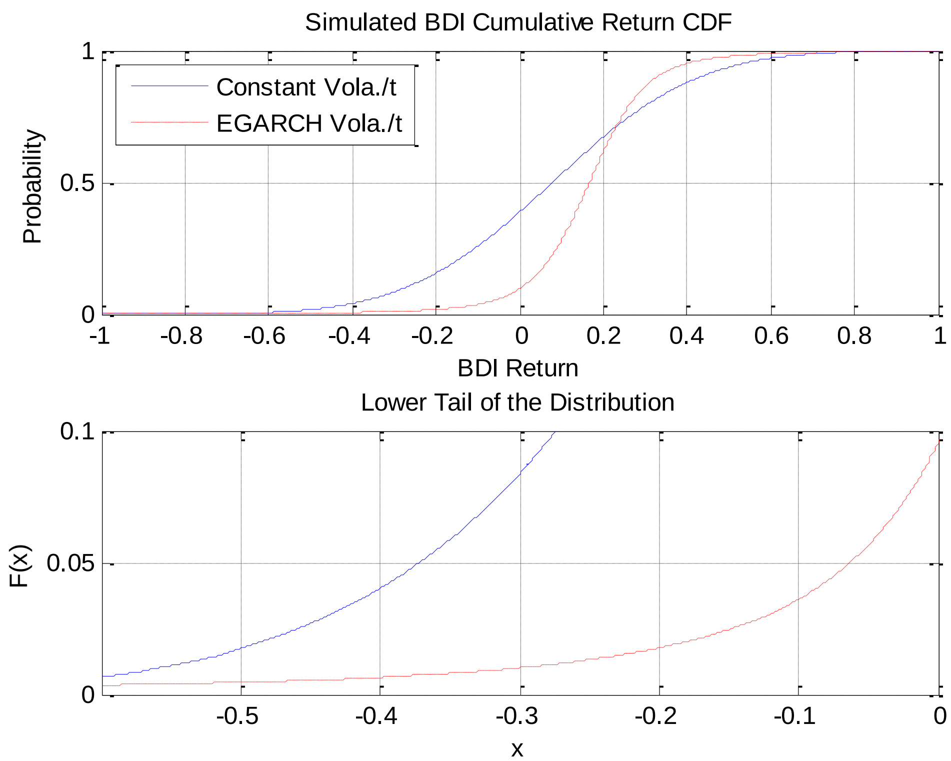


Figure 3.14 BDI VaR distribution function

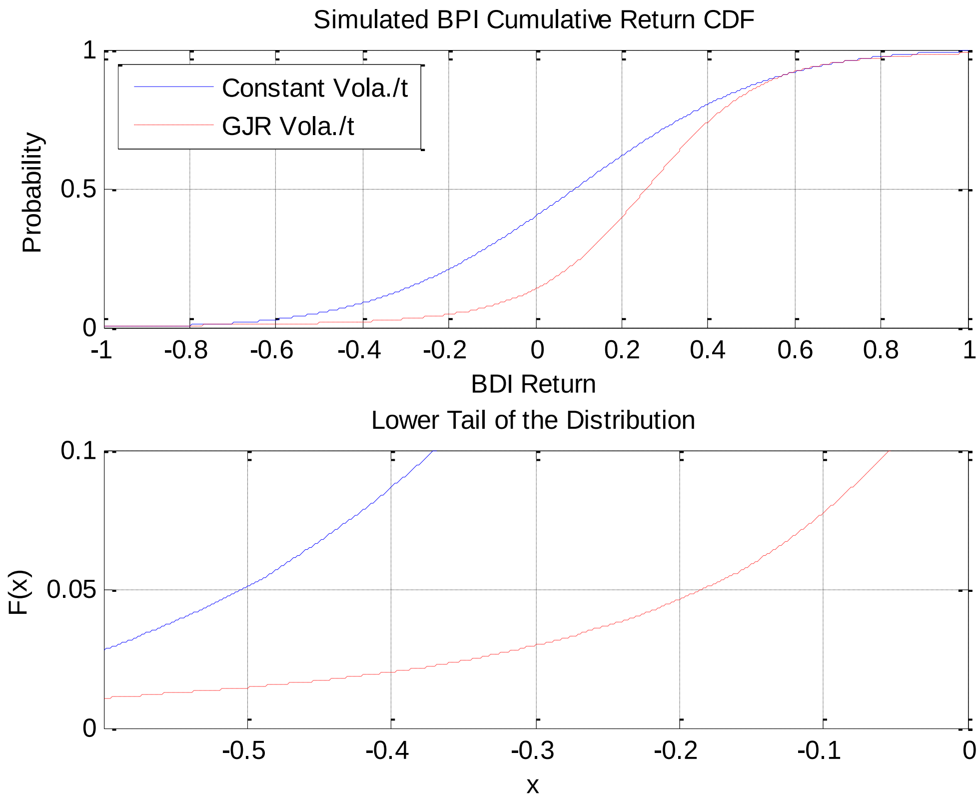


Figure 3.15 BPI VaR distribution function

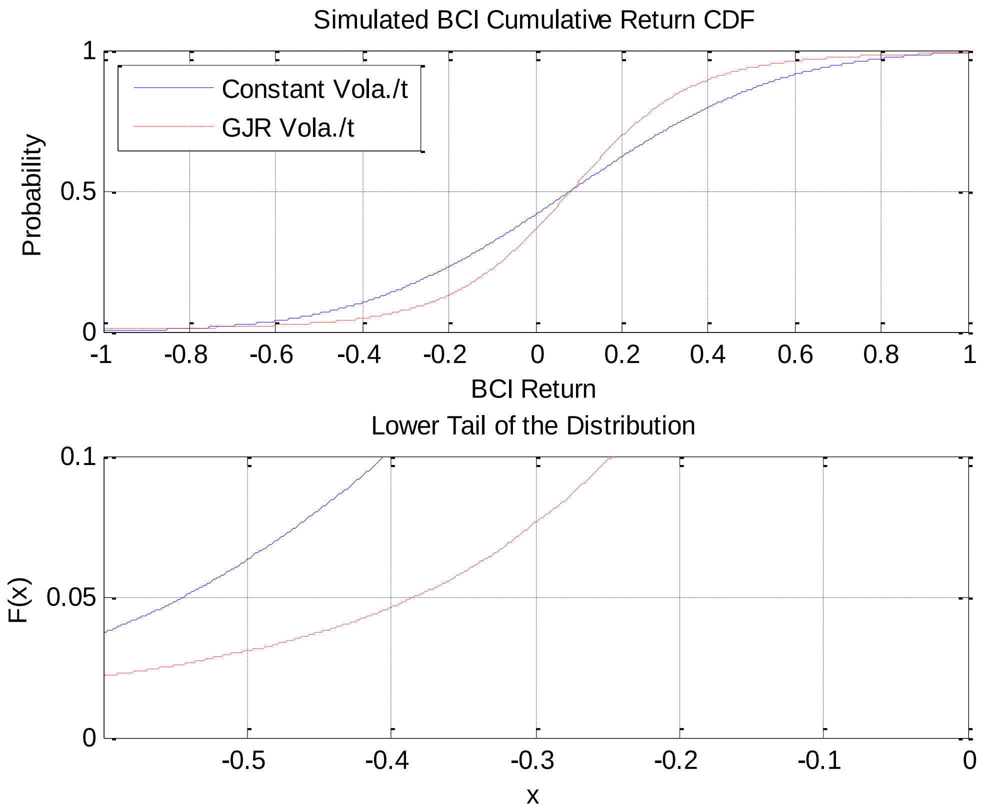


Figure 3.16 BCI VaR distribution function

Table 3.15 compares the VaR percentage losses of the two simulation models over twelve months. In particular, we can see that at the VaR cross-over point both models occur at above 50% for all three indexes. According to this, with the constant volatility model there is a 1% chance that the BDI will drop by more than 55% or more during the 12 months. However, with EGARCH the simulated VaR value is 30%. The very high kurtosis explains why some VaR percentages are near unity.

3.12 Value at Risk with Filtered Historical Simulation

We now assess the VaR of the three indexes as a portfolio of similar weights by Filtered Historical Simulation (FHS). An updated alternative to the Monte Carlo simulation approach is the FHS of Barone-Addesi *et al.* (1999), which is a non-parametric calculation method, introducing a variant of historical simulation methodology. FHS is a promising semi-parametric model and some authors, such as

Zenti and Pallotta (2001), consider it one of the best. This method combines the benefits of the historical simulation and conditional volatility models (Dowd 2006). Most implementations of variance–covariance methods attempt to capture the conditional heteroskedasticity of the risk factors, but they also assume multivariate normality. By contrast, most implications of the historical simulation method are nonparametric in their assumptions about the distribution of the risk factors but they typically do not capture conditional heteroskedasticity, whereas the FHS captures both the conditional heteroskedasticity and the non-normality of the risk factors. FHS is a Monte Carlo approach which is similar to computing VaR using fully parametric Monte Carlo. The difference is that in FHS the innovations are being drawn from a different distribution. Like the Monte Carlo distribution, the FHS method assumes that the distribution of ε_t has mean 0, variance 1 and is *i.i.d*, but it relaxes the assumption of normality in favour of the much weaker assumption that the distribution of ε_t is such that the parameters can be consistently estimated (Pritsker, 2001), so it is possible to capture conditional heteroskedasticity in the data and still be unrestrictive about the shape of the distribution of the returns.

To implement this system we choose an EGARCH model of volatility with a nonparametric specification of the probability distribution of assets returns to assess the Value at Risk. The EGARCH is chosen because it levies the lowest AIC and BIC between all GARCH, EGARCH and GJR variations. Therefore, for this choice we have to rely purely on information criteria. As was explained above, the bootstrapped FHS method requires the observations to be approximately independent and identically distributed, but from the early ACF plot we know that there is some degree of autocorrelation and, more importantly, heteroskedasticity in the original data.

We first extract the filtered model innovations and conditional volatilities from the return series using the ARMA (1,1)-EGARCH (1,1) model from which the series of independent and identically distributed *i.i.d* standardized innovations is formed. To produce a series of *i.i.d* observations, we fit a first-order autoregressive model to the conditional mean of the portfolio returns. FHS retains the nonparametric nature of historical simulation by bootstrapping (sampling with replacement) from the standardized innovations. These bootstrapped standardized innovations are then used to generate time paths of future asset returns; then, the simulation assesses the VaR of the hypothetical three index portfolio over a one month horizon. One of the appealing features of FHS is its ability to generate relatively large deviations (losses and gains) not found in the original portfolio return series.

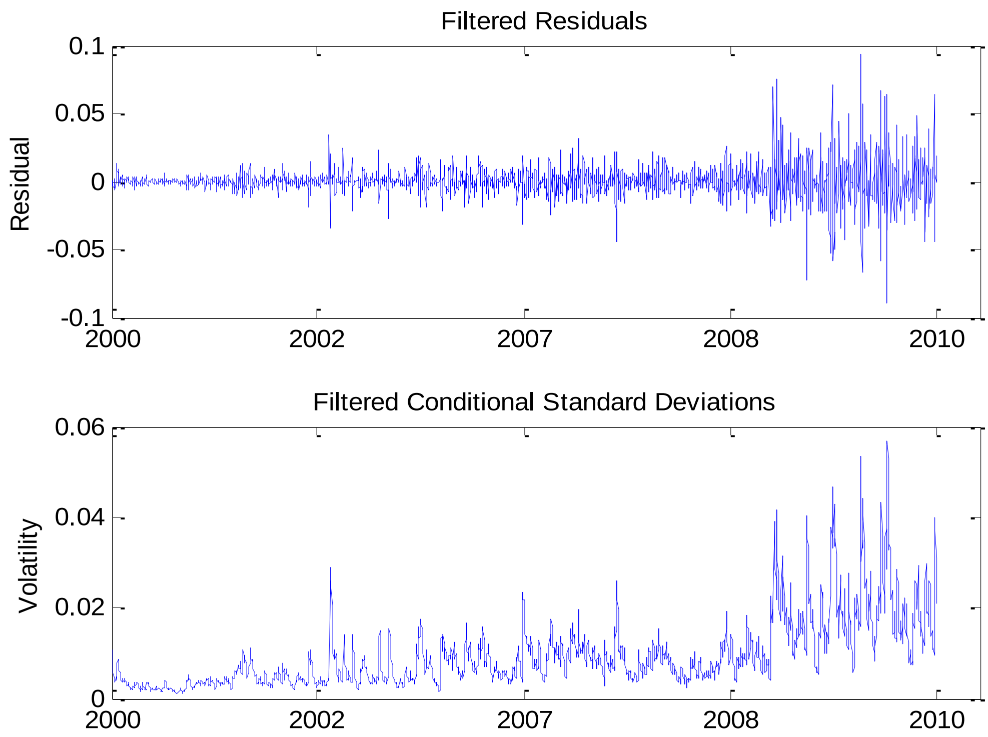


Figure 3.17 Three index portfolio innovations and standard deviations

Table 3.16 EGARCH properties of the index portfolios

	Parameters	*Value*	*Standard Error*	*t-statistics*
ARMA (1,1) EGARCH (1,1)	C	0.00000	0.00000	0.84500
	AR(1)	0.78817	0.01298	60.6877
	MA(1)	0.26541	0.02184	12.1495
	K	-0.24005	0.05080	-4.7248
	GARCH(1)	0.97544	0.00508	191.9163
	ARCH(1)	0.44012	0.03268	13.4659
	Leverage(1)	-0.00076	0.02096	-0.0365
	DoF	3.50951	0.25356	13.8412

Figure 3.17 clearly illustrates the variation in volatility (heteroskedasticity) present in the filtered innovations. FHS bootstraps standardized innovations to generate paths of future asset returns, and therefore makes no parametric assumptions about the

probability distribution of those returns. The bootstrapping procedure produces *i.i.d* standardized innovations consistent with those obtained from the AR(1)/EGARCH(1,1) filtering process described above. We simulate 20,000 independent random trials of standardized innovations over a one-month horizon of 22 trading days.

3.13 Summary of the results

Having simulated the returns of the index portfolio, we now calculate the maximum gain and loss, as well the VaR at various confidence levels, over the one-month risk horizon. Since we are working with daily logarithmic returns, the cumulative returns over the risk horizon are simply the sum of the returns over each intervening period. There is a 5% chance that the value of the portfolio will drop by 87% or more.

Table 3.17 Portfolio VaR results

Maximum simulated loss, [−100*max(cumulativeReturns)] = 210.7%
Maximum Simulated gain, [−100*min(cumulativeReturns)] = 760.5%
VaR = 100 * quantile(cumulativeReturns, [0.10 0.05 0.01]')
Simulated 90% VaR = −39.6%, 95% VaR = −60.3%, 99% VaR= −92.7%

3.14 Summary

We examined the ability of the ARCH models to forecast shipping freight indexes volatility. Volatility forecasting is an important element in successful risk management and trading. It is also a necessity when calculating the price of shipping options. If the underlying index has a lower volatility than the other indexes, there is less probability that the underlying price will hit the exercise price and go above and below for a call and put, and as a consequence the option contract will have a lesser value. But if the volatility is high there is relatively more probability of hitting the exercise price and hence the option is more valuable. For instance, the Black-Scholes option pricing model requires five inputs to calculate the option price. The volatility of the relevant asset return is one of them; the others are the spot price of the underlying asset, the exercise price of option, the Treasury bill rate of return, and time to expiry.

There is also another way of finding the volatility, which is solving the model for finding the volatility with other factors remaining constant; this volatility is called implied volatility. Although the variance gives a good indication of the volatility over a defined period, the shape of the interaction and the elasticity of the demand and supply can be different through the shipping cycle. Thus volatility by variance, which is not a time-varying volatility, is not accurate. GARCH models are very popular in financial modelling, although the aim of this chapter has not been to compare different GARCH models but to use AIC and BIC model selection criteria to choose the best GARCH model. Therefore, we compared models such as GARCH (1,1), GARCH (2,1), etc., according to goodness of fit and chose the one which had the smallest number. We performed different forecasts of volatility for one day and ten days ahead. We also forecasted the recursive 30-day volatility with the chosen models of the model selection criteria and compared the results with those provided by Monte Carlo simulations. For the pre-test examination we performed a few tests. The Engle ARCH test shows significant evidence in support of the heteroskedasticity; it confirms some persistence characteristics of the variance of the innovations and the presence of autocorrelated conditional heteroskedasticity.

We also investigated the properties of the EGARCH and GJR to measure the persistence of shocks to volatility. From the pattern of the ACF it could be argued that between the three indexes BPI has a lower degree of persistence, which means that after a shock it takes a shorter time for it to return to its mean. In the initial GARCH (1,1)-ARMA (1,1) model the value of α, which measures the intensity of outside shocks on volatility, was higher in BPI than in the other two, which means volatility decreases slowly and lasts longer. The BCI has the lowest value. The sum of the coefficients was equal to one, which indicates unit root in conditional variance, and the volatility of shocks is very persistent. The character of memory of self-volatility was highest in BCI and lowest in BPI. Then, we amended the model according to the model selection criteria. In the amended model α has the biggest value in BCI and the lowest value in BDI. The character of memory of self-volatility is lowest in BCI, at 0.28. The BPI is very close, at 0.29, and the highest is for BCI, at 0.40. The sum of coefficients is slightly more than unity for BDI, which may suggest that the shocks do not decrease and have a very small tendency to strengthen. However, this value is almost unity in BDI. For the other two indexes the sum of the coefficients is unity, which suggests that the shocks are very persistent. We also assessed the Value at Risk (VaR) of each of the three indexes over a 12-month holding period and compared the simulation-based VaR results of the two models. The VaR of the indexes as a portfolio was also assessed by Filtered Historical Simulation (FHS).

Chapter 4

Forecasting Shipping Stock Returns

4.1 Introduction

Shipping is a derived demand, and macroeconomic variables should play some role in determining the price of a shipping company's stock. There have been several empirical studies forecasting stock returns with macroeconomic variables (McMillan 2001; Pesaran and Timmermann 1995; Sollis 2005). However, few studies have investigated the effect of macroeconomic and commodity variables on shipping market variables specifically. The international nature of the shipping industry and the complex mechanism through which freight rates are determined by the interaction of supply and demand makes such a study particularly interesting at the global macroeconomic level. The shipping industry is segmented to a large extent, with all the different types and sizes of shipping sector reacting differently to changes in supply and demand (see Chapter 1). From a macroeconomic perspective we are interested in the effect of such changes on the price of shipping companies' stock. Moreover, this study may be useful for investors in shipping stocks since it could provide useful information for diversification and investment timing purposes.

There are two major approaches towards selecting the right stock: fundamental and technical analysis. Fundamental analysis deals with the valuation of the stocks according to fundamentals; this includes rations that are selected from financial statements such as gearing ratio, profit to earning (PE) ratio, return on equity (ROE) ratio, operating cash flow ratio and return on asset (ROA) ratio. Technical analysis deals with the search for recurring stock price patterns. Our study deals with fundamental analysis using basic macroeconomic and financial data. Fundamental analysis is based on the idea that any stock has an intrinsic value, which is a function of an overall state of the economy. Indicators of the overall state of the economy include industrial production level and inflation. The specific indicators of the stock value can be related to the type of industry the company operates in and the company's fundamental microeconomic factors, such as capital structure. There have been several technical-analysis studies of shipping stock. For instance, Alizadeh and Nomikos (2006, 2007b) combined technical trading strategies to ascertain the optimum timing of investment and disinvestment in the second-hand ship market. Their trading strategy is based on signals indicated by fundamental market price indicators such as the ship price earnings (P/E) ratio. They argue that the ratio of the ship price to earnings is a measure of whether the market for second-hand ships is underpriced or overpriced with relation to its fundamentals. They apply the historical spread between price and earnings and set up a strategy that gives a selling signal if the spread is higher than its historical average. Macroeconomic variables and commodity prices are traditionally believed to have an important effect on shipping companies' stock price movements. In fact, the most important cause of the shipping cycle is the business cycle in the world economy. Historically, there has been a close relationship between cycles in world industrial production and cycles in seaborne trade. King's (1966) study was the first to study the determinants of the stock returns. This study, which uses static statistical methodologies, concluded that stock price changes can be expressed in terms of a market, an industry and a company effect. King proposed that stock prices are shaped and determined by developments both at the macroeconomic level, which affects industries and the stock market, and at the microeconomic level, which affects the company's fundamentals and hence its value. King's findings were important in the sense that they became the basis for more academic research in the following years.

The methodology of this chapter is based on Pesaran and Timmermann (1995, 2000), hereafter referred to as PT (1995). Similar studies in industries other than shipping include that by Isimbabi (1994). Isimbabi compared the return of the banking stock to other industry sectors such as utilities, petroleum refining and others. In the USA his study applied a multi-factor model and examined the sensitivity of company returns in every industry to a set of macroeconomic and industry risk factors. However, some studies (e.g. Garcia and Liu, 1999) suggest that macroeconomic factors may not always have explanatory power for stock prices.

The studies which investigate the shipping market are very limited. Grammenos and Marcoulis (1996) examine the cross-section of shipping stock returns by using a set of microeconomic factors. Their study examines 31 shipping IPOs in seven countries for the period 1983–95. Gearing was indicated to be the single most statistically significant factor in explaining IPO stock market performance. The sensitivity of shipping stock returns to global macroeconomic factors has been studied by Grammenos and Arkoulis (2002). They examine the relationship between macroeconomic sources of risk and shipping stock returns. Their paper uses the MSCI World Equity Index as a proxy for the world market. They found that oil prices and laid-up tonnage are negatively related to shipping stocks, whereas the exchange rate variable exhibits a positive relationship.

They found no significant relationship regarding global measures of inflation and industrial production. Generally, they concluded that macroeconomic factors exhibit a consistent pattern in the way they are related to the shipping industry.

A common finding in the general literature on finance is that stock market prices tend to be correlated to macroeconomic factors. Intuitively one also expects some correlation between economic growth, oil and commodity prices and freight rates, and hence shipping stocks. Economic activity and economic development still form one of the most important drivers of shipping demand. Most commodities transported by ships, specifically oil, represent some type of consumption asset and will be used in an industrial process. Freight rate, and consequently shipping companies' stock, is directly dictated by the economic climate. However, shipping stock is also an investment asset and, like that of any other equity, its fundamental value is the discounted expectation of earnings flow, which is why the equity market may indicate the future of freight rate ahead of its price change. However, contrary to what has previously been argued, the mid-2008 market crises somehow showed a strong freight rate in the major segments of the tanker market, although there was no positive movement in macroeconomic indicators. The rise was actually due to the oil being kept in very large carriers by investment funds with the intention of selling it at higher prices in the near future. Therefore, in this instance the oil was treated not as a consumption commodity but as an investment tool like gold. This, clearly, can positively affect a tanker company's stock, in contrast to that of a dry bulk shipping company.

Economic growth is also energy-intensive. A major business of tanker and dry bulk carriers is the transportation of of oil and coal; therefore, any prospect of GDP growth will boost the shipping companies' earnings and consequently the shipping company stock price will add value, although this may not be the case with all types of GDP growth. From a fundamental point of view, economic growth, and hence macroeconomic variables, shape the demand side of freight; then, if the supply side also grows through the formation of new shipping companies and matches the equation, economic growth does not bring any extra earning prospects for the company and so the stock will not move with macroeconomic variables. We will test whether there is any predictive power in our selection of financial and macroeconomic data by the PT (1995) approach.

4.2 Efficient market hypothesis

Under the Efficient Market Hypothesis (Fama, 1970) or EMH, assuming risk- neutrality, in an informationally efficient market asset prices should evolve as a random walk and it should be impossible to beat the market and create an abnormal profit. Under the rational-expectations hypothesis, economic agents use all available information about the future in a rational manner to determine the value of an asset, so in a relatively efficient stock market prices are relatively less predictable and in a perfectly efficient market there is a random price process. That is to say, an investor can only make an abnormal profit if he or she has access to some private information. Depending on whether the information incorporated in current prices is past information, current public information or current private information, markets are said to display weak efficiency, semi-strong efficiency, or strong efficiency. The underlying assumption is that new information is incorporated instantly into prices even when it is first revealed only to an individual, because the individual's consequent trading on private information is itself information-revealing. This does not suggest that if an investor could make an abnormal profit the market would have been inefficient unless a definite price formation structure could have been proved to exist. To summarize: if asset prices evolve as a random walk, the corresponding market must be informationally efficient; and if the market is efficient, market participants must form expectations rationally. This is the random walk hypothesis. Testing the random walk model allows verification of the efficient markets hypothesis and, in turn, of the rational expectations hypothesis.

It should be made clear that market efficiency does not mean that the stock return cannot be forecast. Actually, in an efficient market the return can be forecast if, when defining the EMH, an additional assumption is made regarding the asset pricing model, which is the underlying way in which investors view risk. If investors are risk-neutral they do not require any extra return on investing in stocks, because that is riskier than investing in government bonds. If the investor is risk-neutral we can test for the EMH by testing for a random walk, which means that prices, and therefore returns, should not be predictable, though this depends on the assumption of risk-neutrality. If the investor is not risk-neutral and they have a risk premium, it turns out that we can actually forecast the stock return even if the market is efficient, if the risk premium is correlated with the macroeconomic variables.

In this section we test for the random walk as an examination of market efficiency, but we can suggest from the previous discussion that predictability can be found and the market forecast even under EMH if risk premium is time-varying with macroeconomic variables. Because the macroeconomic variables capture risk premium, if this risk premium is time-varying and correlated with macroeconomic variables we should be able to discover the forecasting power; then, although the markets are efficient we should consistently be able to generate abnormal profits relative to those accruing from a buy-and-hold strategy and so continually beat the market.

There is no single test which could reliably be used to verify the random walk hypothesis against all relevant alternatives, but common tests are the augmented Dickey-Fuller (1979) test and the Phillips-Perron (1988) test. The ADF test was explained in section 2.3. The Phillips-Perron test is similar to the ADF test, but instead of adding additional lags in the regressions to obtain error term with no correlation, it adjusts the ADF-statistics to account for serial correlation. In the simplest specification, the random walk model could be tested by checking whether the implied coefficient of the independent variable is indeed unity – in other words, by evaluating the significance of the unit root. Yet while a unit-root process is a necessary condition for a random walk, it is not a sufficient one. The results from the Phillips-Perron test are given in Table 4.1.

Table 4.1 Phillips-Perron test of prices

$pp\ test\ = 0$	*TestStat*	*CriticalValue*	*p-value*
S&P500 500 (NYSE)	-2.23		0.19
Frontline (NYSE)	-1.25		0.62
VLCCF (NASDAQ)	-1.88		0.34
TK (NYSE)	-1.46	-2.8	0.53
NAT (NYSE)	-1.67		0.43

We have checked both of the above tests, and have found that all the test results and critical values suggest that unit root exists and random walk is not rejected. The critical value for 5% significance is (-2.8). The test statistics are all greater than the critical value; thus we cannot conclude by rejecting the Ho (null hypothesis), which also means that all the series are non-stationary. We use the return series in the calculation of this chapter and we forecast the excess return, which is the difference between stock return and Treasury bill. The return series all are stationary but results are not reported here. Figure 4.1 presents the stock return series.

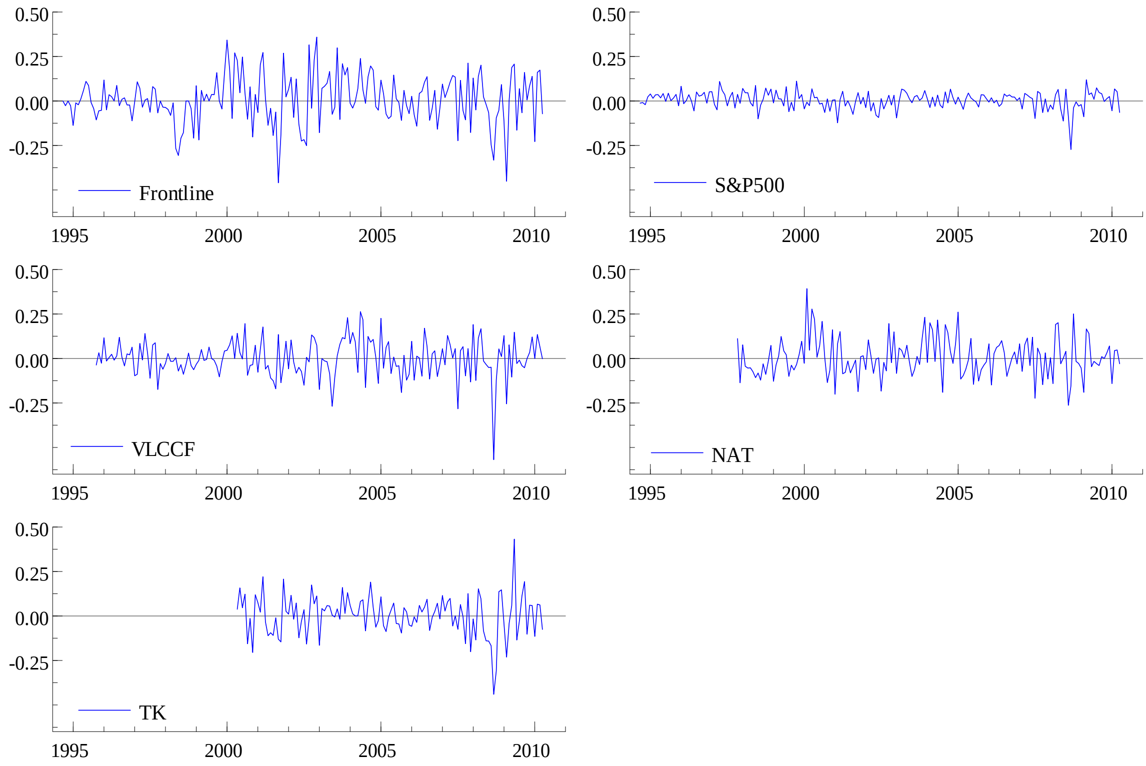


Figure 4.1 Returns series of the forecast variables

4.3 Challenges to EMH

EMH had always been an important topic for financial research because there are vast empirical and theoretical findings in favour of it. Infect until the late 1970s almost all the research findings had some kind of support toward EMH and hence there was strong belief in its validity. Among these strong beliefs was Jensen (1978, p.95) who suggested that "there is no other proposition in economics which had more solid empirical evidence supporting it than the Efficient Market Hypothesis". These strong beliefs attracted more researchers into investigating EMH and as a result of these investigations several foundations that this theory is based on started to be challenged. With all these new studies behavioural finance as an alternative to market efficiency was emerged, behavioural economists explain the imperfections in financial markets information and cognitive biases and other reasoning errors. With behavioural finance view significant deviations from efficiency are expected to remain for long periods of time and hence economic theory does not lead us to believe financial markets are efficient. The challenges to EMH are both theoretical and empirical, for instance the EMH is based on rationality however as Fisher Black (1986) suggests many traders simply trade on noise or fail to act rationally on the available information. If the EMH relies on the rationality of the investors then the psychological evidence do not support rationality, this can be correct for both the individual investors and financial managers as they are also human being. There are also agents that manage other people's money on their behalf and this introduces yet further distortions into their decisions in comparison to what a fully informed investor might wish (Lakonishok et al. 1992).

The investors also have different reactions to the news and may make different choices for their investment; these are all mixes up with other psychological problems such as conservatism. Edwards (1986) identifies conservatism as a state when the individual are very slow to change their beliefs in face of new evidences. Another related issue is called *representativeness heuristic* introduced by (Tversky and Kahneman 1974). Investors that are falling into this category always disregard the reality that a high earning of a particular stock may not last forever and over value the stock. In addition to these investors tend to react together rather than random trade; for instance many of them would try to buy the same stock around the same time; this becomes more significant when noise traders react together and follow each other's advice and mistakes by listening to rumours or imitating their neighbours (Shiller 1984).

Daniel et al. (1988) presents a model in which noise traders are over confident and also suffer from biased self-attribution in their evaluation of their own performance. Hong and Stein (1999) considers a market in which different classes of investors pay attention to different information some only look at fundamental news while others look at past price trends.The behavioural finance argues that in contrast to the EMH, real-world arbitrage is risky and hence it is very limited. The effectiveness of arbitrage relies on the availability of close substitutes for securities whose prices are affected by noise trading.

There are several other empirical challenges, among them the Shiller (1981) work in stock market volatility which showed that stock market prices are far more volatile than could be justified by a simple model in which these prices are equal to the expected net present value of future dividends. Shiller compounds this net present value using a constant discount rate and some specific assumptions about the dividend process. However Shiller's work was subjected to criticism from Merton (1987) which argues that Shiller has misspecified the fundamental value. Shiller's work irrespective of the criticism around it opened the research into EMH to a whole new ear. Other researchers are De Bondt and Thaler (1985) they compared the performance of two groups of companies, extreme looser and extreme winners, the results suggests an extremely high post-formation returns of extreme losers and relatively poor returns of extreme winners. This difference in return is not explained by the greater riskiness of the extreme losers hence they conclude that stock prices overreact, the extreme losers have become too cheap and bounce back, on average over the post formation period whereas the extreme winners have become too expensive and earn lower subsequent return, this explanation fits well with the psychological theory, the extreme losers are those stock with the history of bad news which the investor undervalues these stocks and the extreme winners are those with the history of good news which the investor over values. Shiller (1988) had also investigated the positive feedback trading; he found that home buyers in cities where house prices have risen rapidly in the past anticipate much greater future price raise than home buyers in cities where prices have fallen. Shiller also surveys investors in the wake of the 1987 market crash and finds that most sellers of shares cite price declines as the reason that they have sold because they anticipate further price decline. Similar to this Frankel and Froot's (1988) investigate trading on dollar exchange rate, they evaluate the recommendation of the forecast services in mid 1980s when the dollar was appreciating with the simultaneous increase in the US budget deficit, they found that a typical forecaster expect the dollar to continue to appreciate over the next month but with depreciate within a year and according to the fundamental value, therefore forecasters were recommending to buy dollar when the dollar was overpriced. These short term trend chasing with a knowledge of underlying fundamental value is hard to fit in the concept of rationality.

4.4 Recursive modelling of return predictability

Recent studies in financial econometrics suggest that econometric models can be a useful tool for forecasting stock returns. In this chapter we assess the performance of an investor who relies on these models for forecasting the excess stock returns for shipping companies. We employ a recursive modelling approach (similar to that used by Pesaran and Timmermann 1995, 2000) to simulate investor behaviour in order to analyse whether macroeconomic variables help to forecast shipping stock returns. One advantage of using a recursive modelling approach is that it allows for changes in the structure of the model in every step; it also allows the out-of-sample forecasting ability of a set of regressor variables to be analysed. Each forecast is computed using the most recent sample data. We use three different criteria to evaluate the accuracy of forecasts. The contribution of this chapter to the publicly available literature is that, firstly, we specifically use shipping companies' stock data. Secondly, we apply the recursive forecasting approach of PT (1995) and also consider the transaction costs. Thirdly, we employ different model selection criteria to evaluate the forecast.

We also simulate the performance of $\$100$ for every forecasting model. We use three different criteria to evaluate the accuracy of forecasts, the statistical criterion, the Akaike information criterion and the Bayesian information criterion. We consider a set of macroeconomic and commodity variables so as to forecast the one-step-ahead excess return. In period t the information set contains information up to and including period t; the forecasts combine the available variables in an effective and most efficient way to work out the return. This is done by searching for the optimal forecasting model in each period over a large number of different models which include different combinations of variables. In every step it is not clear which variables should be included in the model nor the correct parameters of the model; now the recursive approach requires that the investor, in order to find the best model, will search in every step over the all possible models to find the best forecast model. As time goes on the investor recursively repeats this search and as data become available the best model will change. We assume that in every period t the investor considers 8 variables (4.1) that may be useful for making a one step ahead forecast of excess return.

$$X_{t,i} = \begin{bmatrix} 1 & X_{1,1} & \cdots & X_{1,8} \\ \vdots & & \ddots & \vdots \\ 1 & X_{t,1} & \cdots & X_{t,8} \end{bmatrix} \tag{4.1}$$

The investor tries to choose the best model in period t by searching over all combinations of up to 8 variables. We use a linear regression model estimated by ordinary least square (OLS) techniques. We therefore estimate the relation between excess return and the 8 variables by estimating the linear regression model of the following format:

$$\hat{r}_{t+1} = \acute{\beta} X_{t,i} + \varepsilon_{t+1,i} \tag{4.2}$$

$$\beta = \begin{bmatrix} \beta_1 \\ \cdot \\ \cdot \\ \beta_8 \end{bmatrix} \tag{4.3}$$

By r_{t+1} we mean the excess return, which is the difference between the stock return and the risk-free return of Treasury bill. We use the OLS technique to model changes in the natural logarithm of the stock price where r_{t+1} is the vector of the excess return in the natural logarithm from period 0 up to and including period t, the subscript $i = 1,2, \ldots$ is the model considered by the investor, and $X_{t,i}$ denotes the set of regressors under model i, which is subset of the set of all the macroeconomic and commodity regressors the investor considers. The vector of the regressors includes a constant. In order to identify the optimal forecasting model among the large number of estimate-forecasting models we use three model-selection criteria in our MATLAB code: adjusted R^2, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The definitions of the model-selection criteria have been taken from Gujarati (2002). All these criteria aim at minimizing the residual sum of squares or increasing the R^2 value. The adjusted R^2 is defined as:

$$R^2 = 1 - \frac{RSS/_{(n-k)}}{TSS/_{(n-1)}} = 1 - (1 - R^2)\frac{n-1}{n-k} \tag{4.4}$$

n is the sample size and k the number of free parameters to be estimated. RSS is the residual sum of squares and TSS is the total sum of squares. We define the Akaike Information Criterion (AIC) in terms of its log transform as

$$ln\, AIC \;=\; \left(\frac{2k}{n}\right) + ln\left(\frac{RSS}{n}\right) \qquad (4.5)$$

where $\frac{2\mathrm{k}}{\mathrm{n}} = penalty\, factor$. We do not include ln before the model in the computation. In comparing the models, we prefer the model with the lowest value of AIC. The Bayesian information criterion (BIC) is defined as

$$ln\, BIC \;=\; \frac{k}{n} ln\, n + ln\left(\frac{RSS}{n}\right) \qquad (4.6)$$

where $\frac{k}{n} ln\, n \;=\; penalty\, factor$. As with AIC, the lower the value of BIC the better the model. We do not include ln before the model in the computation.

4.4.1 Part of the MATLAB code related to the model selection criteria

Part of the MATLAB code written to compute the information criteria is presented below.

```
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X  =  [intercept,newx];
beta = regress(yi,X);
ststs = regstats(yi,X,'linear','tstat');
residual  =  yi-X*beta;
rss  =  transpose(residual)*residual;
%R%best  =  (transpose(yi)*yi-size(X,1)*mean(yi)^2);
% R%makhraj  =  1-rss/best;
% R%results(sho)  =  1-( (size(yi,1)-1)/(size(yi,1)-size(beta,1)))*(1-
makhraj);
%AIC%results(sho)  =
(((2*size(beta,1))/size(yi,1))+log(rss/size(yi,1)));
%BIC% results (sho) =  (((size(beta,1)/(size(yi,1))))*log
(size(yi,1))+ log(rss/size(yi,1)));
%R&AIC% [nextmax,nextmaxno]  =  max(results);
%BIC% [nextmin,nextminno]  =  min(results);
best  =  posiblemod(nextmaxno,:);
```

4.5 Investment strategy

The PT (1995) approach creates one excess return forecast for every step. The sign of this forecast will then be analysed to reach an investment decision. We assume that the investor can decide among two investment strategies. One is to hold stock and the other is to invest in TB. Therefore, the investor can pursue three strategies: the first is to hold the stock, the second is to hold the TB, and the third is to switch between these two. For switching between stock and TB we assume a 20% transaction cost, which will be deducted from the associated period t return. This transaction cost is constant for all the transactions. The decision for switching is determined by the result of the one step ahead forecast for each of the model selection criteria. The investor cannot compare the results of the different model selection criteria at every step, and it is assumed that choice of the selection criteria is constant throughout the whole period of investment. We will compare the results of pursuing either of the statistical criteria, AIC or BIC. In order for the investor to reach a decision, he buys or keep the stocks if the forecast of the excess return is bigger than zero $\hat{r}_{t+1} \geq 0$ or, alternatively, he invests in TB if $\hat{r}_{t+1} \leq 0$.

4.6 Modelling the stock return

In the initial regressors the set of macroeconomic variables includes oil prices, inflation rate, interest rate, industrial production, dividend yield (DY) and price earnings (PE) ratio. The initial set of explanatory variables is subject to change. Inflation is included because it is a potential source of risk. It is particularly important for the shipping industry because of the consequences it has for international trade and, in turn, for the world economy and the profitability of shipping companies. Ferson and Harvey (1994) include such an inflation variable in their study following the intuition that inflation may be priced if it has real effects. For example, higher inflation may signal higher levels of economic uncertainty, which makes consumers worse-off. We will include the different inflation rates, including the US and EU inflation rate, but if the inclusion rate is zero it will be removed from the 8 independent variables and will be replaced with a different variable, so if the inflation was not included in any set of the shipping stock explanatory variables this means that it had been a completely unimportant variable. Initially we have chosen those stocks that have the DY and PE series available. The initial set of regressors is subject to change if the inclusion rate of a variable is zero: this will be explained in section 4.6.

Industrial production is included in the regressors as an important variable. There is empirical evidence for the effect of changes in the level of industrial production on average stock prices. Chen *et al.* (1986) have studied the effect of US industrial production in the US market and Hamao (1988) the effect in the Japanese market. The results of these studies are similar and are not conclusive. Poon and Taylor (1991) study the effects of unexpected changes in industrial production in the UK equity market and find a negative effect on UK equities. Chen and Jordan (1993) find no association between the variable and stock returns, while Hamao (1988) detects a positive association between the variable and Japanese equities. Stopford (1997) reached the conclusion that cycles in the OECD economy invariably mirror cycles in sea trade during the period 1963–95. Since industrial production is the major parameter affecting the demand for sea transport through world trade, the relationship between global industrial production and international shipping stock returns is also expected to be positive.

Oil prices are included as an important factor although the literature on the effect of oil prices in stocks is mixed. Oil consumption is a particularly important indicator of economic performance. Chen and Jordan (1993), for example, find that oil prices are negatively related to stock returns in the USA while Chen *et al*. (1986) find a marginally significant positive relationship. Hamao (1988), on the other hand, examines oil price risk in Japan, but does not establish a significant relationship. In addition to this, fuel prices are probably the most important item of spot freight costs. Therefore, an increase in oil prices would increase costs and decrease the profitability of the shipping company. This suggests a negative relationship between fuel prices and shipping stock returns. Economic activity still remains the most important driver of seaborne trade and oil demand growth. Oil, like other industrial commodities with the exception of gold, is theoretically a consumption asset. Oil is used in industrial processes and does not yield a future expectation of generating revenue. As such, the price of oil should theoretically be tied closely with current conditions; this is where economic activity can have a role to play through oil demand and in shaping the price. Although economic growth is said to be more or less energy-intensive, the impact of economic growth on process through oil demand is uneven across different countries. Among financial variables DY is used as a popular proxy for the time variance of the expected stock return. Fama and French (1988), for instance, estimate the portfolio returns of different horizons to the NYSE index by using DY. They find that the variances of long horizon expected returns can substantially be explained by DY owing to the negative relationship between price dividend rations and expected returns with discount rates.

The initial data set of regressors includes around 50 variables, but only eight variables will be included in the explanatory variables of every stock. If a variable proves to have no role to play in the regression process, which means it is not taken by any of the combination models and hence the inclusion rate is zero, we may replace it with another variable. For example, we have compiled different types of oil price series. During the process of calculation it turns out that most of the oil price series, including the OPEC price, have a very low or a zero inclusion rate but the NYMEX oil price inclusion rate is impressively high. Therefore, we often use NYMEX as a representative of oil prices. In other words, because the previous literature (and common sense) insists that oil prices should take some part in the formation of the shipping stock price, we are keen to show this by substituting different oil price formats until one of the series shows a high rate of inclusion. It is a similar story with the other main variables. Our main data set also includes different exchange rate variables, but the results of the selected exchange rates were poor and hence they are not included. However, shipping is a dollar-earning business and the performance of the company depends on the exchange rate.

The VIX index was included in the initial data set. The VIX is commonly referred to as the ‘fear index’, but analysts differ in how they interpret it. The VIX is derived using the prices of short-dated S&P500 options. The VIX probably offers a fair approximation of investor perception of risk and uncertainty in the near future. In most but not all instances the performance of this index was poor, and it was often replaced with another variable. It could be argued that the selection of the variables is engineered and is based on ex-post information, and the choices are intentionally played with. The studies regarding trading rules commonly suffer from what is called data mining, or data snooping. In fact, the rules obtained may be entirely spurious and reveal little about the true nature of the processes underlying economic activity. However, the purpose of this study is not to invent trading rules but rather to compare the econometric models, and hence this argument is not valid here.

4.7 Description of the input data

In order to study the macroeconomic determinants of the shipping stock market, we apply our model to the prices of Frontline Ltd (FRO). FRO (OSE:FRO,NYSE:FRO) is one of the world largest oil tanker shipping companies. It is based in Bermuda and is controlled by Norway's richest man, John Fredriksen. The company has a fleet of 82 tankers in total, consisting of VLCC, Suezmax and Suezmax OBO (oil, bulk, ore) carriers. The investment in FRO stock will also be compared to the investment in S&P500. The results of the FRO and S&P500 are discussed in section 4.7. In addition, the performance of three more tanker shipping companies stocks is examined and the results discussed in section 4.11. These companies are: Knightsbridge Tankers, Nordic American Tankers, and Teekay Corporation.

An overview of the statistical properties of the FRO stock is presented in Figure 4.2. We compare the statistical properties of the FRO with S&P500 composite index during the same period. The median for FRO is 0.02 and for S&P500 0.01, so the typical return value in S&P500 is half of a typical value in FRO. The maximum and minimum values in FRO are, respectively, around three and two times bigger than those values in S&P500. Both series are negatively skewed; a normal distribution is not skewed and is expected to have a skewness of near zero. The S&P500 has a mean of much less than the median, which suggests that there are extreme values at the negative end of the distribution. The value of kurtosis, which is the measure of peakness, is 3.4 for FRO and 9.2 for S&P500; the kurtosis for normal distribution should be around three. Most of the quantitative models assume normal distribution; therefore it should be considered that the series do not matching the normal distribution. The standard deviation is 0.05 and 0.15 for S&P500 and FRO respectively, so the FRO value is three times bigger. Standard deviation is the measure of the amount of variability or dispersion around the mean. It is also the measure of volatility, which means that the FRO is three times more volatile than S&P500. The mean of the FRO, which is 0.013, is about 35 times bigger than the mean of S&P500, which is 0.00037, $\frac{FRO\ mean}{S\&P\ mean} \approx 35$.

Table 4.2 FRO stock details

Company name/website	*Sector*	*Market*	*Exchange: symbol*
Frontline www.frontline.bm	Oil Equipment and services	Norway	NYSE: FRO OSE: FRO

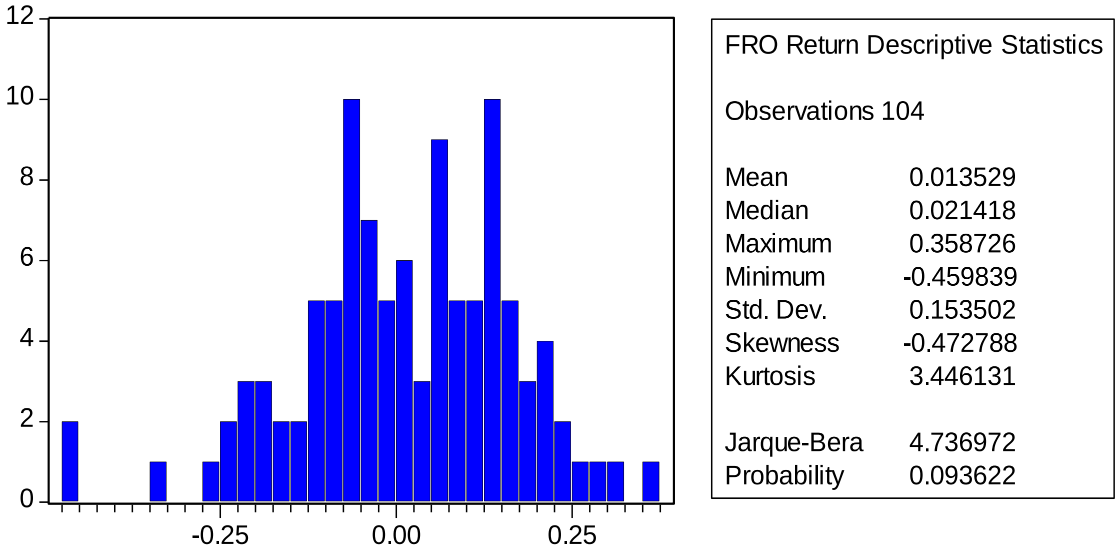

Figure 4.2 FRO descriptive statistics

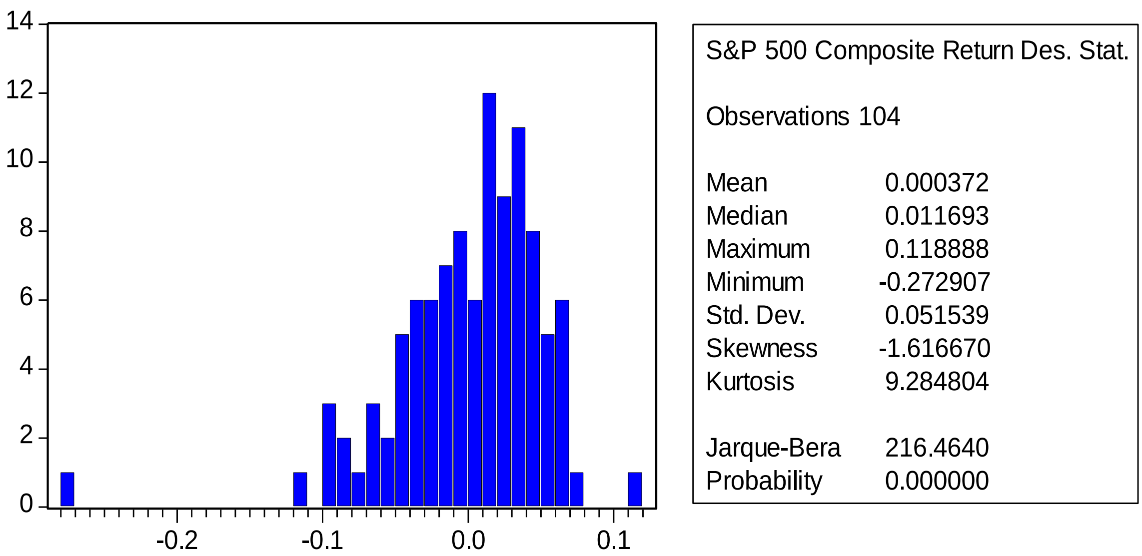

Figure 4.3 S&P500 descriptive statistics

We consider eight explanatory variables that are potentially relevant for forecasting shipping stock returns. They have all been taken from Thomson Financial Datastream. We use mid-month data. The TB is a four-week Treasury bill for the switching matter, but in the regressors group we use the return of a three-month Treasury bill. We account for the fact that macroeconomic data are published with time lag. Therefore we apply the two-month lagged industrial production series and purchasing indexes, but the rest of the regressors are applied with one lag. Table 4.3 presents the details of all the variables for FRO forecast.

The eight variables are all changes in natural logarithms. We have not included any dummy variable. Initially, US unemployment rate, Baltic Exchange Tanker index, Brent crude oil and a few exchange rates, in addition to some inflation rates, were included in the regressors set, but they had zero or a very low inclusion rate and hence were replaced.

Table 4.3 NYSE: FRO variables description

Frontline Variables Description			
Name	Description	Start	Finish
Y	Frontline (NYS)	15/09/1994	15/05/2010
TB	US TB 2ND MKT 4-WK – Middle Rate	15/09/1994	15/05/2010
	Forecasting Period	15/07/2001	15/03/2010
Frontline Stock Regressors	Full length: 188- Effective: 104- start: 85		
X1	S&P500 GSCI Commodity Spot – Price Index	No of lags :	1
X2	Moody’s Commodities Index – Price Index		1
X3	Crude Oil WTI NYMEX Spot U$/BBL		1
X4	MLCX Spot Index – Price Index		1
X5	US ISM Purchasing Man. Index (MFG Survey) SADJ		2
X6	US Industrial Production VOLA		2
X7	US PPI – Finished Goods SADJ		2
X8	US TB 2ND Market 3 Month – Middle Rate		1

4.8 Results of Frontline and S&P500

Table 4.4 reports the performace of the competing strategies for the FRO stock, including the comparison with S&P500 performance during the same period. R_{NE} is the net sum of the returns with the transaction cost deducted. R_{GR} is the gross sum of the returns. R_{BH} is the sum of the buy-and-hold return and R_{TB} the sum of the TB. The buy-and-hold strategy R_{BH} generates the sum of 140% during the full period. The four-week Treasury bill generates 17% during the same peroid. The net return of the switching strategy is less than R_{BH} in all the switching cases. However, the gross returns are all bigger than R_{BH}. The difference between R_{GR} and R_{NE} is that a transation cost of 20% is deducted from returns every time an investor has switched between the stock and the Treasury bill.

Table 4.4 FRO and S&P500: sum of all return series

Frontline	R_{NE}	R_{GR}	R_{BH}	R_{TB}
FRO: AIC	0.97	1.59		
FRO: R-square	0.77	1.49		
FRO: BIC	1.07	1.64	1.40	
FRO: AV	**2.06**	2.72		0.17
S&P500: AIC	0.10	0.33		
S&P500: R-square	0.03	0.23		
S&P500: BIC	0.36	0.19	0.03	
S&P500: AV	**0.49**	0.66		

In Table 4.4, the last column of every section corresponds to the All Variables model hereafter called the AV model. This model includes all the eight variables and does not choose between any combination of variables. The sequence of the best models according to the sum of the returns is 1.FRO: AV 2.FRO: BIC .FRO: AIC 4.FRO: R-square.

In S&P500 the results are different, R_{BH} generates a lower profit than all switching cases or TB. The sequence of the best models is similar to that in FRO. The inevstor is not aware of the best model to use and hence may use the worst-performing model. Outside the switching models, for FRO the buy-and-hold strategy and for S&P500, the TB generates a better return than using the switching models. The PT (1995) approach does not yield any benefit according to these criteria. Between the six switching models only two cases, both with BIC, generate more return than TB.

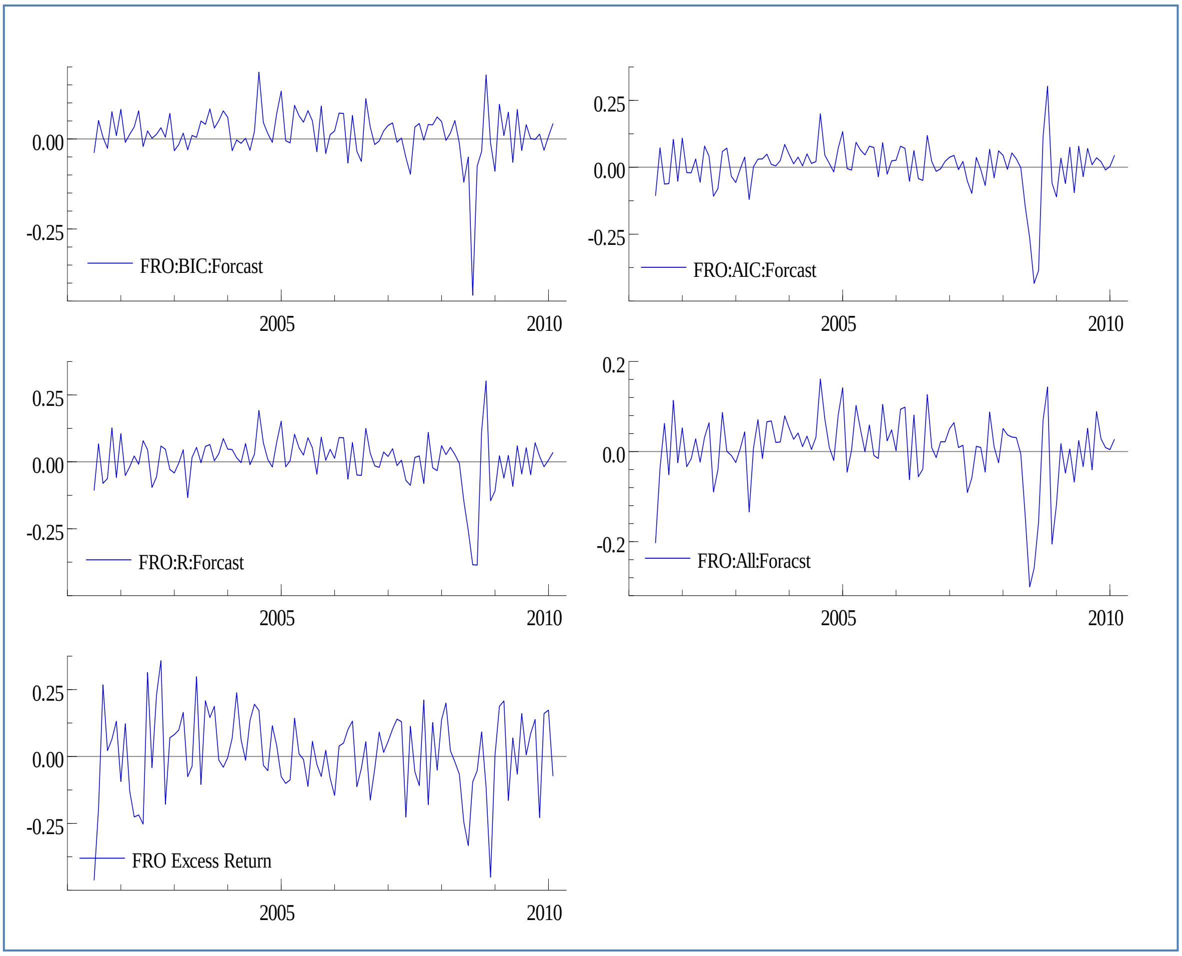

Figure 4.4   Forecast of returns: comparison of FRO selection criteria

Figure 4.4 presents the forecast of returns. The frequency of the return series could be different, which means that the equal summation of two equal series may produce a different sums of investment when we invest an equal sum of money. Therefore, we consider an intial investment of $100 and calculate the final investment using continuous compound. Table 4.5 confirms that the results are similar but not identical to the sum of the returns in Table 4.4. In return series the FRO net switching series had a smaller value than TB, but in investment series all the FRO net switching series had a higher value. As with the return series, in all cases the AV model produces a more accurate signal, so we can conclude that the model selection criteria do not perform accurately during the selected forecast period. During the time the MATLAB code was being tested there were some instances where greatly shortening the time series and forecasting period would have produced a better result in switching series than the AV model.

Table 4.5 FRO and S&P500: end of period investment

<table>
<tr><th>Frontline
100 USD</th><th>W_{NE}
$</th><th>$W_{GR}$
$</th><th>$W_{BH}$
$</th><th>$W_{TB}$
$</th></tr>
<tr><td>FRO: AIC</td><td>264.24</td><td>492.29</td><td rowspan="4">408.37</td><td rowspan="8">119.37</td></tr>
<tr><td>FRO: R-square</td><td>216.94</td><td>444.93</td></tr>
<tr><td>FRO: BIC</td><td>291.80</td><td>518.07</td></tr>
<tr><td>FRO: AV</td><td>791.40</td><td>1520.89</td></tr>
<tr><td>S&P500: AIC</td><td>111.41</td><td>139.48</td><td rowspan="4">103.94</td></tr>
<tr><td>S&P500: R-square</td><td>103.43</td><td>126.00</td></tr>
<tr><td>S&P500: BIC</td><td>121.47</td><td>144.26</td></tr>
<tr><td>S&P500: AV</td><td>163.54</td><td>193.83</td></tr>
</table>

Table 4.5 suggests that with a $100 investment for the period 15 July 2001–15 March 2010, pursuing the switching strategy will generate at least $216.94 in income. This is less than the buy-and-hold strategy, which is $W_{BH} = \$408.37$. We can safely conclude that the AV model is the best-performing model and using the selection criteria signals a wrong decision. Figure 4.4 compares the pattern of investment between the worst-performing model and TB for FRO. The worst-performing model still generates a significantly higher sum than TB.

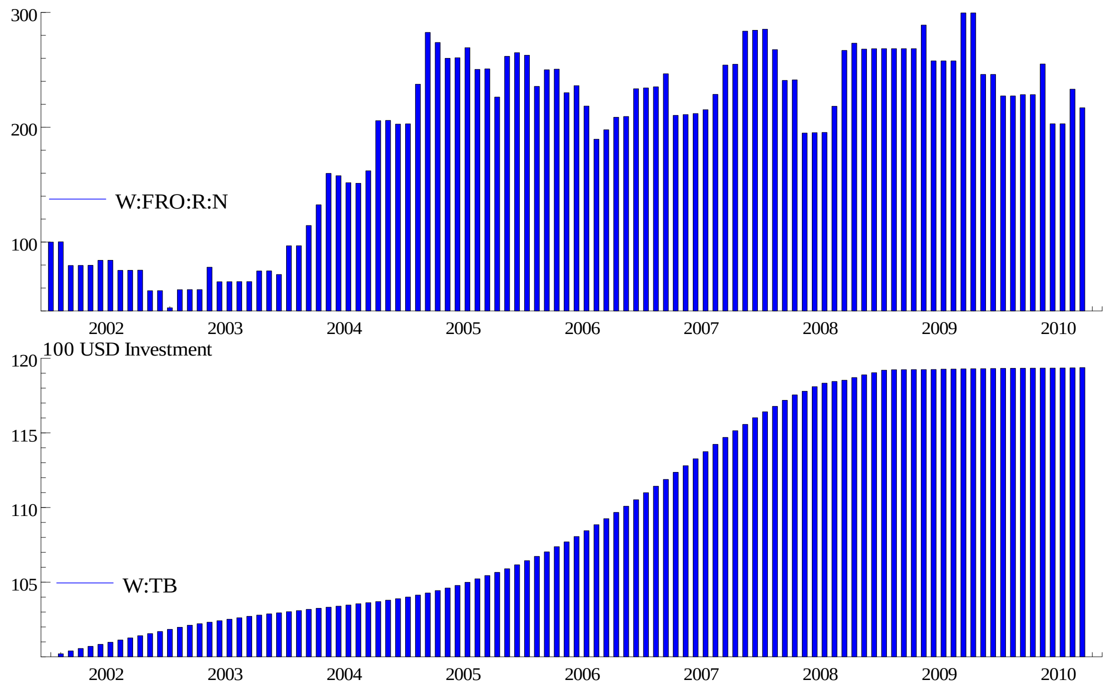

Figure 4.5 TB and the worst-performing model pattern of investment

Figure 4.6 illustrates the pattern of the $100 investment when there is no transaction cost. It is clear that the AV model has performed better than the other alternatives. Only the AV model has successfully predicted the market crash of mid-2008. Figure 4.5 presents a similar investment with no transaction cost deducted. The thick blue line is the buy-and-hold pattern, which performs better than the combination models. The AV model performs better than the others in most years. These graphs confirm that the combination models are severly under-performing relative to the rival strategies. TB is the worst investment except and until mid-2003; a comparison between the wealth creation of TB and the worst-performing combination model is illustrated in Figure 4.6. In most of the investment period, TB under-performs the worst-model selection criterion.

During the time the forecast process was being tested with MATLAB, it was clear that because we have a strong set of regressors the AV model is performing better than the combination models. In cases where the choosen regressors were not strong enough the combination models could have performed better, although testing this on several occasions did not show a conclusive result. The other reason could be that the model selection criteria are not efficient enough.

The results for the investment strategy and the difference between combination models and the AV model seem to be unusual. The problem lies in the way the model-selection criterion works. This is because the stock series are non-stationary and there are structural breaks in the data, so the regression results, and consequently the model selection criterion results, are not correct. Let us assume that in one step of regression X1 and X2 are picked up by (e.g.) AIC but that, if there is a structural break and the correct significant variables are X1 and X3, then in the AV model X1, X2, X3 are all included and hence the results are better. So, the combination models are under-performing because our data contain some structural breaks. We can overcome this by finding the breaks and applying the appropriate beta in the regression, but this could be a potential extension to this chapter and we do not investigate this here.

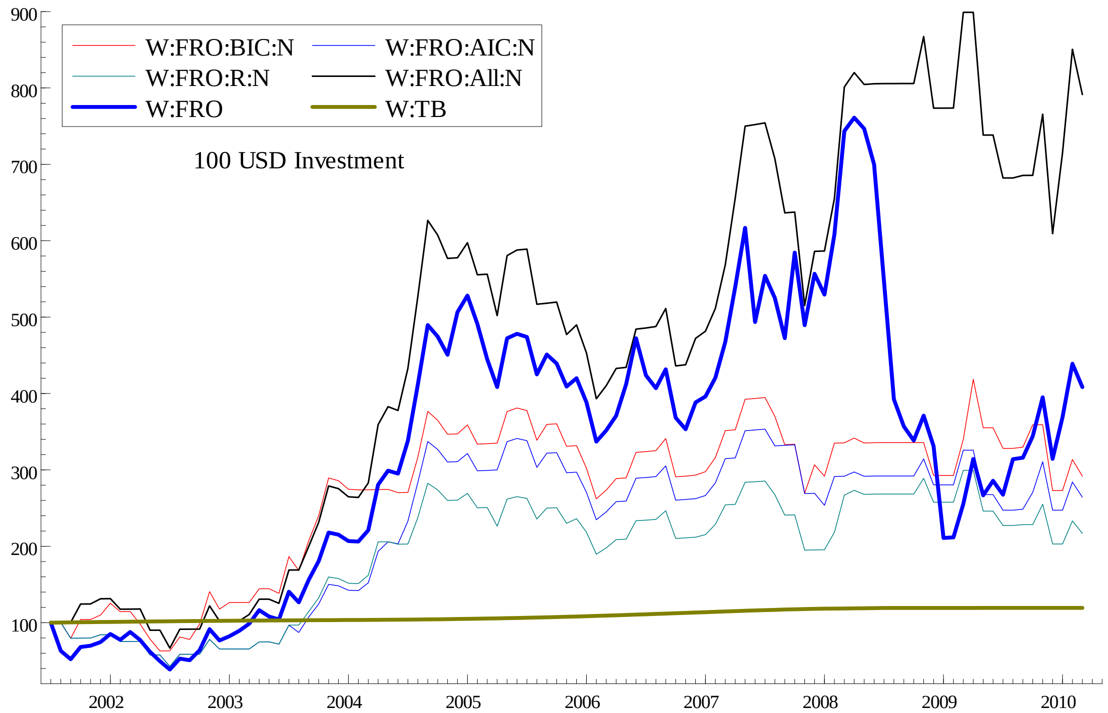

Figure 4.6 Net evolution of $100 investment, 15.07.2001–15.03.2010

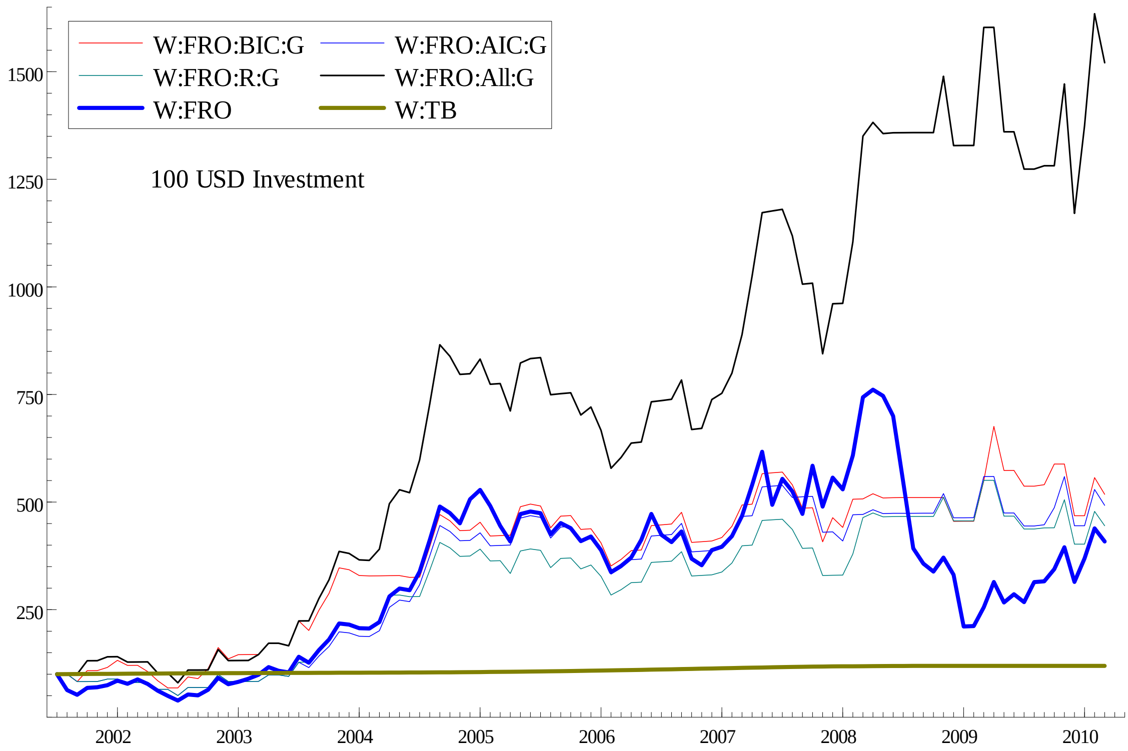

Figure 4.7 Gross evolution of $100 investment, 15.07.2001–15.03.2010

It is quite clear from all the graphs that the TB is not in any way a feasible investment. The percentages for the inclusion of variables for every model are shown in Table 4.6. For the AV model the inclusion is 100% for every step.

Table 4.6 FRO percentage of the variables inclusion

Inclusion rate %		*FRO:AIC*	*FRO:BIC*	*FRO:R-square*
X1	S&P500 Commodity	20.1	0.96	65.3
X2	Moody's Comm.	25	30.7	34.6
X3	NYMEX	100	65.3	100
X4	MLCX	100	70.1	100
X5	ISM purchase	23	0	92.3
X6	US INDUS	12.5	0	21.1
X7	US PPI	0	0	14.4
X8	TB	72.1	23	93.2

Crude Oil WTI NYMEX and MLCX Spot Index have the highest level of inclusion in all three models. US Industrial Production and US PPI – Finished Goods have the lowest level of inclusion. Figure 4.8 compares the FRO with the two strongest regressors.

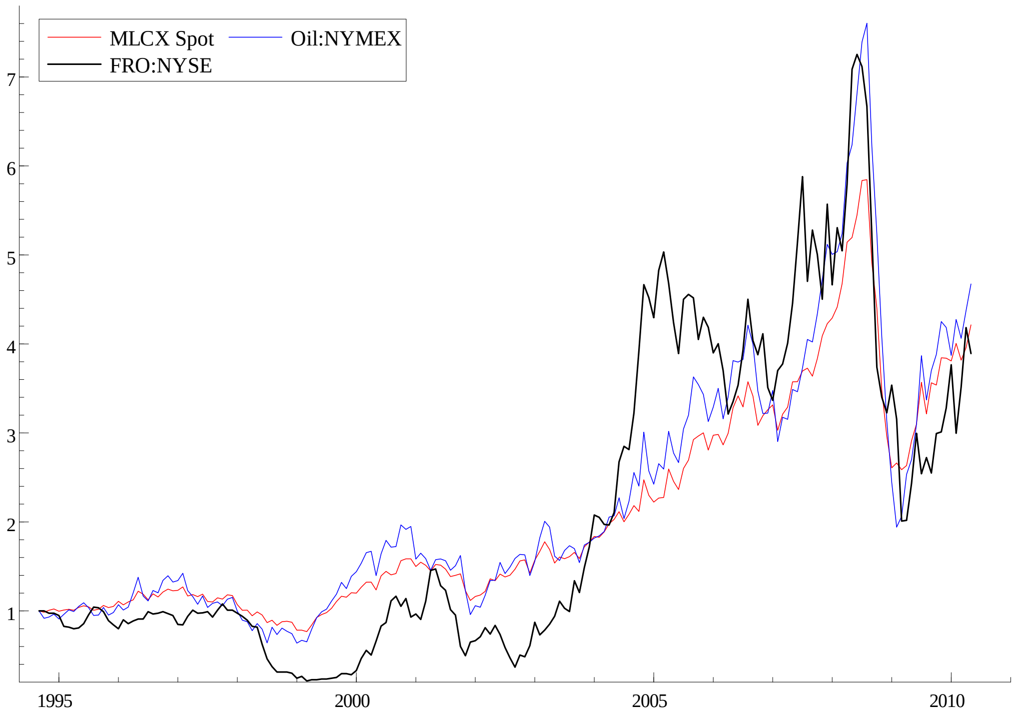

Figure 4.8 Movement of FRO, MLCX and oil price return

It should be noted that the frequency of inclusion is not normally distributed. We now plot the inclusion of variables to find out how many variables are participating in every period of forecast. Figures 4.9, 4.10 and 4.11 show the comparison of different inclusion frequencies throughout the three model selection criteria. We can see from Figure 4.8 that X3 and X4, which have the highest inclusion rates in Table 4.6, are only included from 2003. X2 is almost the only variable included until 2003.

Therefore, only X2 is included in the early years, although X3 and X4 have the highest level of inclusion and perhaps we can argue that X2 (Modey's commodity index) is the most important variable. The AIC pattern of inclusion shown in Figure 4.10 is slightly different from BIC. Both X3 and X4 and fully included. X7, like BIC, has zero inclusion. Figure 4.10 presents the inclusion by R-square; in addition to X3 and X4, X8 also illustrates a high rate of inclusion. In the R-square series all the variables have some level of inclusion; however, from a performance point of view, the BIC, which has almost no inclusion for the four variables, is the best-performing model.

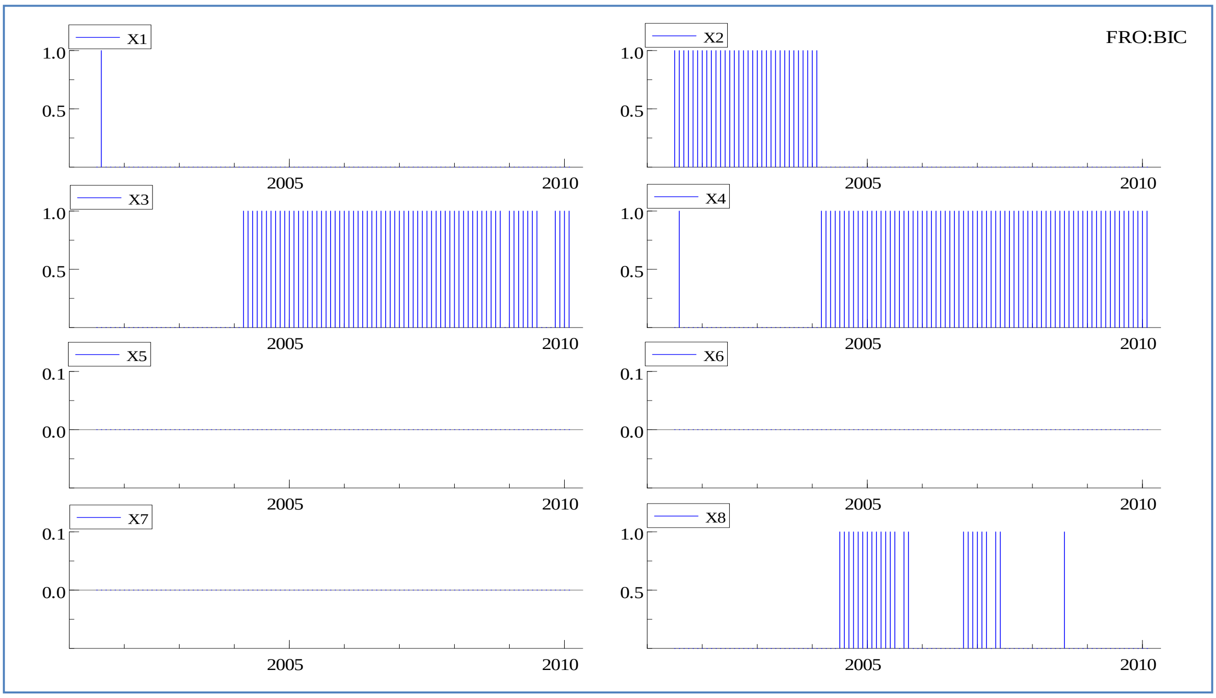

Figure 4.9 Frequency of variables inclusion, FRO: BIC[13]

[13] X1: S&P500 GSCI Commodity Spot – X2: Moody's Commodities Index – X3: Crude Oil WTI NYMEX – X4: MLCX Spot Index – X5: US ISM Purchasing Man – X6: US Industrial Production – X7: US PPI – Finished Goods – X8: US Treasury Bill 2ND Market 3 Month.

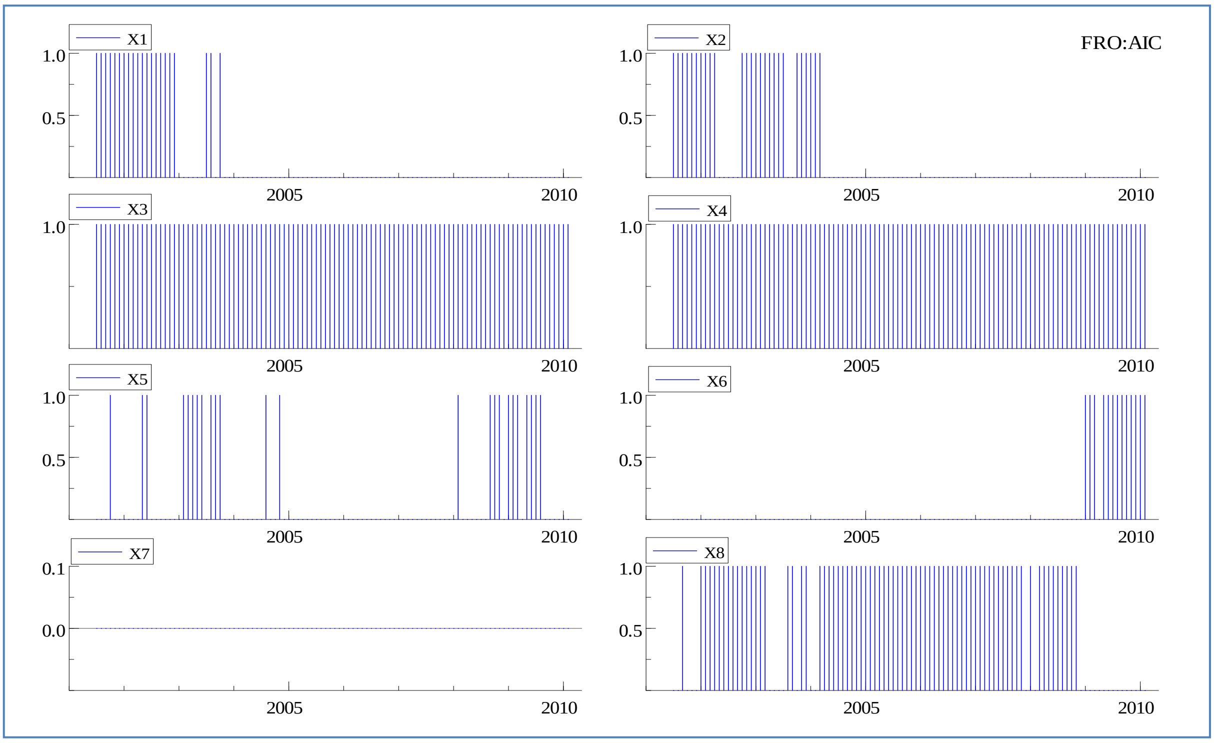

Figure 4.10   Frequency of variables inclusion, FRO: AIC

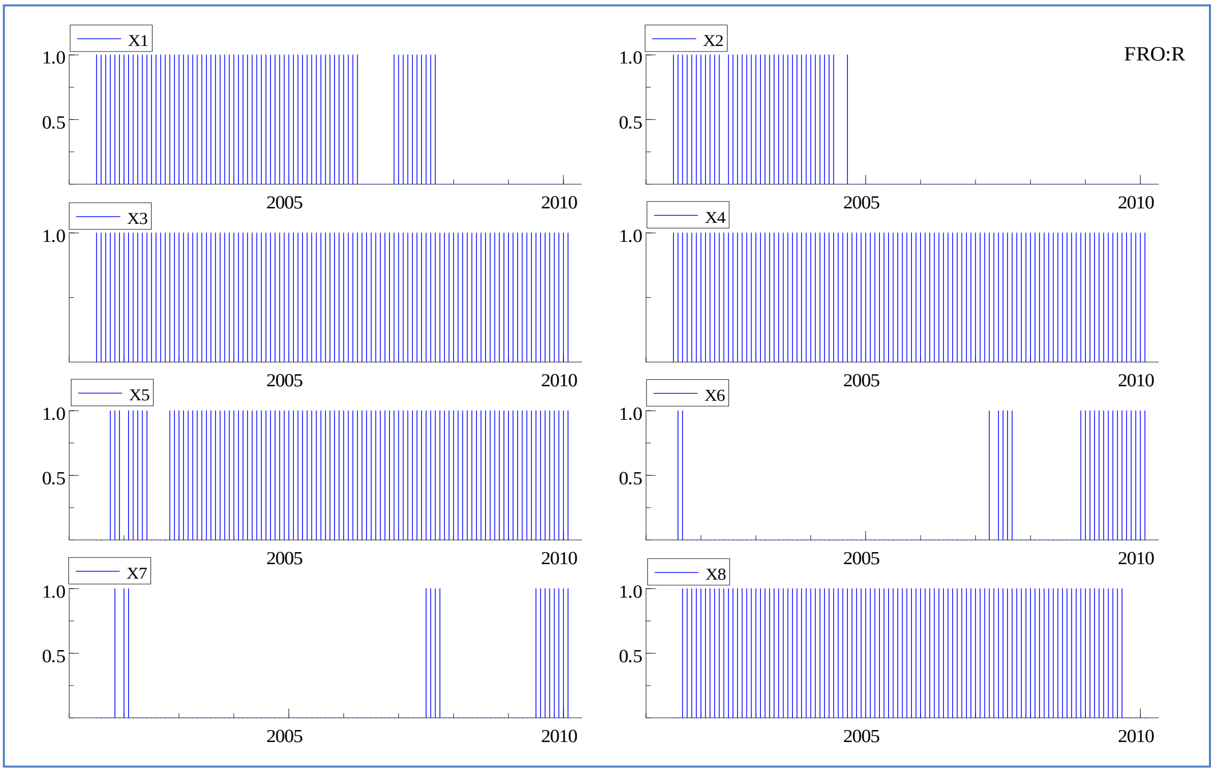

Figure 4.11   Frequency of variables inclusion, FRO: R

4.8.1 Results of S&P500

We compare the inclusion of variables in S&P500 in Table 4.7. The pattern of inclusion is completely different from that for FRO. US Industrial Production has the highest inclusion level. In FRO series, US Industrial Production was a low-performing variable. TB is a moderately performing variable in S&P500, but was a high-performing one in FRO. Figures 4.12, 4.13 and 4.14 show the frequency of inclusions. In BIC, only X3 and X6 play positive roles. BIC was the best-performing switching model in Table 4.5.

Table 4.7 S&P500: percentage of variables inclusion

Inclusion rate	*S&P500:AIC*	*S&P500:BIC*	*S&P500:R-square*
X1 S&P500 Commodity	85.5	0	100
X2 Moody′s Commodity	67.3	0	78.8
X3 NYMEX	87.5	84.6	99
X4 MLCX	15.3	0	54.8
X5 ISM purchase	85.5	7.6	98
X6 US INDUS	100	99	100
X7 US PPI	0.96	0	5.7
X8 TB	20.1	2.8	31.7

The BIC inclusion is similar in both FRO and S&P500 in the sense that they have no inclusion rate for four of the variables. Figures 4.16 and 4.17 simulate the performance of $100 investment in S&P500 and compare the strength of different models. The investment performance for S&P500 is not similar to that for FRO. The thick blue line, which is the buy-and-hold strategy, is under-performing relative to TB in almost half of the years. Only in the boom period 2005–9 does S&P500 perform better than TB. The AV model is still performing better than the rest of the models.

The switching models do not perform very well when transaction cost is inserted into the model. As we can see from the graphs, the combination models are not performing any better than TB. During the crises in 2003 the TB has the best performance. Figure 4.14 presents the panel of excess returns; in it, the BIC looks smoother than the other two switching models.

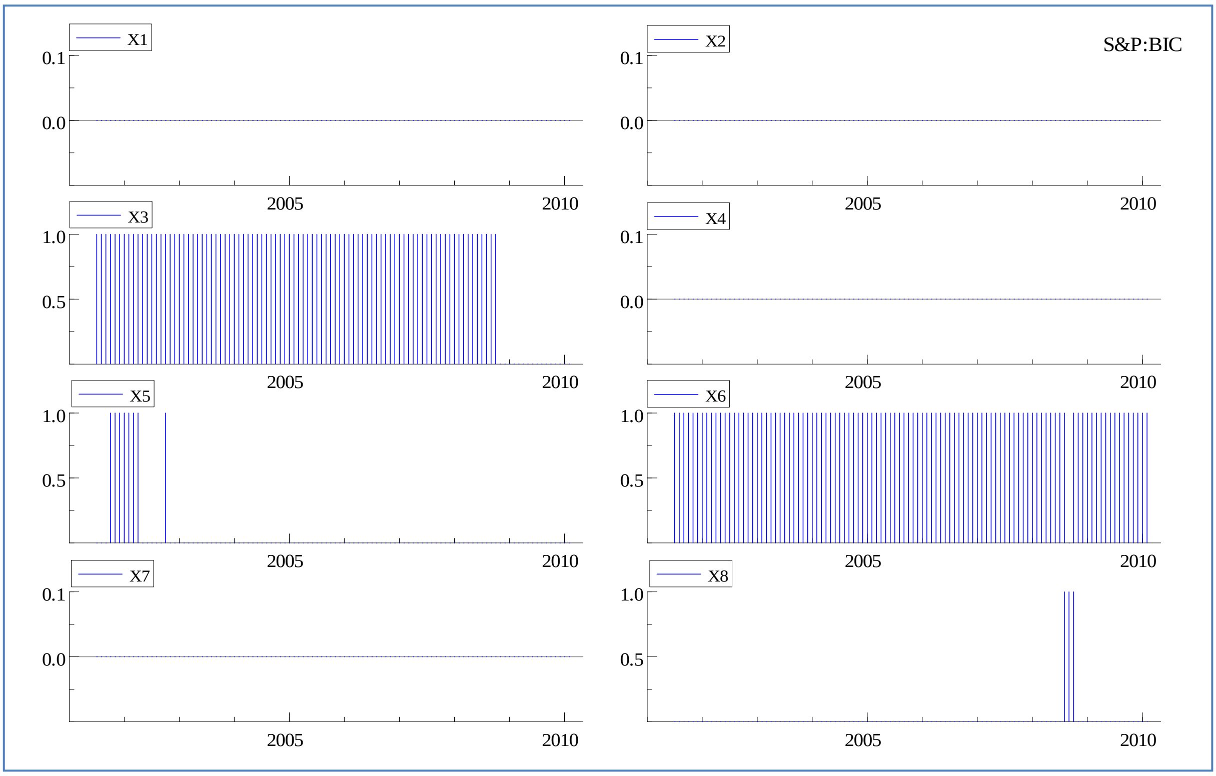

Figure 4.12 Frequency of variables inclusion, S&P500: BIC

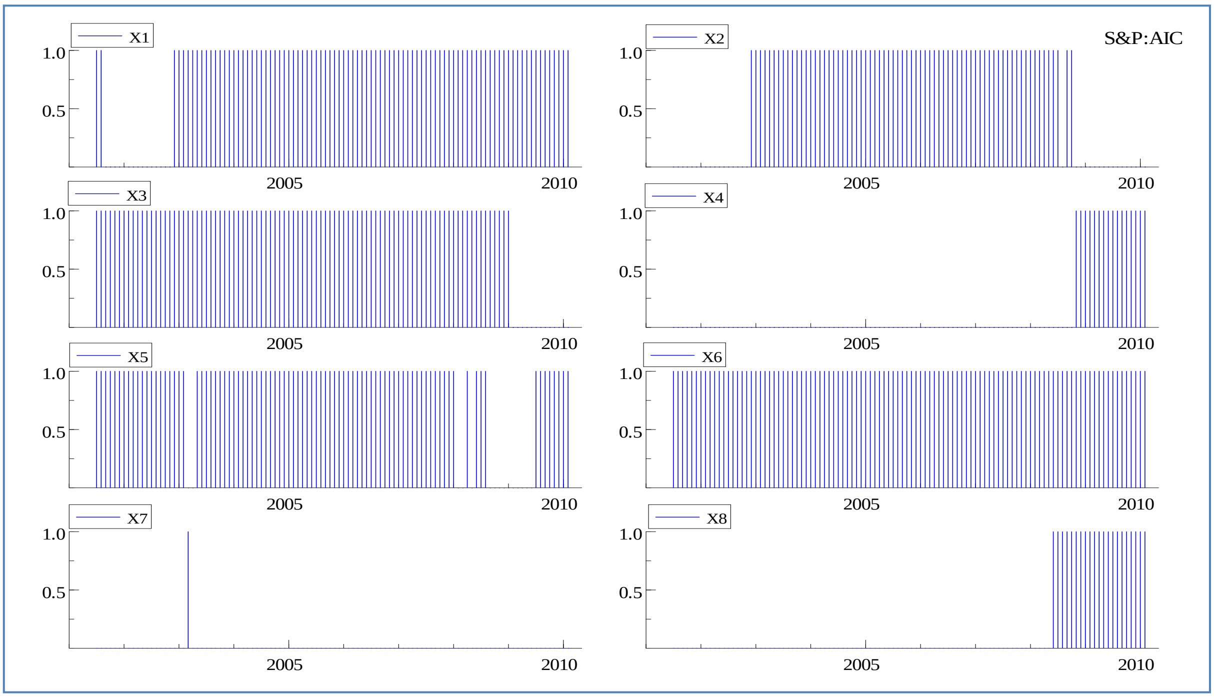

Figure 4.13 Frequency of variables inclusion, S&P500:AIC[14]

[14] X1: S&P500 GSCI Commodity Spot – X2: Moody's Commodities Index – X3: Crude Oil WTI NYMEX – X4: MLCX Spot Index – X5: US ISM Purchasing Man – X6: US Industrial Production – X7: US PPI – Finished Goods – X8: US Treasury Bill 2ND Market 3 Month.

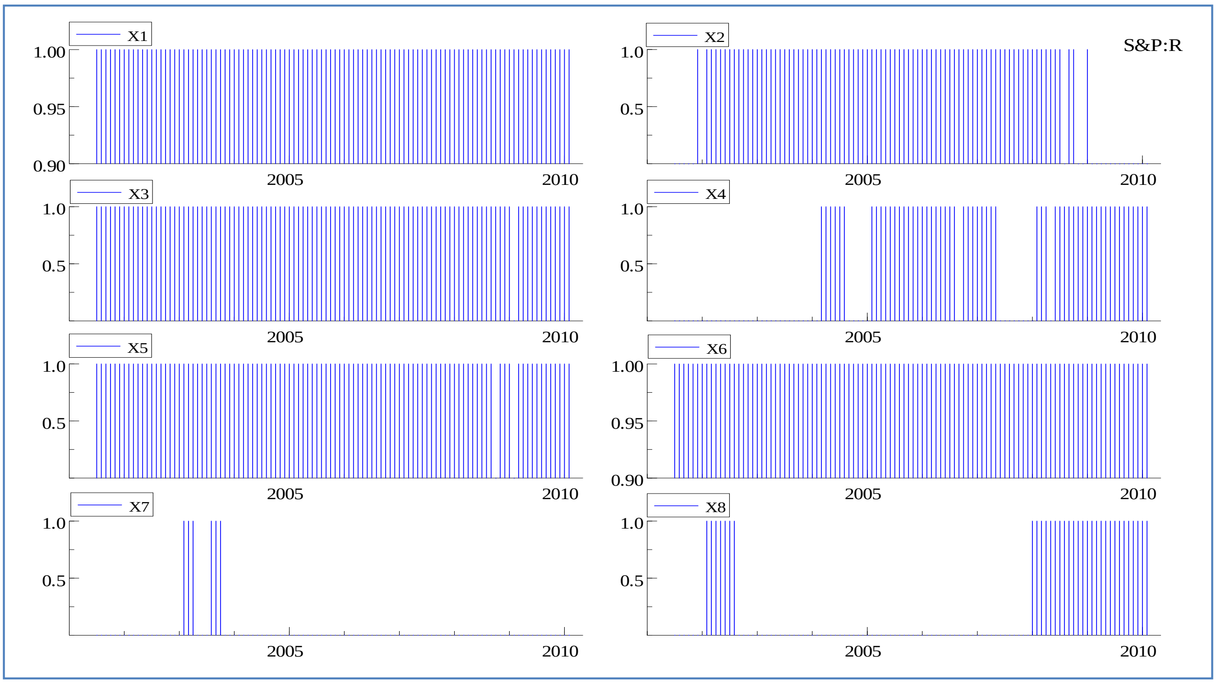

Figure 4.14 Frequency of variables inclusion, S&P500:R[15]

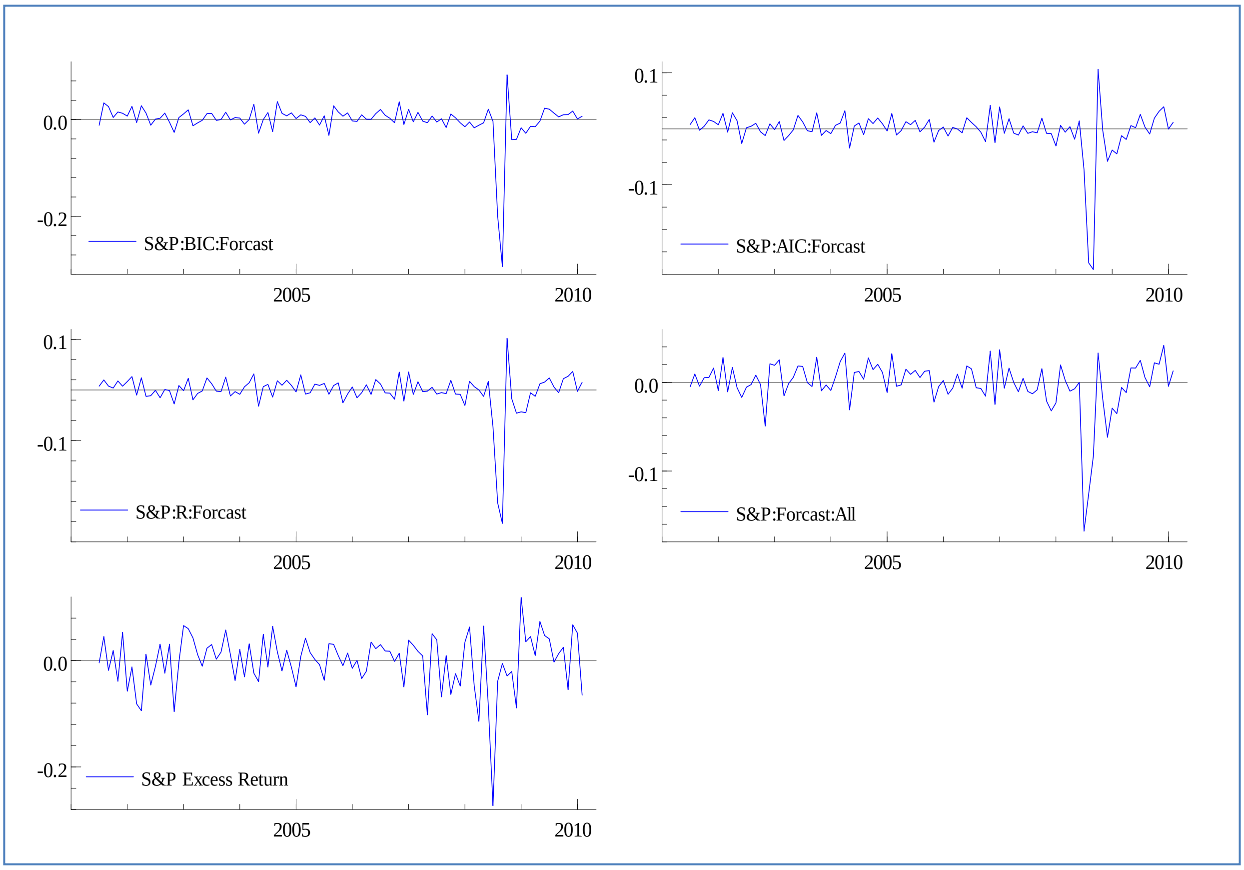

Figure 4.15 Forecast of excess returns: comparison of S&P500 selection criteria

[15] X1: S&P500 GSCI Commodity Spot – X2: Moody's Commodities Index- X3: Crude Oil WTI NYMEX – X4: MLCX Spot Index – X5: US ISM Purchasing Man – X6: US Industrial Production – X7: US PPI – Finished Goods – X8: US Treasury Bill 2ND Market 3 Month.

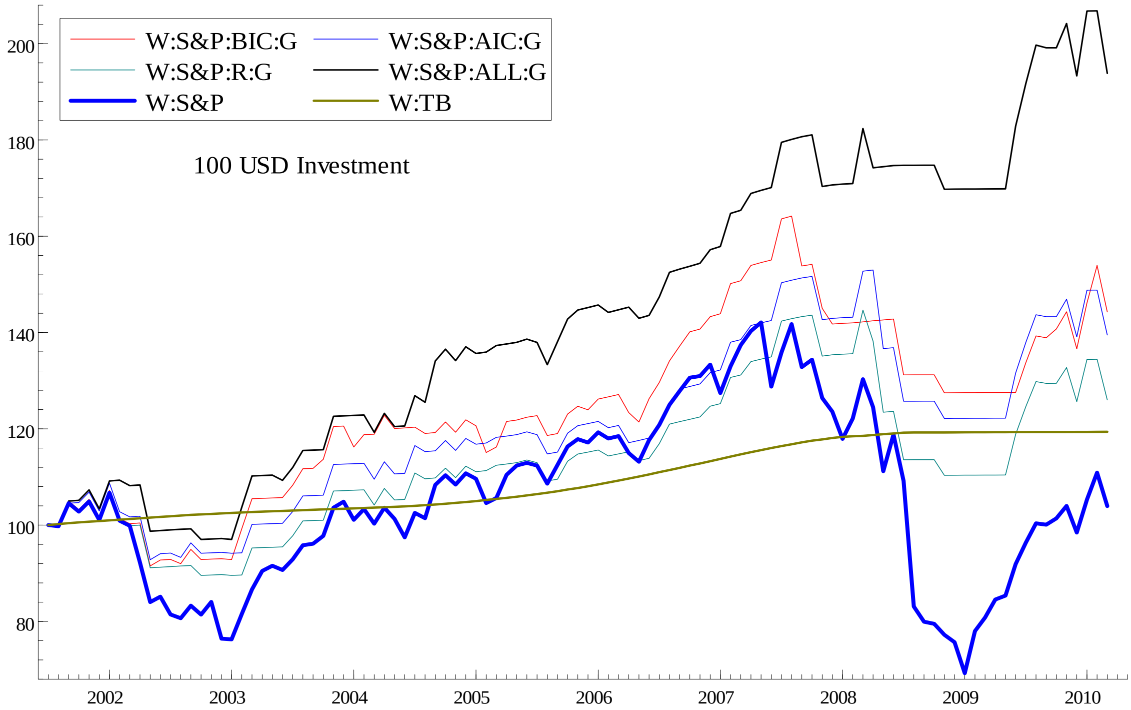

Figure 4.16   Pattern of S&P500 growth investment, 15.07.2001–15.03.2010

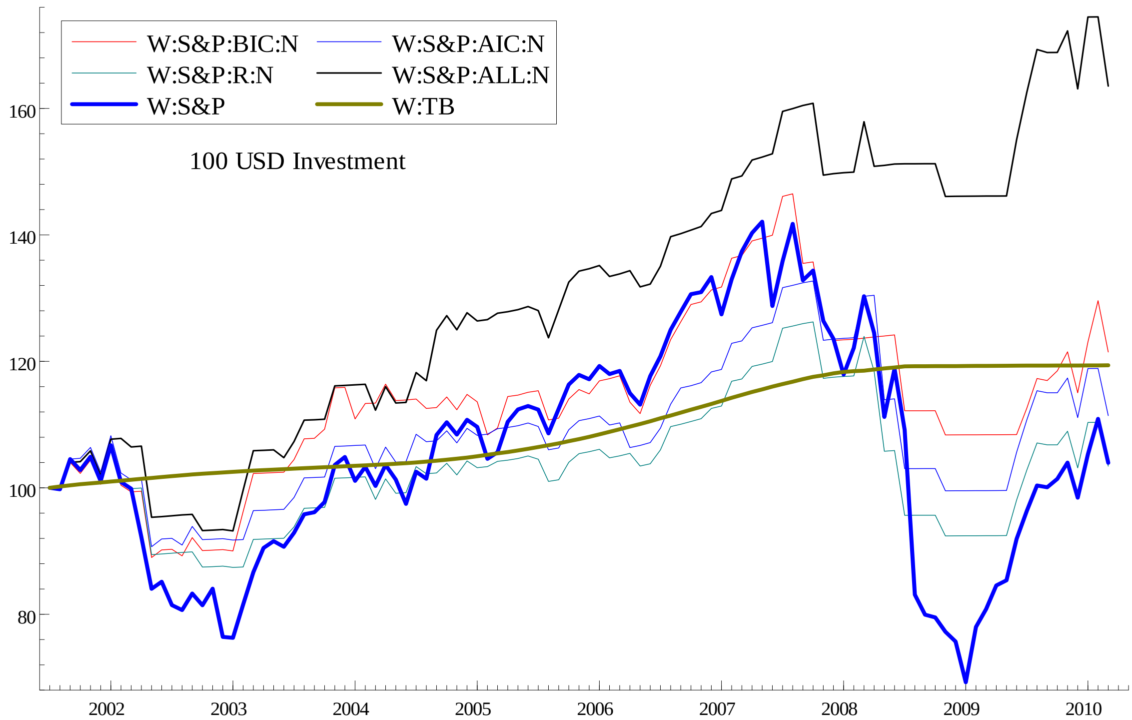

Figure 4.17   Pattern of S&P500 net investment, 15.07.2001–15.03.2010

During the crises in 2003, TB had the best performance. Between 2004 and early 2008, which was a boom period, the buy-and-hold performs relatively well. During the mid-2008 crash, the AV model has the best performance. The switching models realize the correct investing signal at the middle of the crash. During this time the BIC is at the top of the others; however, during this crash even TB outperforms the combination models.

4.9 Comparing the mean of the returns

In this section we check whether the mean return of the switching strategy is different from the TB. We choose the best-performing model of FRO:All:Net and an average performing model of FRO:AIC:Net, and compare them with the TB investment. We perform the t-test, and the results are shown in Table 4.8.

Table 4.8 t-test of the selected switching FRO return series and TB

	TestStat	*CriticalValue*	*p-value*	*Hypothesis*
TB versus FRO:AIC	−0.6043	−0.0196 0.0104	0.5463	Failure to reject
TB versus FRO:AV	4.2488	0.0004 0.0010	0.00002	reject

The mean return of the average performing AIC is not statistically any different from the TB mean, but for the AV model the means are statistically different from each other. Therefore we can conclude that, on the basis of the investor choosing any model selection criteria, the switching return series are not any different from TB.

To create a better understanding of the statistical difference between the alternative strategies, we report the result of the statistical properties for Treasury bill, FRO:N and FRO:G in Figures 4.18 to 4.20. The mean of TB is 5.5, nine times smaller than the means of FRO:N and FRO:G. The maximum return is 72 times bigger in FRO:N than in TB.

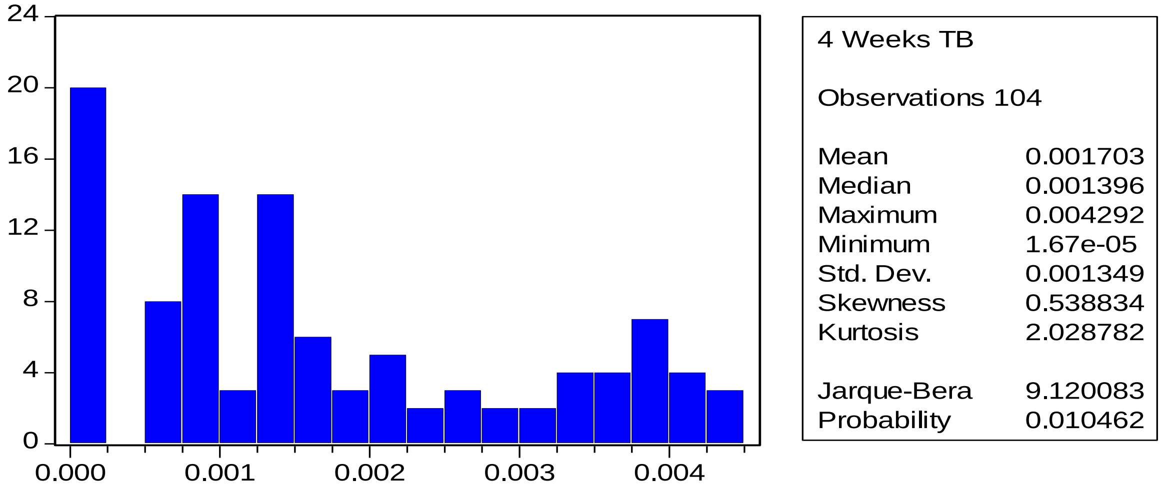

Figure 4.18 Four-week Treasury bill statistics

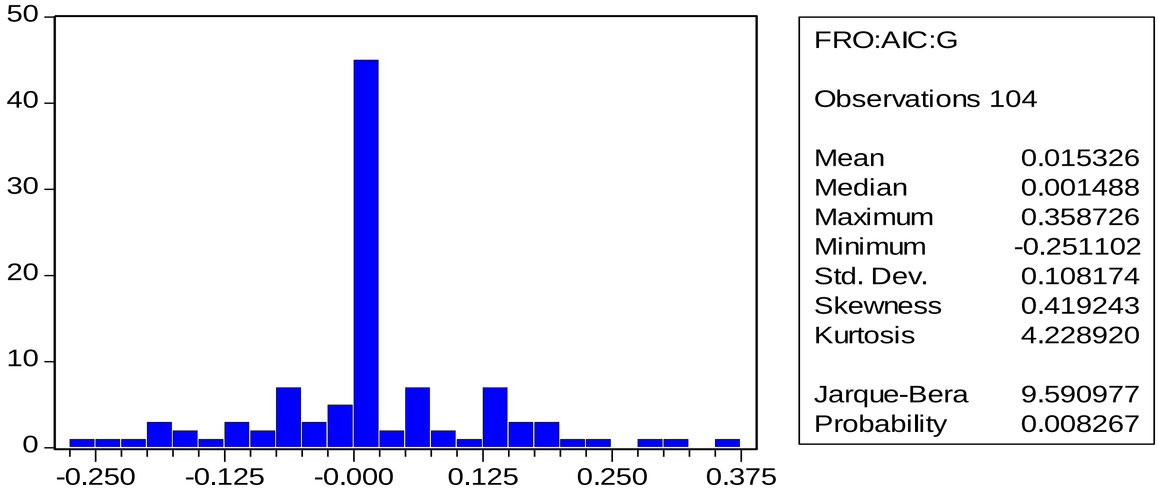

Figure 4.19 FRO:AIC:G return statistics

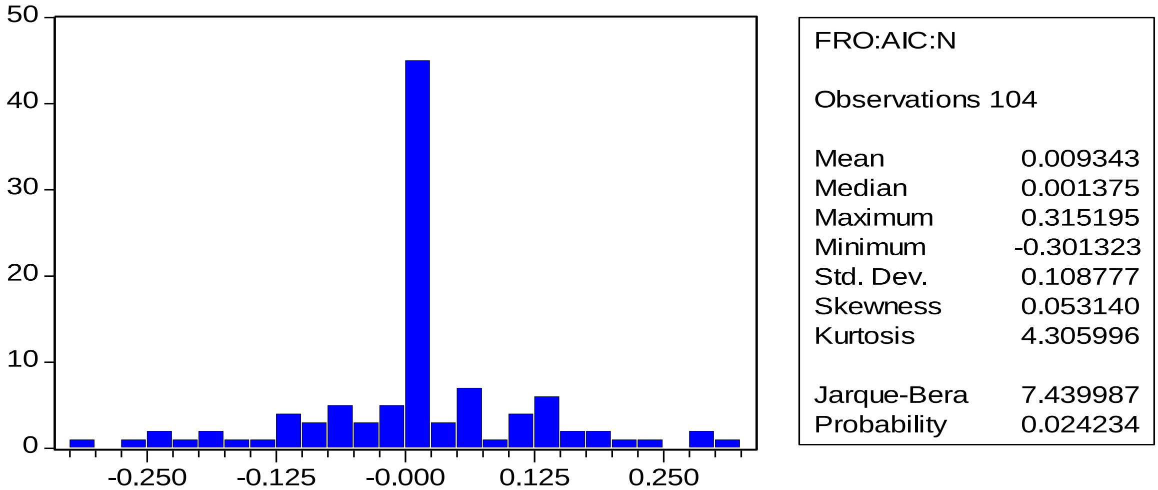

Figure 4.20 FRO:AIC:N return statistics

4.10 Examining the effect of individual explanatory variables

In this section we examine the effect of explanatory variables on an individual basis. We noticed that the AV model is performing better that the combination models. It is unclear at this stage what the investor would have faced if any single variables had been considered as the only explanatory variable instead of a collection of variables. We test the regression variables on an individual basis to find out the individual investment performances.

Figures 4.21 and 4.22 each presents the performance of single variables. Each line demonstrates the $100 investment in FRO stock, which is regressed with a single variable. Figures 4.24 and 4.25 present the investment in S&P500. The black line in all the figures represents the investment with NYMEX oil return; this black line is repeated throughout all the figures to enable visual comparison. Figure 4.21 presents six regressors up until the end of 2009; regression with NYMEX return is on top of the other alternatives. Forecasting based on the S&P Commodity Index will, however, yield a better final sum from early 2009 onwards. In general, NYMEX oil is a better regressor, except after the 2008 credit crunch. Between these six variables the S&P500 Commodity Index does not show any major crash. Through all the figures TB is the best predictor in both FRO and S&P500. Individual regressors seem to be working better than any other combinations or the AV model. For FRO, if the entire investment patern and not the sum of final investment is considered, NYMEX oil is the most important variable and is on top for most of the forecasting period.

The results for S&P500 is different from those for FRO. Figures 4.24 and 4.25 are related to the individual performances of S&P500. NYMEX oil is the standard of visual comparison. TB has the best performance. However, if we consider the entire period and not the final sum then MLCX is the best predictor. In FRO stock, forecasting with TB yields a final investment sum almost four times bigger than switching with FRO R-square. The combination models are the worst-performing ones and the AV model stands in between.

We compare the final sum of investments in Table 4.9. Figures 2.23 and 2.26 present the pattern of investment regressed two variables. In FRO, regressing with two variables of X4-X7 and allowing for combination yields the third-highest final value.

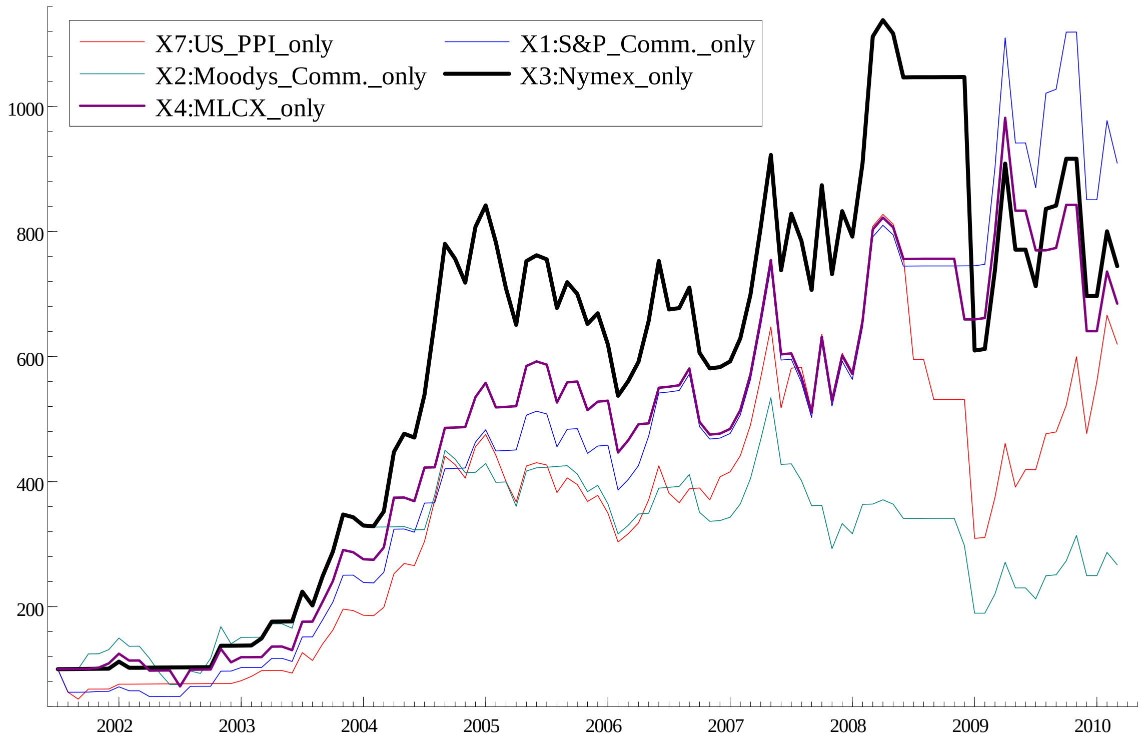

Figure 4.21 FRO forecast with individual variables X1,2,3,4,7

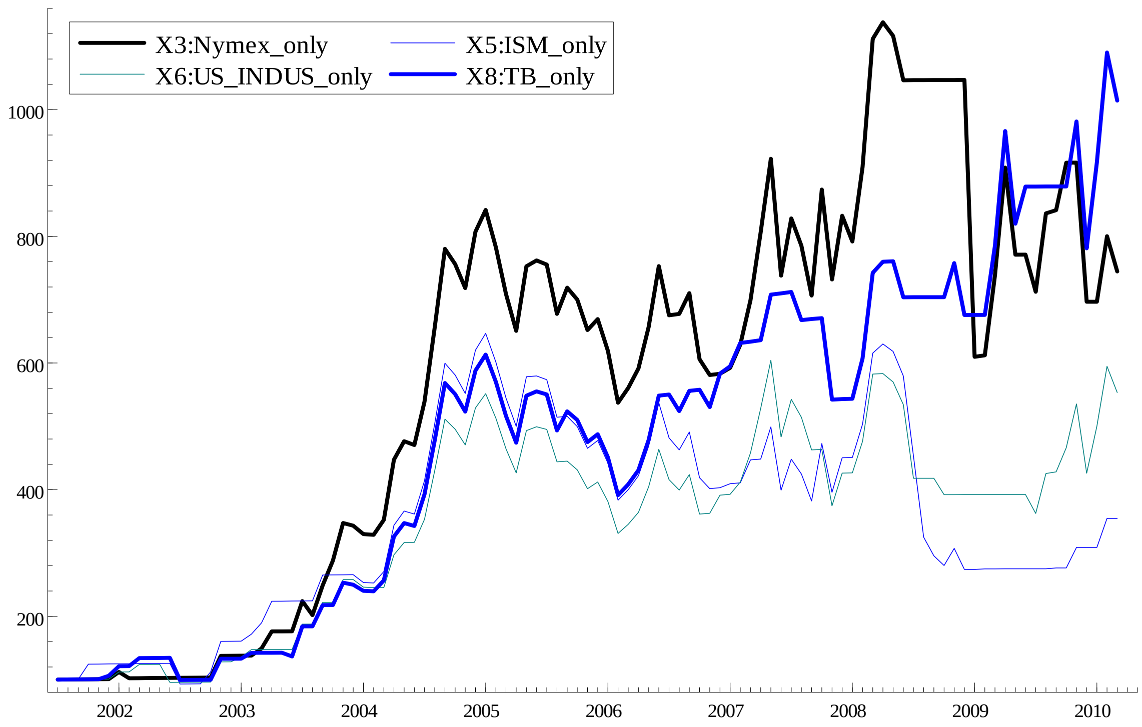

Figure 4.22 FRO forecast with individual variables X3,5,6,8

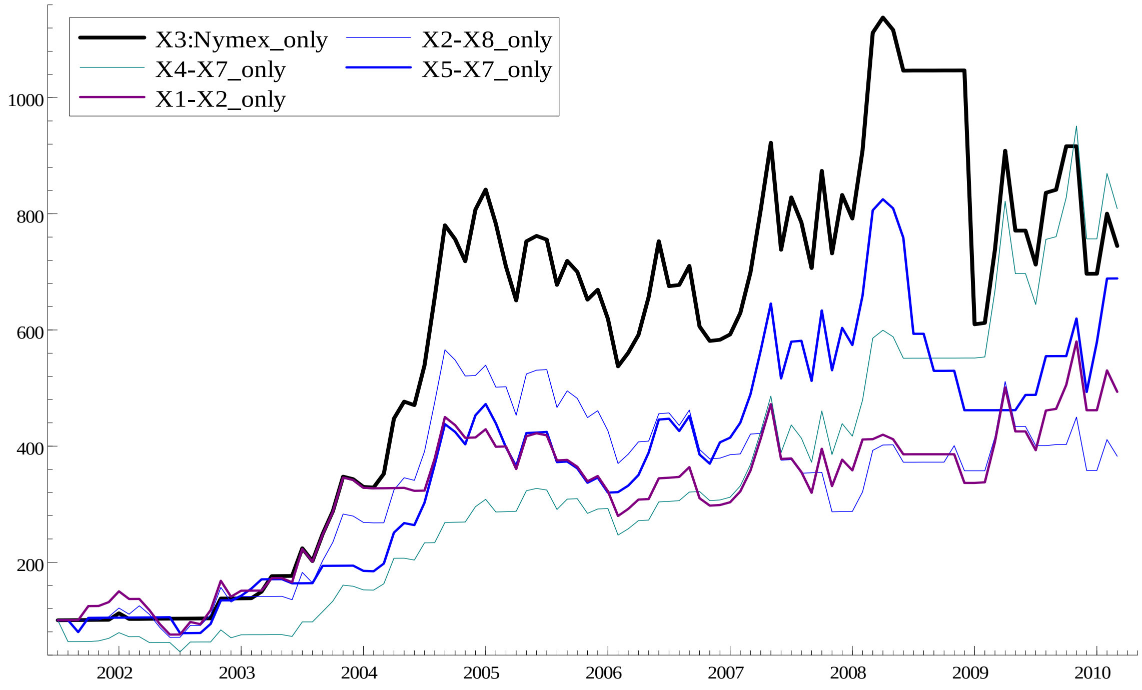

Figure 4.23 FRO forecast with two variables

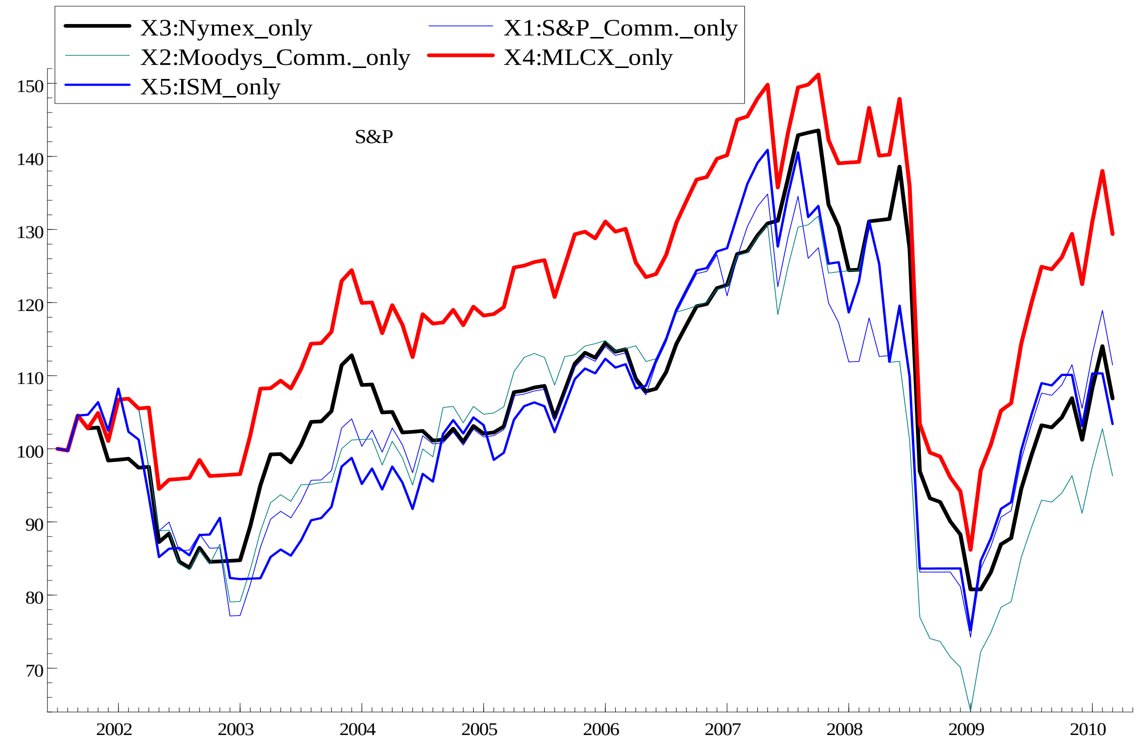

Figure 4.24 S&P500 forecast with individual variables X1,2,3,4,5[16]

[16] X1: S&P500 GSCI Commodity Spot – X2: Moody's Commodities Index – X4: MLCX Spot Index – X5: US ISM Purchasing Man – X6: US Industrial Production – X7: US PPI – Finished Goods.

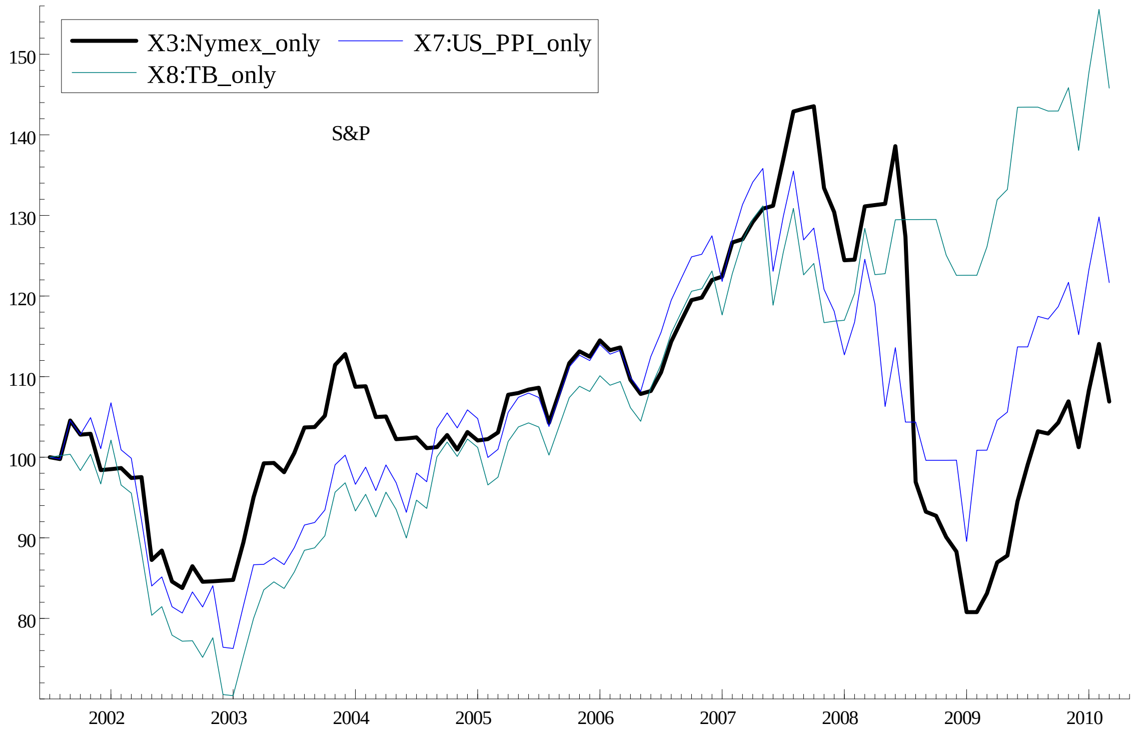

Figure 4.25 S&P500 forecast with individual variables X3,7,8

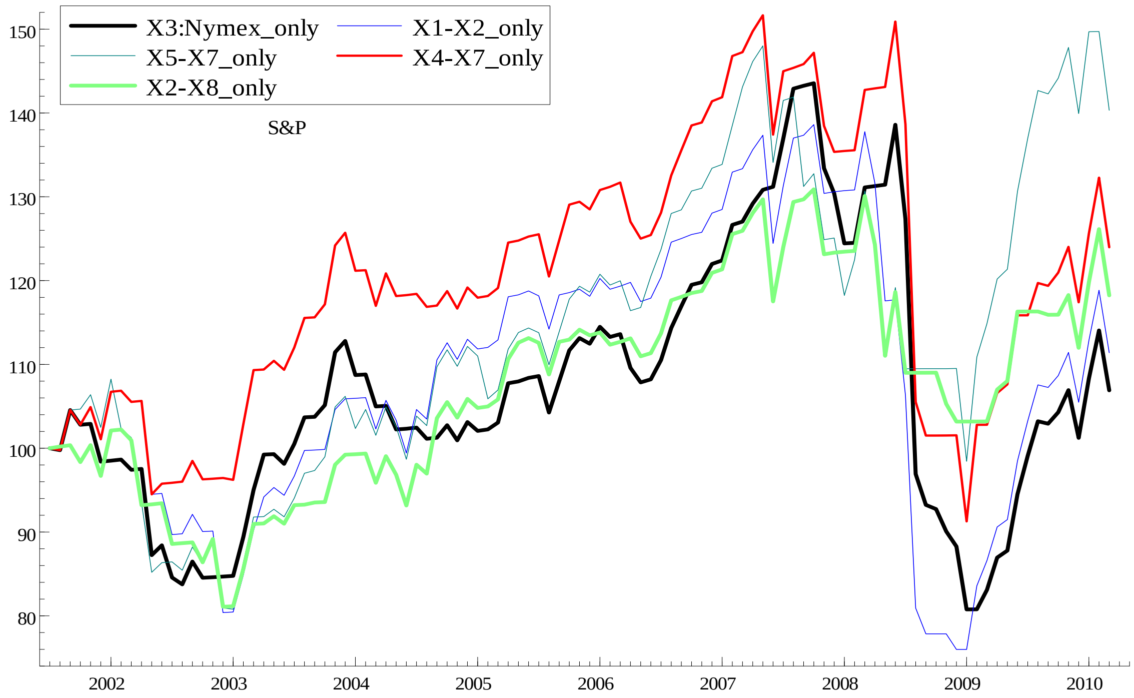

Figure 4.26 S&P500 forecast with two variables

Table 4.9 Final investment of $100: all alternatives[17]

Stock name: forecast variables	W_{NE} \$	W_{BH} \$	W_{TB} \$
FRO: X8: TB	**1014.46**	408.37	119.37
FRO: X1: S&P500_Commodity	909.24		
FRO: X3: NYMEX	744.57		
FRO: X4: MLCX	684.66		
FRO: X7: US_PPI	619.65		
FRO: X6: US_INDUS	553.31		
FRO: X5: ISM	354.64		
FRO: X2: Moodys_Commodity	266.86		
FRO: X4 − X7	808.89		
FRO: X5 − X7	688.63		
FRO: X1 − X2	493.45		
FRO: X2 − X8	382.49		
FRO: AIC	264.24		
FRO: R- square	216.94		
FRO: BIC	291.80		
FRO: AV	**791.40**		
S&P: X8: TB	**145.80**	103.94	
S&P500: X1: S&P500_Commodity	111.46		
S&P500: X3: NYMEX	106.89		
S&P500: X4: MLCX	129.36		
S&P500: X7: US_PPI	121.65		
S&P500: X6: US_INDUS	141.85		
S&P500: X5: ISM	103.39		
S&P500: X2: Moodys_Commodity	96.29		
S&P500: X4 − X7	123.98		
S&P500: X5 − X7	140.32		
S&P500: X1 − X2	111.39		
S&P500:X2-X8	118.23		
S&P500: AIC	111.41		
S&P500: R- square	103.43		
S&P500: BIC	121.47		
S&P: AV	**163.54**		

[17] X1: S&P500 GSCI Commodity Spot – X2: Moody's Commodities Index – X3: Crude Oil WTI NYMEX – X4: MLCX Spot Index – X5: US ISM Purchasing Man – X6: US Industrial Production – X7: US PPI – Finished Goods – X8: US Treasury Bill 2ND Market 3 Month.

Table 4.9 presents the panel of comparison between the final investment sums. The bold rows present the two highest sums, which are forecasting with TB and AV models; they are similar in both stocks. The FRO section in every group is in ascending order; the S&P500 section is not in ascending order. In FRO stock, TB is the highest final sum, followed by S&P500 Commodity, NYMEX oil and X4-X7 (MLCX and US PPI finished goods). In S&P500, the AV model produces the highest final sum, followed by TB, US industrial production and X5-X7 (US ISM purchasing and US PPI finished goods). There is not much similarity between the best four explanatory variables of two stocks. However, TB is the only variable that works well in both FRO and S&P500.

4.11 Results for three more shipping companies' stocks

Until now, the pattern of variables inclusion, the best model and the best explanatory variables have not been similar in FRO and S&P500. We also found that the performace of the variables to the large extent depends on the forecasting period. In his section we analyse three more shipping companies to find out whether any convincing results can be obtained regarding the performance of combination models. The three companies are represented in Table 4.10. These companies are, like Frontline, specialist tanker shipping companies. We use a partly different set of forecasting variables (see Tables 4.11, 4.15 and 4.19) for each of the stocks to avoid any data snooping problems.

Table 4.12 presents the sum of returns for VLCCF stock. The sums of net return are negative for AIC and buy-and-hold strategy, and the AV model produces the highest return. In three out of four models the switching models produce a much bigger return than TB. The buy-and-hold strategy produces the worst results and, as previously, the AV model is the best model.

Table 4.10 Description of the three shipping companies' stocks

Company name/website	*Sector*	*Market*	*Exchange: symbol*
Knightsbridge Tankers	Industrial Transport/ tanker	USA	NASDAQ: VLCCF
Nordic AMER.TKR.Ship	Industrial Transport/tanker	USA	NYSE:NAT
Teekay Corporation	Industrial Transport/tanker	USA	NYSE: TK

4.11.1 Knightsbridge (VLCCF) Tankers

Table 4.11 Knightsbridge tankers variables

VLCCF Variables Description			
Name	Description	Start	Finish
Y	NASDAQ: VLCCF	15/05/2000	5/05/2010
TB	US TB 2ND MKT 4-WK – Middle Rate	15/05/2000	5/05/2010
	Forecasting Period	15/01/2006	5/05/2010
VLCCF Stock Regressors	Full length 120- Effective 52- start 68		
X1	Knightsbridge Tankers. – Dividend Yield	no lags:	1
X2	S&P500 GSCI Commodity Spot – Price Index		1
X3	Moody's Commodities Index – Price Index		1
X4	Crude Oil, WTI NYMEX Spot U$/BBL		1
X5	US Industrial Production VOLA		2
X6	US PPI – Finished Goods SADJ		2
X7	BD IND. PRO. Including CONS.(%YOY) VOLA (Germany)		2
X8	CH Industrial Production Index VOLN		2

Table 4.12 VLCCF sum of returns

VLCCF	R_{NE}	R_{GR}	R_{BH}	W_{TB}
VLCCF: AIC	−0.10	0.12		
VLCCF: R-square	0.44	0.64		
VLCCF: BIC	0.13	0.36	−0.32	0.09
VLCCF: AV	0.54	0.76		

Table 4.13 VLCCF final investment

VLCCF 100 *USD*	W_{NE} $	W_{GR} $	W_{BH} $	W_{TB} $
VLCCF: AIC	90	113.8		
VLCCF: R-square	155.9	189.7		
VLCCF: BIC	111.5	143.5	72.2	110.4
VLCCF: AV	172.7	215.7		

R-square produces the second-best investment result. This is contrary to the previous stock, in which BIC was often the best model selection criterion.

Table 4.14 VLCCF inclusion of variables

Inclusion rate		*VLCCF:AIC*	*VLCCF:BIC*	*VLCCF:R-square*
X1	Dividend Yield	100	100	42.3
X2	S&P500 Comm.	0	65.3	100
X3	Moody's Comm.	100	71.15	100
X4	NYMEX	57.6	98	75
X5	US Ind	0	63.4	100
X6	US PPI	76.9	100	61.5
X7	Germany Ind.	0	96.1	100
X8	China Ind	96.1	100	82.6

Table 4.14 presents the pattern of inclusion of variables. DY has a high rate of inclusion. In addition to China industrial production, Moody's Commodity and US PPI, DY did not have any significant inclusion rate in FRO and was replaced by another variable.

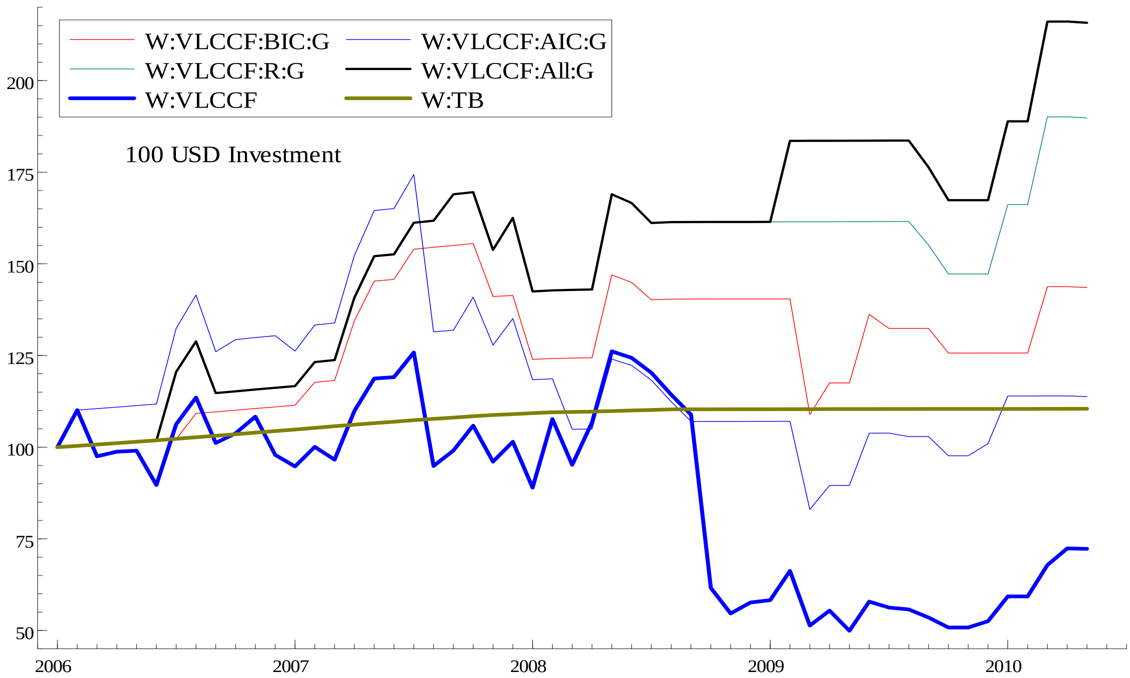

Figure 4.27 Pattern of VLCCF gross investment, 15.01.2006–15.05.2010

Figures 4.26 and 4.27 both indicate the underperformance of the buy-and-hold strategy; the AV model and the R-square selection criterion are performing better than the others. In FRO stock, the R-square was the worst-performing selection criterion. TB, which is the thick red line, has an average performance that is much better than that of VLCCF: AIC. The AV model and R-square perform similarly until 2009.

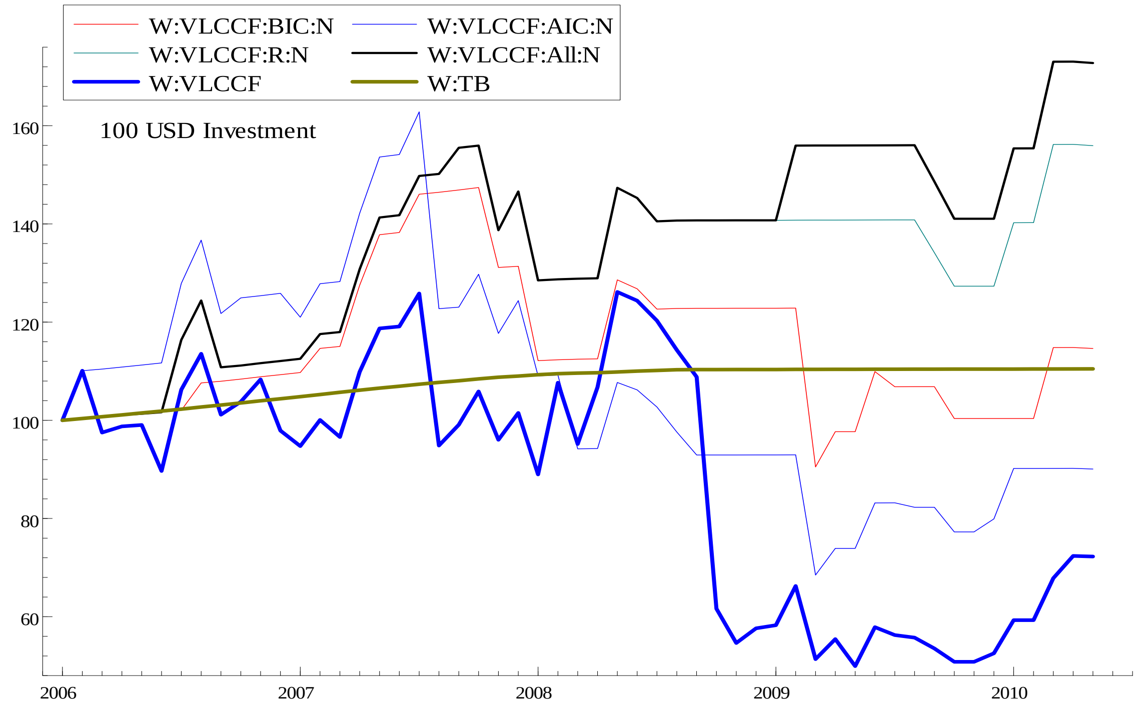

Figure 4.28 Graph of VLCCF net investment, 15.01.2006–15.05.2010

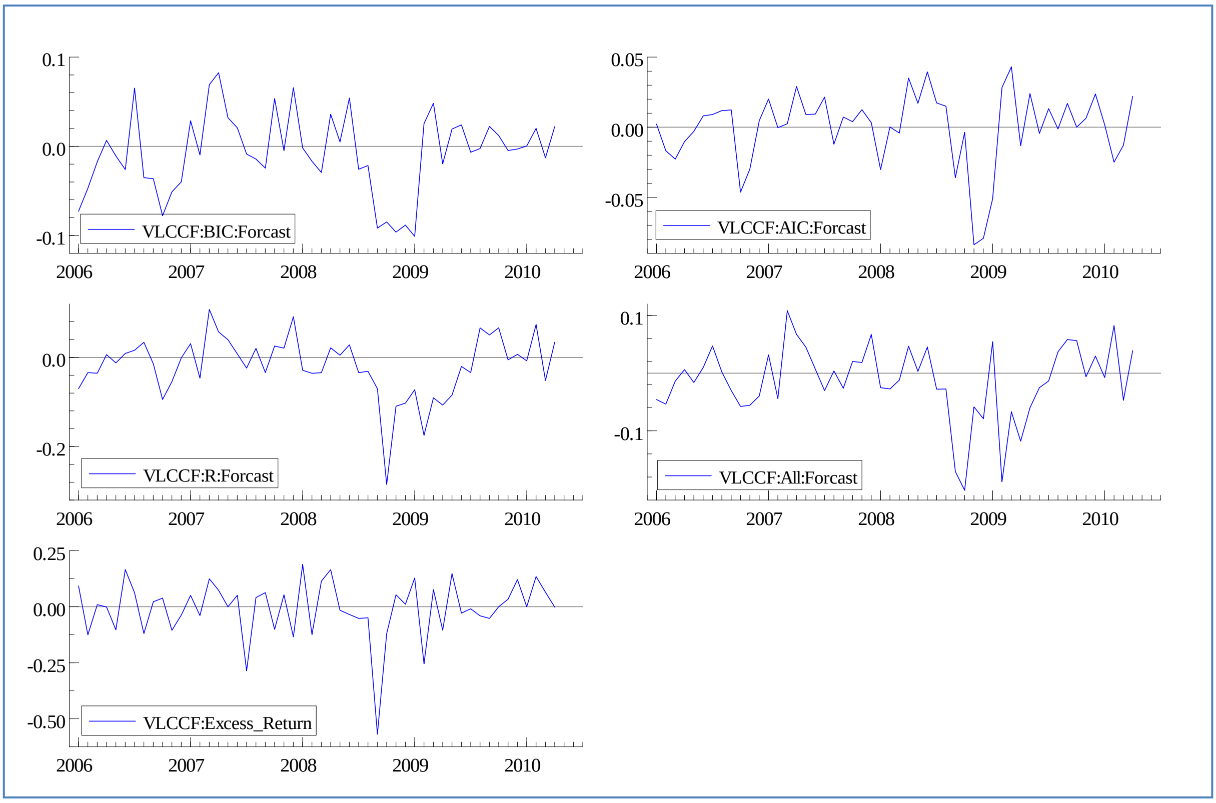

Figure 4.29 VLCCF return: comparison of selection criteria

4.11.2 Nordic American Tanker Ship (NAT)

In this section, the results for the Nordic American Tanker Ship company are reported. Table 4.15 presents the details of the forecasting variables. In addition to the usual set of variables it contains two types of oil prices, NYMEX and Brent Crude Oil. It also contains VIX and TB. VIX was briefly explained in section 4.5.

Table 4.15 'NASDAQ: NAT' variables descriptions

Nordic American Tanker Ship			
Name	Description	Start	Finish
Y	NASDAQ: NAT	15/11/1997	15/05/2010
TB	US TB 2ND MKT 4-WK – Middle Rate	15/11/1997	15/05/2010
	Forecasting Period	15/04/2003	15/05/2010
NAT Stock Regressors	Full length: 150 – Effective: 86 - start: 65		
X1	LME-LMEX Index – Price Index	No of lags:	1
X2	S&P500 GSCI Commodity Spot – Price Index		1
X3	Crude Oil, WTI NYMEX Spot U$/BBL		1
X4	Crude Oil-Brent Cur. Month FOB U$/BBL		1
X5	MLCX Spot Index – PRICE INDEX		1
X6	CBOE SPX Volatility VIX (New) – Price Index		1
X7	US Industrial Production VOLA		2
X8	US TB 3 Month – Middle Rate		1

Table 4.16 NAT sum of return series

NAT	R_{NE}	R_{GR}	R_{BH}	W_{TB}
NAT: AIC	0.45	0.64	0.78	0.15
NAT: R-square	0.33	0.59		
NAT: BIC	0.12	0.45		
NAT: AV	1.68	1.95		

Table 4.16 presents the sum of the returns for NAT. The net returns in most cases (except BIC) are bigger than for TB. However, a buy-and-hold strategy produces an impressive 78%, which is bigger than all the combination models. Of the model

selection criteria, AIC has the best performance; this is different from the previous stocks. As with the previous stocks, the AV model generates the highest sum.

Table 4.17 NAT final investment

NAT	W_{NE} \$	W_{GR} \$	W_{BH} \$	W_{TB} \$
NAT: AIC	158.2	191.3	219.5	116.3
NAT: R-square	139.3	182.2		
NAT: BIC	112.9	157.6		
NAT: AV	538.4	704.9		

Table 4.17 presents the final investment and shows results similar to the results for summation of returns. The AV model produces almost 2.5 times more return than the buy-and-hold strategy, but the rest of the combination models do not perform better than the buy-and-hold strategy. BIC is the worst-performing model selection criterion.

Table 4.18 NAT: percentage of variables inclusion

Inclusion rate %		*NAT:AIC*	*NAT:BIC*	*NAT:R-square*
X1	LME	3.4	3.4	3.4
X2	S&P500 Commodity	100	81	100
X3	NYMEX	26.7	1.1	27.9
X4	Brent Crude	0	0	0
X5	MLCX	9.3	0	60.4
X6	VIX	15.1	1.1	61.6
X7	US INDUS.	19.7	0	23.2
X8	TB	60.4	15.1	81.3

Table 4.18 presents the inclusion rate of variables for NAT. Brent Oil has a zero rate of inclusion. It appears that although Brent Oil is an accepted benchmark, it does not play any role in the price discovery process. TB had a moderate level of inclusion in previous stocks, but it has a high rate of inclusion in addition to S&P500 Commodity Index. NYMEX oil is a relatively moderately performing variable. Figures 4.30 and 4.31 show the evolution of the \$100 investment. Figure 4.32 shows the panel of returns. It is clear that the AV model forecast is a closer match to the actual excess return. The AIC model is the smoothest-looking graph.

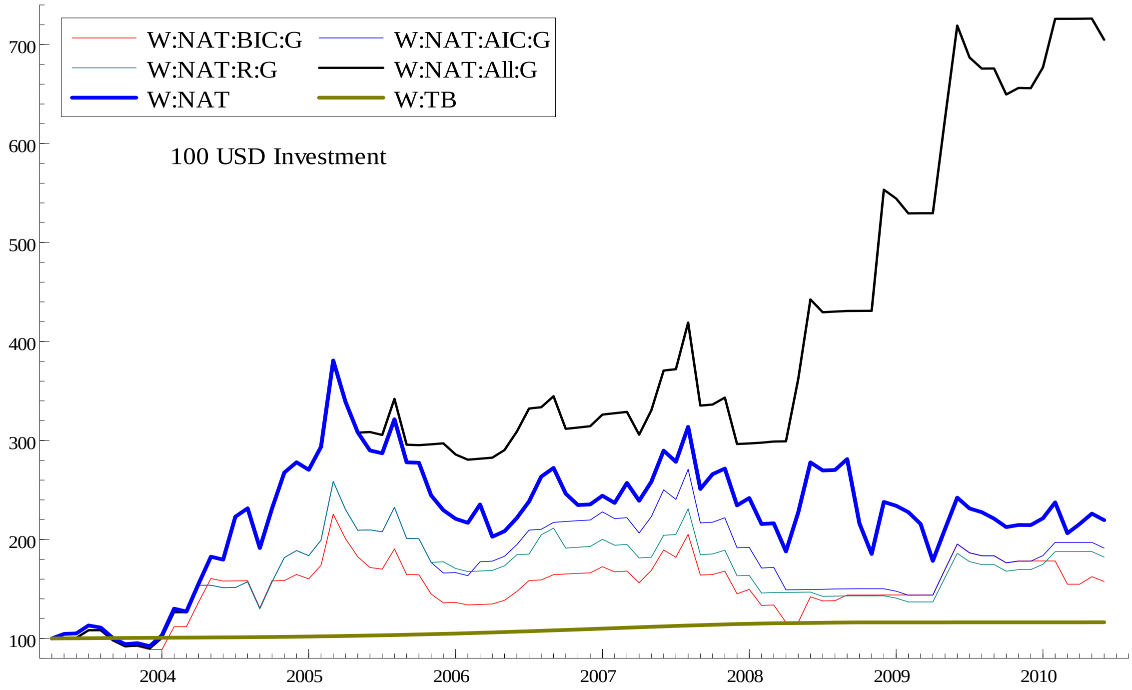

Figure 4.30 Pattern of NAT gross investment, 15.04.2003–15.05.2010

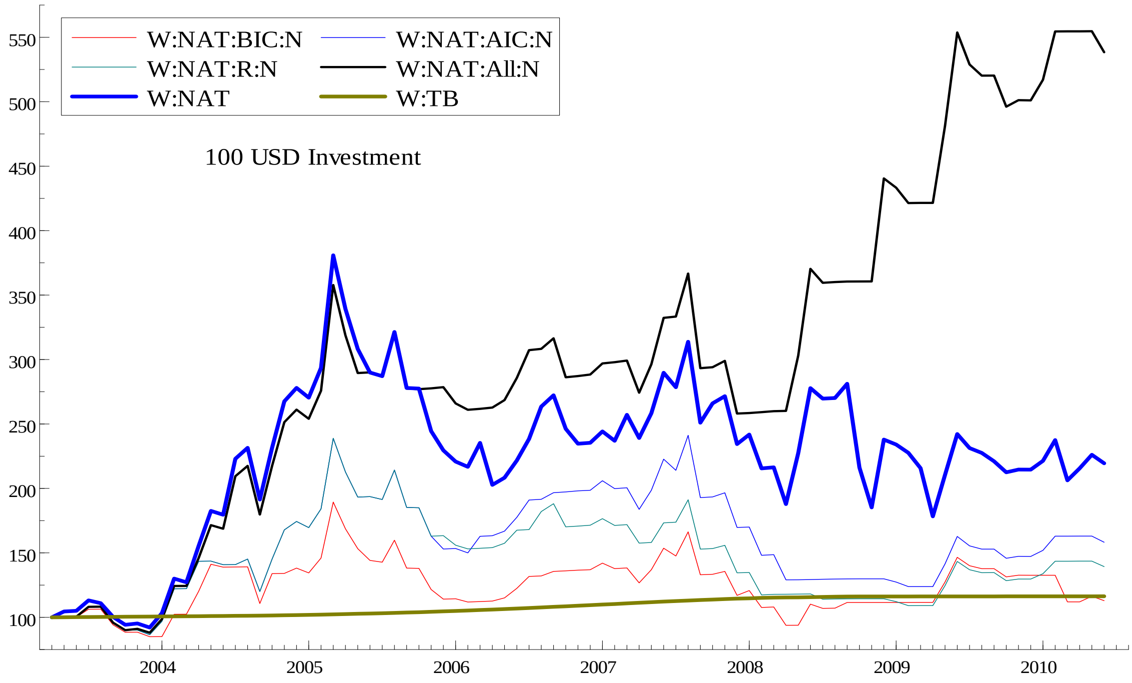

Figure 4.31 Pattern of NAT net investment, 15.04.2003–15.05.2010

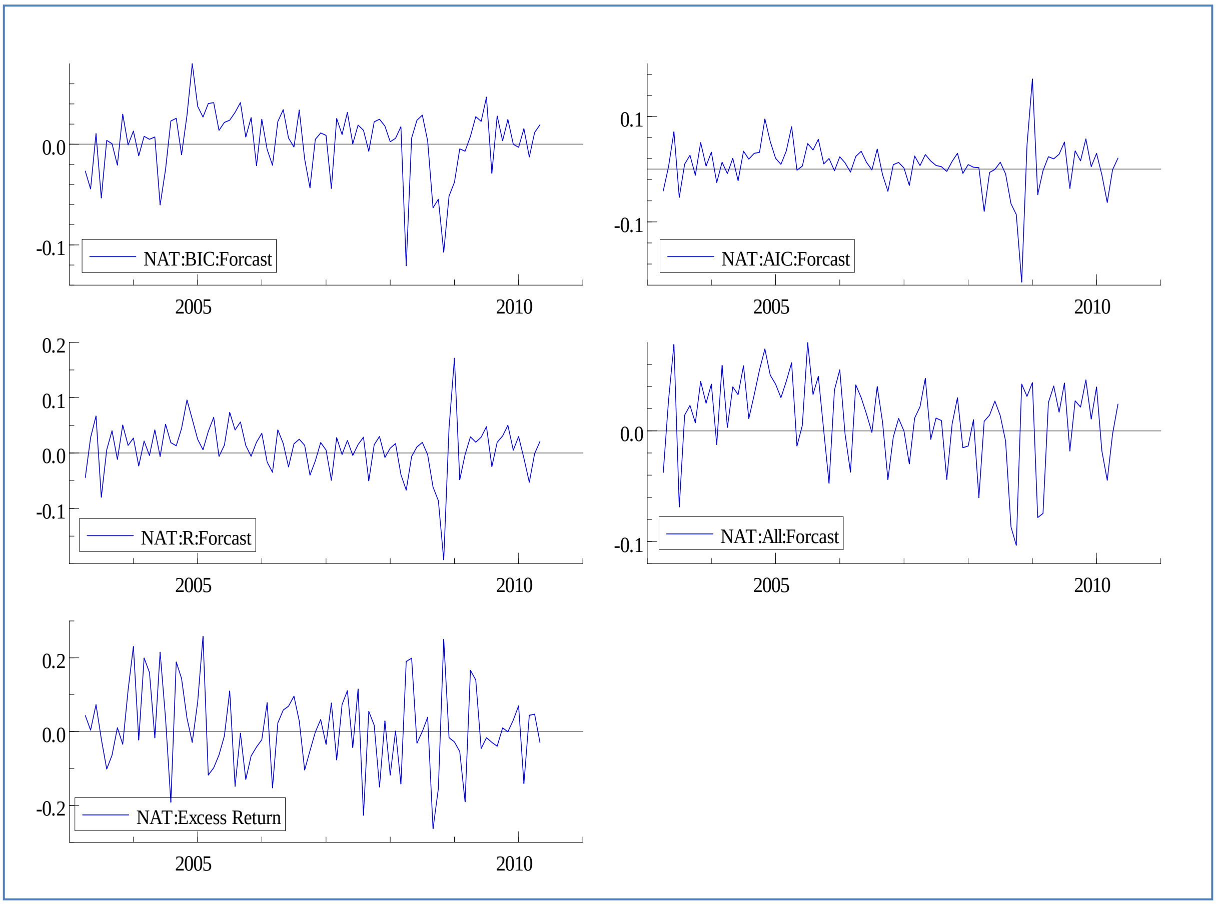

Figure 4.32 NAT: comparison of selection criteria

The final sums of gross investment with combination models are all higher than TB investment. As we were expecting, AV's is the best performance. As regards the combination models, AIC is on top of the others. One difference between the NAT pattern of investment and the previous stocks is that most of the models, most of the time, perform better than TB. However, the 2003 crash is not included in the NAT forecast.

4.11.3 Teekay Corporation

The set of regressors for Teekay Corporation stocks includes two sets of oil prices and three sets of industrial production indexes for the USA, Germany and China. DY is also included. Table 4.19 describes the specifications of the variable. Table 4.20 presents the sum of returns and Table 4.21 the final value of the investment.

Table 4.19 'NYSE:TK': description of variables

Teekay Corporation			
Name	Description	Start	Finish
Y	NYSE:TK	15/10/1995	15/04/2010
TB	US TB 2ND MKT 4-WK – Middle Rate	15/10/1995	15/04/2010
	Forecasting Period	15/12/2001	15/04/2010
Stock Regressors	Full length 175 – Effective 101 – start 74		
X1	Teekay – Dividend Yield	No of lags: 1	
X2	Crude Oil, WTI NYMEX Spot U$/BBL	1	
X3	US CPI – All Urban: All Items SADJ	2	
X4	Crude Oil-Iranian Light FOB U$/BBL	1	
X5	US Consumer Confidence Index SADJ	2	
X6	US Industrial Production VOLA	2	
X7	CH Industrial Production Index VOLN	2	
X8	BD Ind. Pro. Inc. const. (%YOY) VOLA	2	

Table 4.20 TK: sum of return series

TK	R_{NE}	R_{GR}	R_{BH}	W_{TB}
TK: AIC	0.16	0.61	0.67	0.17
TK: R-square	0.91	1.15		
TK: BIC	0.20	0.68		
TK: AV	2.08	2.47		

Of the combination models, R-square has the best performance. The sum of returns for the AV model is significantly higher than for the other models. Although the final net value of AIC is only slightly less than TB, the return on the final investment is $117.5 whereas for Treasury bill it is $108.

Table 4.21 TK: final investment

TK	W_{NE} \$	W_{GR} \$	W_{BH} \$	W_{TB} \$
TK: AIC	117.5	172.1	148.2	108
TK: R-square	250.1	294.2		
TK: BIC	122.8	183.2		
TK: AV	746.8	1103.8		

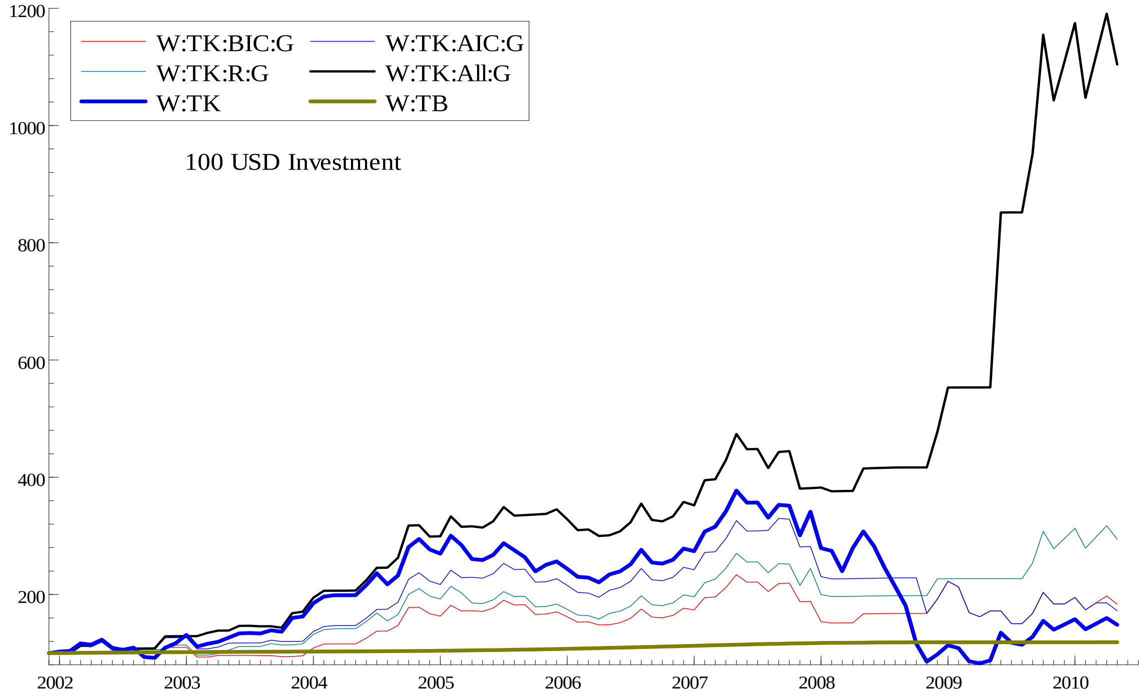

Figure 4.33 Pattern of TK gross investment, 15.12.2001–15.05.2010

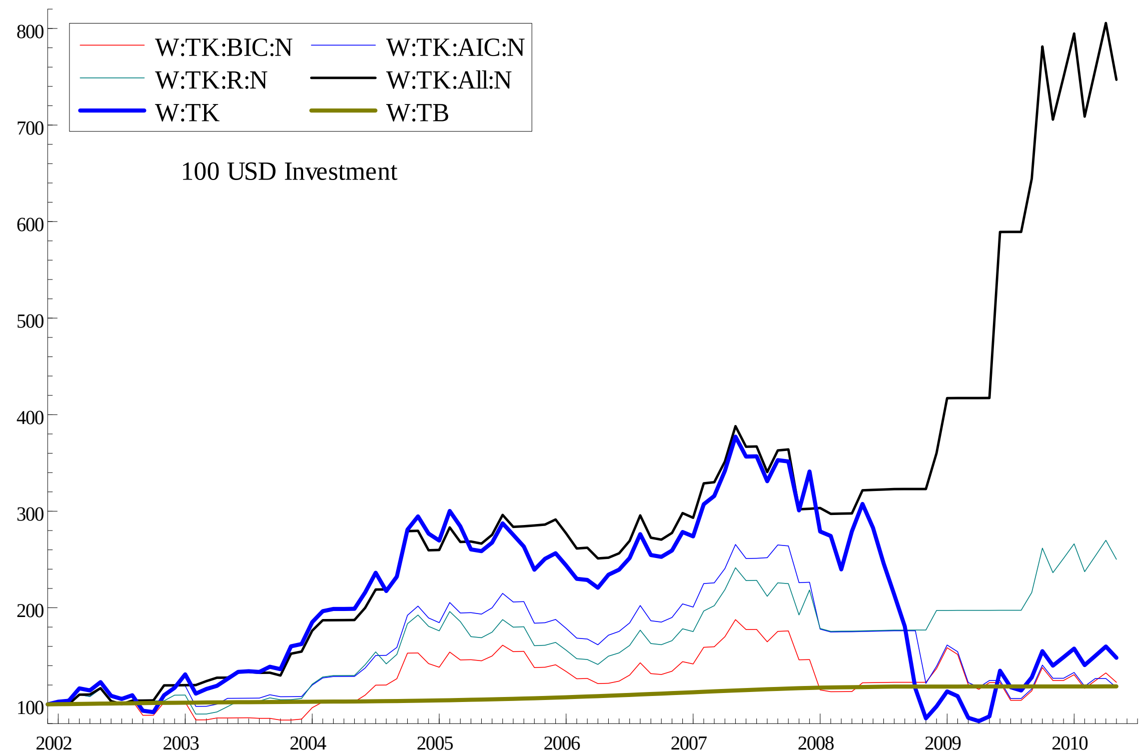

Figure 4.34 Pattern of TK net investment, 15.12.2001–15.05.2010

Table 4.22   TK: inclusion of variables

Inclusion rate		*TK:AIC*	*TK:BIC*	*TK:R-square*
X1	DY	0	0	0
X2	NYMEX	100	100	79.2
X3	US CPI	83.1	100	98
X4	Oil-light	100	100	79.2
X5	US Con cof	100	100	85.1
X6	US IND	76.2	82.1	49.5
X7	China IND	14.8	100	20.7
X8	Germany IND	92	100	66.3

Figures 4.32 and 4.33 represent the patterns of TK investments. Up until 2008 the buy-and-hold strategy and the AV model perform similarly, but the AV model was able to predict the mid-2008 crash and hence the AV final sum is five times bigger than the buy-and-hold strategy. Table 4.22 presents the pattern of inclusion of the variables. DY does not have any inclusion rate. The two oil prices, Iran Light and NYMEX, have the highest rate of inclusion and both are exactly similar. TB does not perform acceptably except at times of depression.

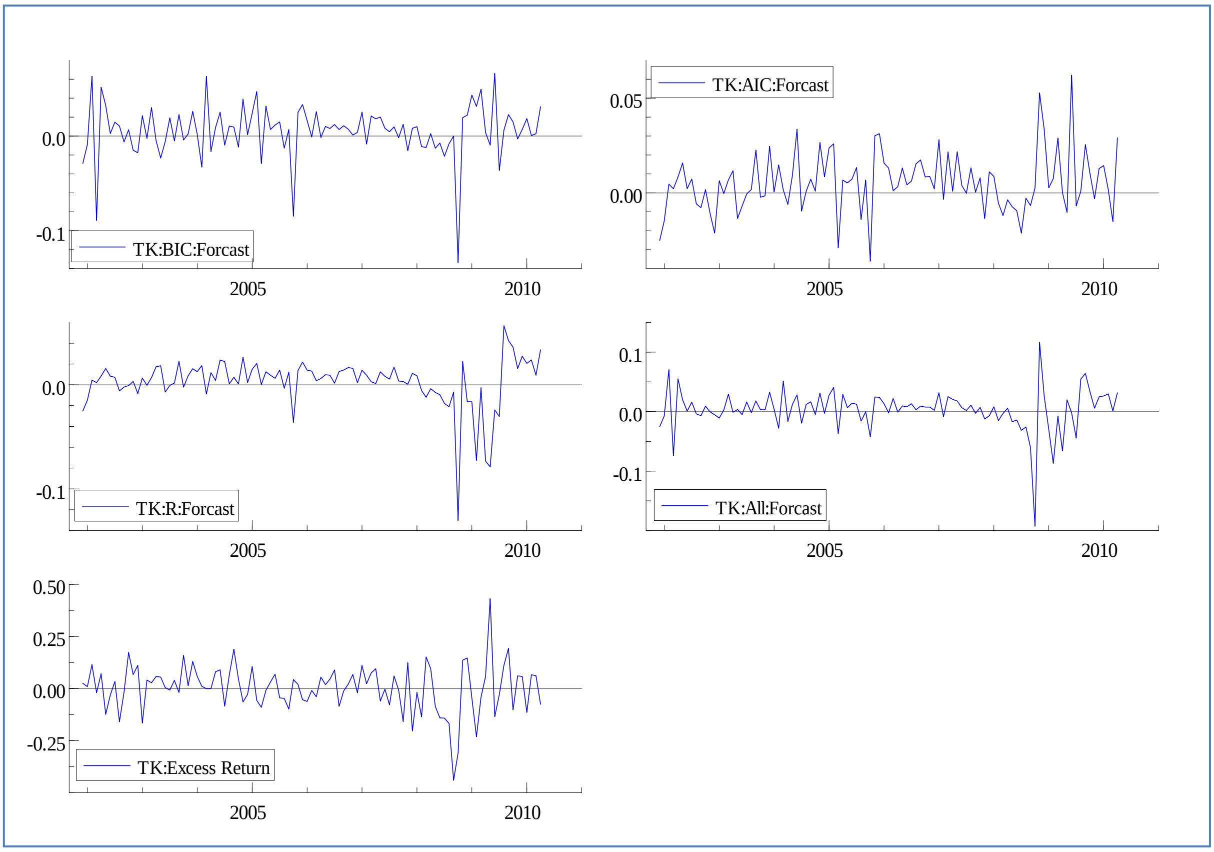

Figure 4.35   NAT: comparison of selection criteria

Table 4.35 is the graph of returns. The R-square after the AV is the best performing model.

4.12 Remarks

The AV model's performance is better than other alternatives that allow for variables permutation. This is becase the model delection criterions are not performing efficiently in long series and in the existance of the structural breaks, similarly it can be argued that model delection criterions are performing efficently when structural breaks do not exist. If, however, the regressors are replaced with weak, irrelevent variables, the combination models will perhaps perform better. Between the model selection criteria there is no specific pattern of privilege and hence we cannot select the best model. Of the base set of regressors, NYMEX and US Industrial Production often have the highest rate of inclusion.

If we shorten the forecasting period to before the 2008 financial crisis, NYMEX oil is the best individually performing variable. In FRO stock, the buy-and-hold strategy, and in the case of S&P500 TB, perform better than the worst-performing switching model. In FRO and S&P500, of the six switching models only two, both using BIC, generate more return than TB. In FRO, NYMEX and MLCX Commodity Index have a high rate of inclusion. US Industrial Production and US PPI have the lowest. TB also has a relatively high rate of inclusion. Table 4.23 presents the sequence of the best models with their most-included variables.

In S&P500, in contrast to in FRO, US Industrial Production has a high rate of inclusion and TB is a moderately performing variable. For both S&P500 and FRO, BIC is the best-performing model selection criterion. In FRO, forecasting with TB as the only regressor yields a final value four times bigger than relying on R-square switching. In VLCCF stock, the DY has a relatively high rate of inclusion and the R-square is the best-performing switching model. In NAT, the TB has a relatively high rate of inclusion. In TK stock the AV model final value is five times bigger than that for the buy-and-hold strategy. In TK stock, US consumer confidence, US cpi and NYMEX have a high rate of inclusion and the R-square is the best-performing model selection criterion.

Table 4.23 Overview of the best-performing models

Stock	*Investment winning models*	*Most-included variables*
FRO	All – BIC-AIC-Rsquare…TB	MLCX, NYMEX
S&P500	All – BIC-AIC-Rsquare…TB	US INDUS, NYMEX
VLCCF	All – Rsquare-BIC...TB...AIC	DY, US PPI, China INDUS (All %100)
NAT	All – AIC-Rsquare…TB…BIC	S&P500 Comm,TB
TK	All – Rsquare-BIC-AIC…TB	NYMEX, US CPI, Oil light, US Conf, China INDUS, GER INDUS (All %100)

Table 4.24 compares the AV model with the buy-and-hold strategy and TB. The third column illustrates the extra wealth that can be created using the AV model. Between 93% to 500% more wealth can be generated by following the AV model than by following the buy-and-hold strategy. Between 37% to 700% more wealth can be generated by following the AV model than by following TB.

Table 4.24 Percentage comparison of extra wealth creation of AV model with others

Stock	*AV model compared to ...*	*% more from AV model*
S&P500	buy-and-hold	93%
	TB	37%
FRO	buy-and-hold	93%
	TB	560%
VLCCF	buy-and-hold	140%
	TB	56%
NAT	buy-and-hold	140%
	TB	360%
TK	buy-and-hold	500%
	TB	700%

% if FRO is forecasted by TB regressor only; the gain is 150% and 850% more than buy-and-hold and 1 month TB.

4.13 Summary

We used fundamental analyses to predict the shipping companies' stock returns. PT (1995) methodology was used to find any evidence of predictability in the stock return. Previous, similar studies have found that gearing is the most statistically significant factor in shipping IPO stock. Oil prices and laid-up tonnage have been found to be negatively related to shipping stocks, exchange rate variables exhibit a positive relationship, and there is no significant relationship regarding inflation and industrial production. The EMH suggests that in an informationally efficient market asset prices evolve as random walk and it is impossible to beat the market. However, this does not imply that if our simulated investor could make an abnormal profit the market would have been inefficient unless a price formation structure can be proved to exist. If asset prices are a random walk the EMH is valid, and if EMH is valid the market participants must form expectations rationally. However, market efficiency does not mean that the stock return cannot be forecasted: it actually can be forecasted in an efficient market. If an investor is risk-neutral we can test the EMH by testing for random walk, which means that prices are not predictable, and this depends on risk neutrality. If the investor is not risk-neutral they have a risk premium and they require some premium. Then, if the stocks are riskier than bonds we can forecast stock return because the risk premium should be correlated with macroeconomic variables. Because macroeconomic variables capture the risk premium, if this risk premium is time-varying and correlated with macroeconomic variables we should be able to find the forecasting power although the markets are efficient. We employed different model selection criteria and compared them with the AV model. The PT (1995) forecast searches at every period for the best model from different combinations of variables and according to the relevant information criterion signal. The investor can hold the stock or TB or switch between the two, but there is a 20% of returns transaction cost for switching. This is almost equal to 1.5% of the price. The investor will buy or keep the stock if the forecast of the excess return is bigger than zero. For FRO stock, the buy-and-hold strategy generates 140% profit and the TB 17%, but if we use the switching strategy with the AV model the net profit is around 200%. In FRO stock, applying model selection criteria generates less profit than a buy-and-hold strategy. However, during the same period, for S&P500 all the model selection criteria generate more profit than buy-and-hold. The reason the combination models do not work correctly perhaps lies in the way model selection criteria work: because the stock series are non-stationary with structural breaks, it turns out that the variables are not correctly selected. Another three tanker shipping companies were also forecasted. The set of explanatory variables, in addition to the forecast period, is different in each of these stocks. For FRO and S&P500 the BIC was the best model selection criterion between the three models; however, this is not the case with the other three stocks.

Chapter 5

Summary of Findings and Conclusion

5.1 Summary

Chapter 1 of this thesis introduced the global shipping market. It explained how the shipping industry facilitates global trade by connecting the sources of supply and demand for raw materials and goods. It began with a preliminary comparative analysis of freight rate, US GDP and S&P500 growth. This analysis shows that from 1970 to 2009, the natural logarithms of US GDP and shipping fleet have grown by 8.6% and 6.1% respectively. It also showed that time-charter and spot rates are highly correlated with each other. In return series, dry bulk freight rates are more highly correlated with S&P500 than with the tanker freight rate. This could be because the demand for oil is less affected by the world economy than the demand for dry bulk. We found that the shipping order book is 52% and 49% correlated to the time-charter rate and second-hand prices, and 9.4% correlated to S&P500. Ship demolition decreases during times of economic boom and high freight rates. Demolition is -26% correlated to S&P500 and -62% correlated to LME index, which may indicate that there is more demolition when metal prices are low. The average bulk and tanker new-build prices are 78% correlated to each other and 31% correlated to LME, but demonstrate no relation with S&P500. Second-hand bulk and tanker prices are 25% and 16% correlated to S&P500.

In Chapter 2, the economic value of forecasts of the freight rate in the bulk shipping industry for ship operators was tested. The ship operator is assumed to allocate the ship between a spot charter and a TC market according to forecasts of the quarterly excess freight rate. The forecasts are computed using a regression model with macroeconomic and commodity variables as regressors, since TC rates are formed by the market participants' expectations about the future spot rates. There is a term-structure relationship between spot and TC rates. The term structure is derived from the no-arbitrage argument model. This means that a ship operator should not be able to make a much greater profit by contracting the ship in the TC market than by contracting it in the spot market for a series of voyage charters equal to the length of the TC. The economic benefit of this forecasting approach in excess of a fixed policy approach is used to test the validity of the EMH for the dry bulk freight rate industry. The forecast is from the perspective of a two-ship operator of Capesize and Handymax dry bulk classes who is trying to maximize their profits. The ship operator can make 23% and 11% more earnings than could be made via TC rates in the Capesize class if the excess freight is forecasted with commodity variables and macroeconomic variables respectively. In the Handymax class the ship operator cannot make any extra money. Therefore, the results of the forecast are mixed and cannot be used to disprove the EMH. Hence, it can be concluded that the market is fairly efficient. In Handymax and Capesize, there is respectively a 38% and a 9% difference between the forecast signs of two explanatory variables. In the case of Capesize the 9% difference occurred mainly during 2008–9, and during the other years the forecasts are similar. For Handymax contrary to the Capesize during 2008-2009 the forecasts are similar. Most of the differences in respect of Handymax occurred during 2003–6. The forecasted series are not statistically different from either TC or spot rates. Between the regressors, crude oil WTI price and interest rate are statistically significant explanatory variables in both series.

Chapter 3 quantified and discussed the volatility of freight rates with variations of ARCH models for freight traders and freight investors. The characteristics of the volatility were investigated by analysing three freight rate indexes of Baltic Exchange: BDI, BPI and BCI. The BDI is an aggregate freight rate index representing dry vessels. The BPI and BCI are the daily benchmarks for freight rates for Panamax and Capesize vessels. The chapter began with some preliminary analysis showing that the index returns are stationary, meaning that the hypothesis of normality is rejected and that the series have fat-tail and high kurtosis. The pre-test ARCH test indicated the existence of ARCH effect. We filtered the data with GARCH (1,1) and ARMA (1,1) assuming student's-t distribution; then, by applying the model selection criteria, a more appropriate GARCH specification was chosen. Between the variety of GARCH (p,q) models with different p and q, the selected specification is ARMA (2,1) for all indexes and GARCH (4,1), GARCH (3,1) and GARCH (1,1) respectively for BDI, BPI and BCI. The result showed that the BCI response to outside shocks is greater than others'. The BPI response to outside shocks is also very close to the BCI. The BDI response to outside shocks is 20% lower. The memory of volatility is higher in BDI. The memory of volatility in BCI is not as long as in others and is 40% less than BDI, but is very similar to BPI. The sum of coefficients is slightly more than unity for BDI, which may suggest that the shocks do not decrease and have a very small tendency to strengthen. However, this value is almost unity in BDI. For the other two indexes the sum of coefficients is unity, which suggests that the shocks are very persistent. The asymmetric character of daily return between past innovations and current volatility was also examined with variations of EGARCH. The results suggest that in the context of asymmetric functions the link between current volatility and past innovation shocks is statistically significant for all the three indexes, which means that the effects of the unexpected shocks are distinguished in all three indexes. The persistence of shocks to volatility is statistically significant for all indexes; the BCI has the smallest value, which suggests that the shocks persist less than in other series. The leverage was positive for BDI and negative for BPI and BCI, but none was statistically significant, which means there is no evidence of asymmetric volatility. We also performed different recursive forecasts of volatility for one day and 10 days ahead with eight models, and the forecast was evaluated by RMSEF. We then forecast the recursive 30-days volatility with the GARCH models that had been selected earlier in the chapter according to their goodness of fit and compared the results with Monte Carlo simulations. The application of Value at Risk (VaR) with different high quantile GARCH models was presented. For instance at the 95th quantile, the estimates of BDI VaR are approximately 37% and 6% for daily EGARCH and constant volatility models respectively.

In Chapter 4 we used macroeconomics and financial variables to analyse the predictibility of the shipping stock return. It was argued that if risk premiums are time-varying and correlated with macroeconomic variables, macroeconomic variables might have forecasting power for shipping stock. This was investigated using the regression-based approach of Pesaran and Timmermann (1995). We found that allowing for different combinations of macroeconomic variables generally does not help forecasting. In our data set, which includes four shipping stocks and the S&P500, applying the AV model generates 93% to 500% more wealth than a buy-and-hold strategy. When the explanatory variables are analysed individually, it is found that the US Treasury bill and NYMEX oil price have a much better forecasting power than the others. If we shorten the forecasting period to before the 2008 financial crisis, we find that NYMEX oil is the best individually performing variable. In FRO and S&P500, between the six switching models only two cases, both using BIC, generate more return than TB. In FRO, the NYMEX and MLCX commodiy indexes have a high rate of inclusion. US industrial production and the US PPI have the lowest rate of inclusion. TB also has a relatively high rate of inclusion. In S&P500, in contrast to in FRO, US industrial production has a high rate of inclusion and TB is a moderately performing variable. For both S&P500 and FRO, the BIC is the best-performing model selection criterion. In FRO, forecsting with TB as the only regressor yields a final investment four times bigger than relying on R-square switching. In VLCCF stock, the DY has a relatively high rate of inclusion and the R-square is the best-performing switching model. In NAT, the TB has a relatively high rate of inclusion. In TK stock, the AV model's final wealth is five times bigger than can be obtained by a buy-and-hold strategy. Here, US consumer confidence, US CPI and NYMEX have a high rate of inclusion and the R-square is the best-performing model selection criterion. In the stock series that was analysed between 93% to 500%, more wealth can be generated by following the AV model than can be generated by a buy-and-hold strategy. Between 37% to 700% more wealth can be generated by following the AV model than it can by following TB. The reason the combination models do not work perhaps lies in the way model selection criterion works: because the stock series are non-stationary with structural breaks, it turns out that the variables are not correctly selected. Our set of data contains one or two periods containing serious stock market crashes and hence the results of the investnent strategy were mixed. We explained that combination models are underperforming because our data contain some structural breaks. A suggestion for further research is that this might be overcome by finding the breaks and applying the appropriate beta in the regression.

5.2 Conclusion

The empirical results in chapter 1 suggest that dry bulk freight rates are more highly correlated with S&P500 than with the tanker freight rate. This could be because the demand for oil is less affected by the world economy than the demand for dry bulk. We found that the shipping order book is more correlated to the freight rate and second hand ship rather than the general state of the economy. Among the shipping variables; stock prices, time-charter dry rate and second-hand dry prices and scraping volume are more correlated with S&P500 than other variables.

In chapter 2 we tested the hypothesis that a ship operator should not be able to make abnormal profit by contracting the ship in the TC market in comparison to contracting it in spot market for a series of voyages charters equal to the length of the TC. The ship operator can make 23% and 11% more earnings than could be made via TC rates in the Capesize class if the excess freight is forecasted with commodity variables and macroeconomic variables respectively. In the Handymax class the ship operator cannot make any extra money.The results of the forecast are mixed and cannot be used to disprove the EMH. Hence, it can be concluded that the market is fairly efficient.

In chapter 3 the empirical results showed that the responses of three freight rate indexes are not similar to each other and the specification of their GARCH forecasting model is not identical either. The result showed that the BCI response to outside shocks is greater than that of the others. The memory of volatility in BCI is not as long as in others and is 40% less than the BDI. In the BDI the shocks do not decrease and have a very small tendency to strengthen, for the other two indexes the shocks are very persistent. The persistence of shocks to volatility is statistically significant for all indexes; in the BCI the shocks persist less than in other series. There is no evidence of asymmetric volatility among the series. The specification of the best forecasting model was also not similar between the series.

In chapter 4 the empirical investigation showed that applying the model that includes all variables generate 93% to 500% more wealth than a buy-and-hold strategy. Between 37% to 700% more wealth can be generated by following the AV model than it can by following TB. When the explanatory variables are analysed individually, it is found that the US Treasury bill and NYMEX oil price have a much better forecasting power than the others. In shipping stock the NYMEX and MLCX commodiy indexes have a better explnataory power than the other variabes. In the S&P500 US industrial production has a high rate of inclusion and TB is a moderately performing variable. overall BIC is the best-performing model selection criterion.

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