Can shipping freight rate risk be reduced using forward freight agreements?

Kan fraktraterisiko i skipsfart reduseres ved hjelp av forward freight agreements?

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Abstract

This thesis investigates the forecasting performance and hedge efficiency of 50 Forward Freight Agreements (FFA) in bulk shipping from 2005 to 2012. We find that the hedge ratios estimated with the conventional method offer high hedge efficiency for the majority of the FFAs in the in-sample period. By holding these hedge ratios through an out-of-sample period, we find that the hedge efficiency is not robust for the majority of the contracts. This is likely due to time varying covariance between freight rate returns and FFA returns, in addition to changing variance in FFA returns. Our findings suggests that the conventional method of calculating optimal hedge ratios does not outperform a naive hedge. Furthermore, we find that FFA prices are unbiased predictors of subsequent spot freight rates in 42 of 50 contracts across the four segments. However, they are only stable predictors when we consider current- and one-month contracts. The forecasting performance decreases when the forecasting horizon increases. The basis provides unbiased forecasts of subsequent freight rate change in 42 of the 50 contracts. It does not provide stable forecasts in the Capesize and Panamax segments. The forecasting power of the basis in the Clean and Dirty tanker markets are medium, and increases with the forecasting horizon. The basis on five month contracts written on TC5 and TD5 is relatively high with R^2 at 0.65 and 0.58, respectively.

Keywords: Shipping; Forecasting; Hedging; Unbiasedness hypothesis; Risk Management; Forward Freight Agreements;

Sammendrag

Denne oppgaven tar for seg Forward Freight Agreements (FFA) som et verktøy for å sikre og prognostisere fraktrater i shipping. Vi finner at den variansminimerende sikringsraten gir en høy variansreduksjon in-sample for majoriteten av de undersøkte FFA-kontraktene. Resultatene out-of-sample viser derimot at denne sikringsstrategien ikke er robust for de fleste av kontraktene. Variansreduksjonen reduseres betraktelig fordi risikoen i fraktrate- og FFA-markedet i større grad er tidsvarierende i out-of-sample perioden, sammenlignet med in-sample perioden. Resultatene viser samtidig at variansminimerende sikringsrate ikke gir en signifikant lavere porteføljevarians, sammenlignet med porteføljevariansen fra en naiv sikringsstrategi. Videre finner vi at FFA-prisene er forventningsrette prognoser på fremtidige fraktrater i 42 av totalt 50 kontrakter. Analysen viser at prognosene bare er stabile når vi betrakter kontrakter med forfall i inneværende- og neste måned. Prisvariasjonen i disse kontraktene forklarer rundt 90 prosent av variasjonen i den påfølgende fraktraten. Prognosene blir dårligere når vi øker prognostiseringsvinduet med kontrakter som har lenger løpetid. Videre finner vi at basis er forventningsrett prognose på fremtidige fraktrate-endringer i 42 av totalt 50 kontrakter. I markedet for Capesize- og Panamax fartøy gir ikke basis stabile prognoser grunnet lav forklaringskraft. I tankmarkedet gir basis en middels forklaringskraft som stiger etterhvert som vi øker prognosevinduet. Prisvariasjonen i basis til fem måneders-kontrakten forklarer henholdsvis 58- og 65 prosent av variasjonen i den påfølgende fraktrate-endringen for TC5 og TD5.

Nøkkelord: Skipsfart; Sikring; Prognostisering; Forventningsretthet; Risikostyring; Terminkontrakter; Baltic Exchange;

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Pål-Andreas Alnes   Mats Andreas Marheim

1. Introduction

Can shipping freight rate risk be reduced using Forward Freight Agreements (FFA)? We investigate Baltic Exchange data on 50 FFAs and 10 associated trading routes in order to answer the following questions:

- Can hedging in FFA reduce freight revenue variability?
- Does econometric based hedging strategies outperform naive strategies?
- Are econometric based hedging strategies robust out of sample?
- Are FFA prices good predictors of subsequent spot prices?

We expect FFA hedging to generate a substantial reduction in freight rate variability and to be robust out of sample, but are uncertain on the magnitude of this risk reduction. Based on talks with market participants, we do not anticipate econometric based hedging strategies to significantly outperform naive strategies. We expect to find that the forecasting performance varies across vessel types and forecasting horizons. In general, business risk can be divided into price risk, credit risk and pure risk (Harrington & Niehaus, 2003). For a shipping company these risks can be associated with change in company value due to fluctuations in freight rates, operating costs, interest rates or asset prices (ships). The vessels running costs like manning and repairs are virtually constant, and may be controlled in the same way as in any other business. However, the vessels earnings may vary substantially from year to year, and month to month. For a shipping company, freight rate risk is arguably the most significant of all risks. Freight rate fluctuations affect the shipping companies cash flow and ship values. From 2003 to mid-2008 bulk shipping freight rates increased by 300 per cent, and then dropped 95% in the last quarter of 2008. The fluctuations have made investors like Fredriksen, Niarchos and Onassis extremely wealthy, but also forced giant companies like OSG, Genmar and Sanko to file for chapter 11. Hedging tools like time-charter contracts and contracts of affreightment (COA) have long been recognized as risk management tools by shipowners and charterers. In the early 1980s they realized that risk management techniques applied on commodities -and financial markets could be developed for risk management in the shipping industry. This led to BIFFEX, the first exchange-traded freight futures contract in May 1985, and development of the over-the-counter market for Forward Freight Agreements (FFA) in the mid-1990s. Shipowners and charterers could now hedge their freight rate risk through future positions in time -and voyage charter contracts. This also gave them the opportunity to include the markets expectations for the future path of the freight rates in the decision process. The BIFFEX contract was de-listed due to low liquidity in 2001. Forward freight agreements (FFA) grew almost exponentially from 1992 to 2008 and are still traded.

1.1. Outline

Chapter one provide an introduction to the most important supply and demand drivers for seaborne transport, how ships are employed, investigated vessel types, Baltic Exchange, Forward Freight Agreements (FFA) and Freight futures.

Chapter two presents literature on hedging and forecasting of shipping freight rates using freight futures and FFAs.

Chapter three provide descriptive statistics and dynamics in our data on freight rates and the FFAs.

Chapter four gives an overview of the methods used to analyze forecasting performance and calculate the hedge ratios and variance reduction.

Chapter five presents the hedging results for each segment. Reduction in freight revenue variability using econometric based hedge strategies are compared to a traditional naive strategy. In -and out-of-sample results are presented to give an indication on the robustness of the hedge.

Chapter six presents the forecasting performance for FFAs in each segment, using econometrical methods. We analyze the unbiasedness hypothesis and the stability of the forecast.

Chapter seven summarizes the key findings and presents the conclusions of this thesis.

1.2. Supply and demand for seaborne transport

Seaborne transport is for many commodities the only, or by far the most economical mode of transport. Imports and exports of raw materials and semi-finished products are the single most important shipping demand driver. The main cargoes transported are crude oil, iron ore, coal and grains. The economic centers of North America, Europe and Asia dominate the maritime trade. Brazil and Australia are the largest exporters of iron ore and coal, while China is the largest importer. Shipments with crude oil from the Middle East Gulf to Asia and North America dominate the seaborne transport of wet cargoes. The shipping industry can be characterized as capital intensive, cyclical, volatile, and seasonal (Kavussanos & Visvikis, 2006). The supply side of maritime transport responds slowly to changes, while demand may change rapidly and on an irregular basis, which in turn causes volatile freight rates. The single most important demand factor is the world economy. Fluctuations in the growth rate affect demand for raw and semi-finished materials, which in turn affect the demand for sea transport. Time lags, stock building, mass psychology and multiplier effects enhance the freight rates fluctuations. The share of traded goods transported by sea, and average distance from exporter to importer is crucial. Random shocks in climate, resources, political frameworks and commodity prices may cause large shifts in demand. Finally, transport from distant locations will only take place if the total price (or quality) included transport cost is lower compared to the alternative. Inelastic short-term demand cause peaks in the freight rate, and rates tend to become volatile when they move above the vessels operating costs Stopford (2009).

Supply and demand	
Supply	**Demand**
The world economy	World fleet
Seaborn commodity trade	Fleet productivity
Average haul	Shipbuilding
Random Shocks	Scrapping
Transport costs	Freght revenue

Table 1.1: *Ten important factors affecting demand and supply for seaborne transport. Compiled from Stopford 2009.*

Supply starts with the size of the merchant fleet, and is influenced by shipowners, bankers, charterers and regulatory authorities. The number of ships built or scrapped determines fleet rate growth. It takes around a year to build a merchant vessel, 2-3 years if the shipyards are busy. Average economic life of a ship is around

25 years, which results in a low number of vessels scrapped each year. This means that it takes years, not months before the fleet size adjust after a large shift in demand. Fleet productivity is determined by the vessels speed, port time and deadweight utilization. When supply is low, rates rise and give incentive for owners to order more vessels. When supply is high and the freight rate low, vessels decrease speed to safe fuel, goes into lay-up or is sold as scrap.

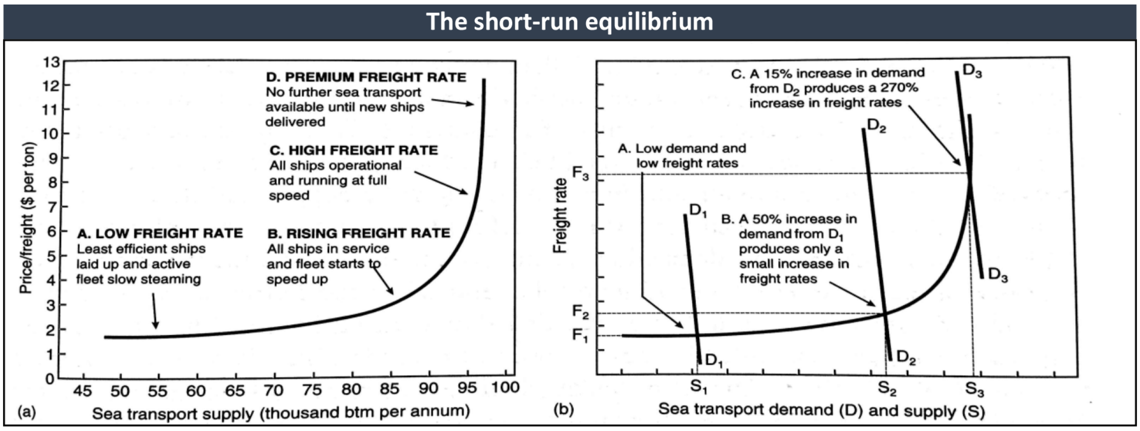

Figure 1.1: *Short-run equilibrium: (a) short-run supply function; (b) short run adjustment. Compiled from Stopford 2009.*

The short-run supply curve is shown in figure 1.1a. It illustrates the ton miles of transport available at various levels of freight rates, for a given size of fleet. When freight rate is low, inefficient ships are laid up. As the freight rate increases, laid up ships enters the market until all ships are operational, which in turn causes the supply to increase. Further on, we note that the short-run supply curve become more inelastic when freight rate increases. When the market reaches premium freight rate, the elasticity is almost perfect and no further supply is obtained by increasing freight rate. In a market situation with high and premium freight rates, all ships will be operational and running at full speed. Further supply will only be available when newbuildings enters the market. Turning to the short-run adjustment with demand curves, we can elaborate how freight rates are determined. Freight rates are settled were supply equals demand. Figure 1.1b shows three equilibrium points, all with different supply/demand levels. When demand is low, freight rates are settled at point F_1. Because the supply curve is elastic in periods with low freight rates, an increase in demand to point B will only result in a slight increase in freight rates. At point C, the supply curve become inelastic and the shift in demand is sufficient to treble the level of freight rates to point F_3.

Short-run supply and demand are also influenced by seasonal cycles, both short and long. Examples of seasonal cycles are the high volumes of grain transported from August and the end of the year, and high demand for shipments with oil to the Northern Hemisphere in the winter. Short cycles, also called business cycles, may have duration between 3 to 12 years. Long cycles are related to regional, economic or technological change (Stopford, 2009).

Two centuries of cycles			
Period	**Demand Growt**	**Supply tendency**	**Market tone**
1869-1914	Fast	Expanding	Competitive
1920-1930	Fast	Overcapasity	Weak
1930-1939	Falling	Overcapasity	Depressed
1945-1956	Very fast	Shortage	Prosperous
1956-1973	Very fast	Expanding	Competitive
1973-1988	Falling	Overcapasity	Depressed
1988-1997	Slow	Expanding	Competitive
1998-2007	Very fast	Shortage	Prosperous
2007-2013	Slow	Overcapasity	Depressed

Table 1.2: *The market tone from 150 years of shipping cycles. Compiled from Stopford 2009 and various sources.*

Shipping cycles the past 150 years are summarized in table 1.2. There have been two periods of prosperity, the 1950s and the period from 1998 to 2007. Both can be explained by growing demand for seaborne freight services and shortage of shipbuilding capacity. Three of the periods have been characterized by unusual competitiveness, with growth in trade and increased shipbuilding capacity. The weak shipping markets of the 1920s, was followed by a decrease in trade, and shipbuilding overcapacity in 1930s. The last years shipping market are characterized by first of all overcapacity of ships. The growth has been positive, much due to large Chinese imports of raw materials.

1.3. Deployment of ships

The main participants in the freight market are the shipowners and the charterers. Shipowners have vessels for hire, while charterers have cargo to transport. It is common practice that parties enter into a contractual agreement called a charter party. Most common charter parties are voyage charter, time charter, bareboat charter and contract of affreightment (COA). Costs and responsibilities are distributed differently under each contract. If the shipowner and charterer enters into a:

- *voyage charter,* the shipowner agrees to transport a specific cargo between two ports. Freight is paid at a fixed price per ton, e.g. 15$/mt for transport of 150 000mt of coal from Richards bay to Rotterdam. Contract of affreightment (COA) is an agreement on performing a series of cargo parcels at a fixed price per ton.
- *time charter,* the charterer decides which ports to call, and which cargo the vessel shall carry. In return, he pays a fixed rate per day in addition to port and fuel costs. If the vessel is fixed on a voyage charter or COA the shipowner pays for port costs and bunkers.
- *bareboat charter*, the charterer manages the vessel and pays for operating and voyage costs.

The shipowner (or charterer) can secure the revenue (cost) for a period of time equal to the length of the contract. Either the shipowner or the charterer loses money when the spot freight rate or hire deviates from the agreed price. The shipowners gain is the charters loss and vice versa (Stopford, 2009).

1.4. Vessel types

Approximately 90% of all traded volume is transported by sea. Large installments, like drilling rigs and long pipes have no other alternative of transportation and are transported by purpose built vessels. Other goods like coal, grain, ore, petroleum products and consumer goods (containers) utilize the economies of scale in shipping to reduce transport costs. Tankers, bulkers and container vessels are built to carry these goods. It can therefore be more economical to import goods from thousands of miles away by sea, than to obtain the goods from some domestic location. Vessels that transport dry cargo in bulk are generally called bulk carriers. These vessels are the work horses of the fleet and transport coal, iron ore, grains, bauxite, paper rolls, fertilizer and cement. Bulk carriers are characterized by hatches raised above deck level to cover the large cargo holds. Vessels transporting crude oil, petroleum products and chemicals are called tankers. Tankers are similar to bulk carriers, but can be distinguished by the pipelines and vents on deck. This thesis investigates freight rates and Forward Freight Agreements (FFA) associated with these two segments, which again can be divided into subcategories of vessel types and sizes:

- **Capesize** bulk carriers typically transports coal or iron ore and has a displacement of 100,000 to 180,000 dwt. In general it serves deep-water terminals and can access 19% of the world ports. This vessel is too big for the Suez- and Panama Canal, and have to go round the Cape of Good Hope and Cape Horn.
- **Panamax** bulk carriers are primarily used for transporting grain or iron ore. Typical displacement is between 60,000 to 70,000 dwt. These vessels can enter approximately 27% of the ports in the world. It is the largest that can pass thru the Panama Canal.
- **Very large crude carriers** (VLCC) are large tankers with 120,000 - 200,000 dwt displacement. They are primarily used for large shipments of crude oil between the Arabian Gulf to U.S, Western Europe and Japan. These vessels are to large to transit the Suez laden, but can be ballasted through on the return voyage.
- **Suezmax** are midsized tankers with 120,000 - 200,000 dwt displacement primarily used to transport crude oil. This is the largest ship that can transit the Suez Canal fully loaded. A typical trading route for a Suezmax is between West Africa and the U.S. Atlantic coast.
- **Aframax** tankers mainly transport crude oil and have a displacement of 60,000

- 120,000 dwt. They typically trade in routes with short distances and areas with limited port resources. These vessels are recognized as the work horses of the tanker fleet. Their size allows them to operate in areas where crude production is relatively low, or where restrictions on draft or size prevent the use of Suezmax or VLCCs.

- **Long range 1** (LR 1) are coated product tankers with displacement from 55,000 to 90,000 dwt. By products one usually mean light distillates of crude oil like kerosene, gasoline and naptha. Due to an expansion of refinery capacity in the Middle East, India and China this is a vessel category that is increasing in popularity.

1.5. Baltic exchange and investigated trading routes

Reliable price information is crucial to obtain a well-functioning market. The leading provider of freight market information is the Baltic Exchange. Freight rate information is calculated on a daily basis using data from an independent panel of shipbrokers. Information is based on shipbrokers assessments of the market level for each trading route. These assessments are based on recent fixtures, current negotiations and the balance between supply of ships and demand for transport (Alizadeh & Nomikos, 2009). Freight information is reported to the market 13:00 London time, and is the aritmetric average of all received assessments that day. The Baltic Exchange provides daily assessments on over 50 of the largest shipping routes. In addition they report weekly sale & purchase and demolition assessments as well as daily forward prices. The first Baltic index was published in 1985. It consisted of 13 voyage routes covering bulk vessels from 14,000mt to 120,000mt. Today, the Baltic Exchange produces indices covering a wide range of vessel and cargo types. Examples of Baltic indices are Baltic Capesize Index, Baltic Panamax Index, Baltic Clean Tanker Index, and Baltic Dirty Tanker Index. The most important trading routes in each segments makes up each index. In the Capsize segment we investigate route C3, C4, C5 and C7. These are voyage charter routes quoted in US dollars per metric tons of transported cargo. The most important iron ore routes, C4 and C5, reflect transport from Brazil to China and Australia to China, respectively. C4 and C7 are the most important coal routes and mirrors transportation from South Africa and Colombia to The Netherlands, respectively. In the Panamax segment we have investigated route P2A_03 and P3A_03. These are trip-charter routes quoted in dollars per day. P2A_03 is based on delivery in Skaw-Gibraltar, with redelivery in the Taiwan-Japan region Duration of this voyage renge between 60-65 days. P3A_03 is based on delivery in Japan-South Korea, with redelivery in the same region. This voyage has duration of 35-50 days.

Overview of selected routes from Baltic Exchange				
Segment/Route	**Vessel size**	**Cargo basis**	**Route description**	**Index**
Capesize				
C3	150 000mt	Iron Ore	Tubarao/Qingdao	Baltic Ex. Capesize Index
C4	150 000mt	Coal	Richards Bay/Rotterdam	Baltic Ex. Capesize Index
C5	150 000mt	Iron Ore	W Australia/Qingdao	Baltic Ex. Capesize Index
C7	150 000mt	Coal	Bolivar/Rotterdam	Baltic Ex. Capesize Index
Panamax				
P2A_03	74 000mt dwt	Grain	Skaw/Gibraltar	Baltic Ex. Panamax Index
P3A_03	74 000mt dwt	Grain	Japan/South Korea	Baltic Ex. Panamax Index
Clean Tanker				
TC5	55 000mt	Clean Products	Ras Tanura to Yokohama	Baltic Ex. Clean Tanker Index
Dirty Tankers				
TD3	265 000mt	Crude Oil	Middle East Gulf/Japan	Baltic Ex. Dirty Tanker Index
TD5	130 000mt	Crude Oil	West Africa/USAC	Baltic Ex. Dirty Tanker Index
TD7	80 000mt	Crude Oil	North Sea/Continent	Baltic Ex. Dirty Tanker Index

Table 1.3: *Overview of investigated trading routes. Complied from various sources.*

Routes in the tanker segment are quoted in Worldscale[1] points. We examine the TC5 route, which along with TC2 is the most important routes for clean tankers. The TC5 reflects transportation from Saudi Arabia to Japan by a LR1 tanker loaded with naphtha condensate. Within the dirty tanker segment we investigate route TD3, TD5 and TD7. These are the most important dirty routes in terms of physical trade. Route TD3 is operated by a VLCC, and reflects transportation of crude oil from the Middle East to the Far East. TD5 is operated by a Suezmax vessel for transportation of crude oil from West Africa to US. Finally, TD7 is operated by an Aframax tanker and mirrors shipments with crude oil from the North Sea to the Continent (Alizadeh & Nomikos, 2009).

[1] Used as basis for calculation of tanker spot rates. Worldscale points show the cost of transporting a tonne of cargo using the standard vessel on a round voyage, also known as Worldscale 100(Stopford, 2009).

1.6. Freight futures

A futures contract is an agreement between two parties to buy or sell an asset at an agreed price and time in the future. The underlying asset may be a commodity, stock, freight (voyage charter) or hire (time charter). The party with the long position agrees to buy the asset, while the party with the short position agrees to deliver the asset. It is a zero-sum game, meaning that the loss of one participant equals the gain of the other Hull (2012). Futures contracts are highly standardised in terms of maturity, quantity, quality and variety (Geman, 2005). An exchange specifies the features of the contract, while a clearinghouse guarantees the performance (Hull, 2012). Futures contracts are settled daily against the price on the underlying asset. The exchange will require traders to deposit funds into a margin account which is adjusted according to price movements in the underlying assets. The first freight derivative was the Baltic International Freight futures Exchange (BIFFEX) contract in 1985 (Stopford, 2009). Shipowners was now able to hedge their risk in the physical market. The contract was traded at the London Commodity Exchange, and settled daily against the cash equivalent value of the Baltic Freight Index (BFI). The underlying asset, the BFI, was calculated on the basis of 11 dry-cargo routes. The BIFFEX contract was regarded as innovative when first launched, and was well received by market participants. It succeeded in mirroring the performance of the BFI-index, but failed to capture fluctuations on the 11 individual routes which constituted the index. In reality, hedging with the BIFFEX contract was more like a cross-hedge. Cross hedging with an index based contract is only successful when the routes (or stocks) constituting the index, and the index move together. When a large number of routes compose the index, the relationship between single routes and the index will not be very strong. Poor hedging performance and introduction of Forward Freight Agreements (FFA) led to low trading activity in the BIFFEX, and was eventually de-listed in 2002. The New York Merchantile exchange (NYMEX) has offered freight futures since 2005 (Geman, 2008). They offer futures contracts on nine tanker routes.

1.7. Forward Freight Agreements

Forward contracts share many of the same characteristics as futures, but there are some differences. Forward contracts involve physical delivery of the underlying asset. However, in many cases the delivery of the asset does not take place, but are settled in cash (Kolb & Overdahl, 2007). Moreover, forward prices may deviate from futures prices due to margin rules, differences in transaction costs and tax treatments (Kolb & Overdahl, 2007). The market for Forward Freight Agreements (FFA) emerged in the early 1990s as a response to the poor hedging performance of the BIFFEX contract (Alizadeh & Nomikos, 2009). FFAs gave shipowners (and charterers) the possibility to hedge the freight (voyage charter) or hire (time charter) on a specific voyage or route. Typically the underlying asset is one of the routes at the Baltic Exchange. In years following after 1992, the FFA market grew almost exponentially. Before the downturn in 2008, the total FFA market had a value of US$125 billion (Oakley, 2008). FFA rates are based on Baltic Forward Assessments (BFA) produced by the Baltic exchange. Similar to the reported freight rates, BFAs are reported as the average of the assessments from a panel of FFA brokers. Freight derivatives are used by a large number of market participants. Shipowners (20%), charters and operators (30%), trading companies (40%) and financial houses and banks (10%) make up the majority of the trade in freight derivatives like FFAs (Geman, 2008). Standard contracts are most common, since they offer higher liquidity than customized contracts (Stopford, 2009). FFAs are traded either over-the-counter (OTC), or through a hybrid exchange like SSY and Marex Spectron (Imarex). In the OTC market, FFAs are negotiated through a broker. The process is similar to the one in the physical market. The broker will try to find a counterpart with opposite expectations for the future path of the freight rates. In other words, FFAs (also known as freight swaps) are principal-to-principal contracts. In a hybrid exchange the FFAs are traded on screen and cleared directly through one of the clearinghouses. OTC traded FFAs can also be cleared. In fact, 99% of all positions are cleared and margined daily through a clearinghouse (Baltic Exchange). The clearinghouse guarantees that the counter party fulfils its financial obligations. Examples of clearinghouses are London Clearing House (LCH), Norwegian Futures and Options Clearinghouse (NOS) and Singapore Exchange (SGX). Cleared FFAs share many of the same characteristics as exchange traded futures. At the end of each day, market participants receive the difference between contract price and the underlying freight or hire rate. Contracts are settled at the end of each month on the basis of the average spot freight rate in current month. In some contracts (not part of this thesis), the settlement price is calculated as the average of the last seven days. The main terms of an FFA agreement covers:

- The agreed route. For example Tubarao in Brazil to Baoshun in China.
- The contract rate at which differences will be settled. For example 40$ per metric ton of transported cargo. This is effectively the forward price.
- The day, month and year of settlement. For example November 2014.
- The size of the contract. Measured in number of lots[2] traded.

It is possible to trade FFAs with monthly, quarterly and yearly maturities. The shortest matures within current month, while the longest has three years maturity. In this thesis we follow the literature and focus on contracts with monthly maturities. Table 1.4 provides an overview of the FFAs we investigate in this thesis.

Baltic Exchange routes and corresponding FFA contracts						
Segment/Route	**Forward Freight Agreements (FFA)**					
Capesize						
C3	FFACUR	FFA+1	FFA+2	-	-	-
C4	FFACUR	FFA+1	FFA+2	FFA+3	-	-
C5	FFACUR	FFA+1	FFA+2	-	-	-
C7	FFACUR	FFA+1	FFA+2	FFA+3	FFA+4	FFA+5
Panamax						
P2A_03	FFACUR	FFA+1	FFA+2	FFA+3	FFA+4	FFA+5
P3A_03	FFACUR	FFA+1	FFA+2	FFA+3	FFA+4	FFA+5
Clean Tanker						
TC5	FFACUR	FFA+1	FFA+2	FFA+3	FFA+4	FFA+5
Dirty Tankers						
TD3	FFACUR	FFA+1	FFA+2	FFA+3	FFA+4	FFA+5
TD5	FFACUR	FFA+1	FFA+2	FFA+3	FFA+4	FFA+5
TD7	FFACUR	FFA+1	FFA+2	FFA+3	FFA+4	FFA+5

Table 1.4: *Overview of selected forward freight agreements (FFA) from the Baltic Exchange. Monthly maturities only.*

The first column denotes the trading route associated with the FFA. This may thought on as the underlying asset. The FFACUR denote a forward contract that matures at the end of the current month. The settlement price is then calculated on the basis of the average spot price the current month. FFA+1 denotes a contract that matures at the end of next month. For the +1, the settlement price is calculated on the basis of the average spot rate the next month.

[2] The definition of one lot is either one day of charter or 1000 mt of transported cargo.

2. Literature on risk management in shipping

Very little research has been done on freight futures and forwards, compared to futures and forwards on commodities and financial assets. The majority of the studies are on the now de-listed BIFFEX futures contract, and not on forward freight agreements (FFA). A reason for this has been the poor availability of data to support empirical work (Kavussanos & Visvikis, 2006). Most studies are focused on the dry bulk segment and conducted on a low number of routes and contracts in each paper. We will start by presenting relevant hedging literature and then move over to prediction performance.

One of the first hedge efficiency studies on the BIFFEX contract was performed by Thuong and Visscher (1990). They analyzed weekly data from 1986 to 1988, using the conventional hedging method (OLS) to calculate optimal hedge ratios. Their significant variance reductions range from 33% to 9%, depending on route. An early survey performed by Collinane (1991) six years after the launch of freight futures, concluded that shipowners did not accept the BIFFEX as a proper hedging tool. Kavussanos and Nomikos (2000) investigated weekly spot and futures prices from 1988 to 1997. They found a variance reduction from 4.0% to 19.2%, depending on the underlying route when investigating the BIFFEX contract. They also found that that the alternation of the BIFFEX to include time charter contracts in the BIFFEX had no significant effect on hedging performance. Variance reduction when hedging was still well below other commodity and financial markets. Dinwoodie (2003) found that shipowners are worried that the use of FFA might expose their risk management policies to other market participants. Kavussanos and Visvikis (2010) investigated in and out-of-sample variance reduction using weekly data on route C4 and a basket of time-charter routes from 2004 to 2008. Hedge ratios were calculated using the conventional method (OLS), VECM and VECM-GARCH-X. Depending on model the in sample results showed a variance reduction from 56%

to 60% on C4, and 55% to 64% on the basket of time charter routes. Variance reduction out-of-sample varied from 79% to 86% for route C4 and 63% to 66% for the basket. The VECM-GARCH-X method of calculating optimal hedge ratios, and a naive hedge outperformed all models in- and out of sample, respectively.

Kavussanos and Nomikos (1999) investigated the unbiasedness hypothesis of BIFFEX prices. Using monthly observations from 1988 to 1997 they found that acceptance or rejection depends on the contracts time to maturity. They also found that futures prices provide forecasts of realized spot prices that are superior to forecasts generated from error correction-, ARIMA, exponential smoothing, and random walk models. Their findings are supported by Haigh (2000) who found that one-month BIFFEX contracts are accurate for forecasting prices one month ahead, but are poorly suited for predicting two- and three months spot prices. Kavussanos et al. (2004) investigated the unbiasedness hypothesis of four Panamax FFA contracts with one, two and three month maturity. Their findings suggest that FFA prices one and two months before maturity are unbiased predictors of subsequent spot prices. Moreover, they suggest that the validity of the unbiasedness hypothesis depends on the selected trading route and the time to maturity of the contract, similar to the results from the BIFFEX papers. Grober (2010b) also investigates the unbiasedness hypothesis for Panamax FFAs. Using monthly data from 2005 to 2010 he finds that all investigated FFAs are unbiased predictors of prevailing spot rates. Grober also discovered that the FFA price leads the spot rate when volatility is low and vice versa when volatility is high. Recent literature by Kavaussanos and Nimonkos 2000, Haigh et al (2004) and Kavaussanos and Viskvis (2004) suggests that freight rates are non-stationary. On the other hand, Tvedt (2003) and Koekebakker (2006) suggest that freight rates are stationary. Tvedt uses an augmented Dickey fuller (ADF) test, while Koekebakker uses a non-linear version of the ADF test.

3. Descriptive statistics on freight rates and forward freight agreements

Our data consists of 50 Forward Freight Agreements (FFA) and 10 corresponding trading routes from 2005 to 2012. The data is collected from the Baltic Exchange. We have used three different data sets to answer the questions from the introduction:

- The descriptive statistics is based on weekly observations of FFA prices and spot freight rates from 2005 to 2012. The data is collected each Friday.
- FFA hedging performance (chapter 5) is investigated using monthly data. FFA prices and spot freight rates are collected the 13. each month. When the 13. falls on a weekend, we have used the first available trading day in advance. The in-sample period spans from 2005 to July 2011, the out-of-sample from July 2011 to December 2012. Note that there may be some minor differences in sample-size across segments. This applies only to the in-sample analysis.
- The forecasting section (chapter 6) is based on monthly data. The FFA prices are collected the first day of each month. Settlement prices, which are the average spot freight rate current month, are collected at the end of each month. In this part we used the entire sample from 2005 to 2012.

Before we start with the analysis we will briefly inform on some of the methods used in this chapter. This is followed by descriptive statistics on each segment and a short summary. In line with literature on shipping risk management, and to make the variables tractable, we calculate the percentage change in FFA- and spot prices using continuously compounded returns:

$$r_t = ln(\frac{P_t}{P_{t-1}}) = ln(P_t) - ln(P_{t-1}) \tag{3.1}$$

where P_t and P_{t-1} is the price of either the spot fright rate or FFA price at time t and $t-1$, respectively. ln is the natural logarithm. It is common to think of risk as deviations from the average return. Standard deviation is often used to measure the variables dispersion, and is calculated as follows:

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(r(s)-\overline{r})^2} \tag{3.2}$$

where n is the number of observations, $r(s)$ is one observation of the variable, and $\overline{r}$ the mean. Furthermore, we capture the time-varying volatility by calculating rolling standard deviations. This is done using a rolling window of observations. A small window of 52-weeks is chosen at the beginning of the sample and has been turned into a series of annualised standard deviations, σ_1. The sample is rolled by one observation at a time, meaning that one observation is dropped and another is added for each roll. A new standard deviation, σ_t is then calculated. The series will reflect change in volatility over time. One problem with this method is that it assigns equal weights to observations in the window over which the standard deviations are estimated. Because past events are believed to have lesser impact on volatility compared to recent past events, this approach may be inappropriate. We address this issue using exponentially declining weights. We calculate the exponentially weighted rolling variance as:

$$\sigma_t^2 = \lambda\sigma_{t-1}^2 + (1-\lambda)r_{t-1}^2 \tag{3.3}$$

where λ represents the weighting coefficient, which has a value between 0 and 1. A high value yields higher persistence in volatility. Is this thesis we have used a value of 0,94, which has been shown to be sufficient to capture the dynamics of volatility(Alizadeh & Nomikos, 2009). Reported means[1] and standard deviations[2] in this thesis are annualized.

[1] $r_{yearly} =\approx r_{weekly} * 52$
[2] $S_{yearly} \approx S_{weekly} * \sqrt{52}$

3.1. Freight Rates Descriptive Statistics

Freight rates descriptive statistics										
Route:	P2A	P3A	C3	C4	C5	C7	TC5	TD3	TD5	TD7
2007-2009										
Annualised Mean	6 %	-15 %	-2 %	-9 %	-8 %	-2 %	-22 %	0 %	-26 %	-25 %
Annualised Std.Dev	81 %	136 %	86 %	84 %	98 %	80 %	63 %	135 %	126 %	150 %
Kurtosis	3.00	3.52	2.25	1.23	1.29	1.36	1.77	1.50	0.65	0.66
Skewness	-0.70	0.29	-0.65	-0.12	-0.33	-0.30	0.01	-0.06	0.15	-0.12
Count Positive	79	75	79	73	78	77	70	68	70	75
Count Negative	72	76	72	78	73	74	81	83	81	76
% Negative	48 %	50 %	48 %	52 %	48 %	49 %	54 %	55 %	54 %	50 %
2005-2012										
Annualised Mean	-14 %	-27 %	-10 %	-14 %	-10 %	-11 %	-6 %	-6 %	-12 %	-7 %
Annualised Std.dev	66 %	109 %	66 %	65 %	76 %	65 %	50 %	116 %	113 %	126 %
Kurtosis	3.06	3.75	3.51	3.11	2.35	1.98	2.53	2.13	1.82	2.67
Skewness	-0.38	0.32	-0.57	-0.11	-0.14	-0.28	0.21	0.14	0.36	0.32
Count Positive	196	191	204	188	199	192	149	187	191	188
Count Negative	206	211	198	214	203	210	179	215	211	214
% Negative	51 %	52 %	49 %	53 %	50 %	52 %	55 %	53 %	52 %	53 %

Table 3.1: *Descriptive statistics on spot freight rate logarithmic returns from 2007 to 2009, and 2005 to 2012. Based on weekly observations.*

Summary statistics on spot freight rates for the ten investigated routes are presented in table 3.1. It shows that the volatility in the period 2005 to 2012 was high, and even higher in the sub period 2007 to 2009. The latter is most likely related to the global financial crises. The standard deviation of Capesize routes C3, C4, C5 and C7 ranged from 66% to 76% over the entire period. In the Panamax market, the volatility on route P2A are to the Capesize market, but significantly higher on route P3A with a 109% standard deviation. The TC5 route in the Clean tanker market has the lowest volatility, while the Dirty tanker routes TD3, TD5 and TD7 has the highest of the investigated routes. The Dirty tanker routes has extremely high standard deviation, ranging from 109% to 126%. The excess kurtosis[3] are positive and significantly different from zero on all routes. Skewness[4] is significantly different

[3]When a distribution exhibit positive excess kurtosis it is said to have heavy tails, implying that the distribution puts more mass on the tails of its support than a normal distribution. In other words, distribution tends to contain more extreme values. $ExcessKurtosis = K(x) = E(\frac{(X-\mu_x)^4}{\sigma_x^3}) - 3$

[4]Skewness defines whether the distribution of the variable is symmetric around its mean, or if its skewed to either left or right. $Skewness = E(\frac{(X-\mu_x)^3}{\sigma_x^3})$. Negative skewness coefficients imply that long positions are associated with higher risk since more extreme losses are placed on the left side of the log distribution.

from zero and negative on routes P2A, C3 and C7, but positive on P3A, TD5 and TD7. The returns exhibit fat tails, which means that the probability of extreme negative or positive returns are higher than in the normal distribution. This is supported by the results from the Jarque Bera test[5] in table A2.1. High Jarque-Bera statistics may be a result of extreme events in the time series. Annualised means are negative for all routes. P3A stands out in that it is has a considerably more negative mean compared to the other routes. Overall, the freight market seems to perform poorly in terms of returns.

Return correlations[6] between spot freight rates for the different routes are presented in table 3.2. We observe positive return correlations within routes in the the Capesize market and Panamax market. This is natural because the routes are operated by the same vessels, which means that the supply and demand factors are the same. This can also be related to operational flexibility and the fact that the same vessel over time can be operated on different routes. If the FFAs share the co-movements, this indicates that routes can be cross-hedged. But due to the large amount of contracts, we will not conduct cross-hedge analysis in this study. The results also indicate low correlations between the routes in the dirty tanker market. This is most likely due to the different routes are operated by vessels of different size and type. The results indicate low co-movement between the sectors. This most likely as a result of independence between supply and demand factors across the different sectors. Examples are regional imbalances between supply and demand, differences in cost of transportation and uniqueness for each market.

	C3(S)	C4(S)	C5(S)	C7(S)	TC5(S)	TD3(S)	TD5(S)	TD7(S)	P2A_03(S)	P3A_03(S)
2006-2012										
C3(S)	1									
C4(S)	0,83	1								
C5(S)	0,82	0,85	1							
C7(S)	0,90	0,86	0,80	1						
TC5(S)	0,13	0,12	0,13	0,13	1					
TD3(S)	0,13	0,12	0,11	0,14	0,17	1				
TD5(S)	0,02	0,00	0,03	0,00	0,11	0,33	1			
TD7(S)	0,00	0,01	0,01	-0,01	0,07	0,17	0,27	1		
P2A_03(S)	0,46	0,44	0,40	0,45	0,13	0,02	0,04	0,01	1	
P3A_03(S)	0,41	0,42	0,39	0,42	0,17	0,00	0,02	0,01	0,75	1

Table 3.2: *Return correlations between spot freight rate routes from 2005 to 2012 using weekly observations.*

[5] $JB = \frac{N}{6}(Skewness^2 + (\frac{(EKurtosis-3)^2}{4}))$

[6] $\rho_{x,y} = \frac{Cov(X_i,Y_i)}{\sigma_x \cdot \sigma_Y} = \frac{\sigma_{X,Y}}{\sigma_X \cdot \sigma_Y}$

3.2. Capesize

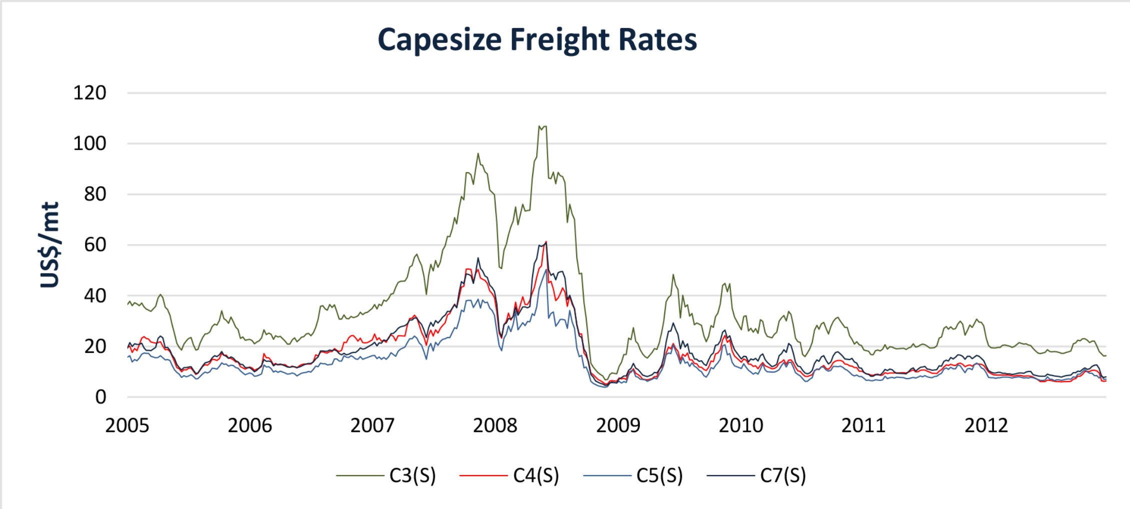

Figure 3.1: *Freight rates ($ per mt) on routes C3, C4, C5 and C7 from January 2005 to December 2012 using weekly observations.*

Figure 3.1 shows the spot rate development for Capesize bulk carriers. The Capesize market peaked in November 2007 and June 2008. During the period from 2004 to 2008, the size of the bulk carrier fleet increased significantly. 282 (10.9 mill dwt) bulk carriers was delivered to the scrap yards, but as much as 1,539 (114 mill dwt) new vessels was built. In addition to newbuildings, 9 mill dwt of oil tanker tonnage was converted to bulk carriers (Shipping Statistics and Market Review - ISL Infoline). Increased fleet size has been a contributing factor to subsequent decline in spot rates. The iron ore routes C3 and C5, are highly influenced by the world steel production. Australia and Brazil are the largest exporters of iron ore. The largest importers are by far China, followed by EU and Japan. Chinese production and consumption of coal have great impact on the Capesize coal routes, C4 and C7. High freight rates in routes C4 and C7 from 2004 to 2007, may be attributed to a 41% increase in coal production and consumption (Shipping Statistics and Market Review - ISL Infoline). In the last quarter of 2008 the global financial crisis hit the Capesize market. In the short period from June 2008 to November 2008, the rates declined from 107 to 7 (C3), 61 to 5(C4), 61 to 4 (C5), 61 to 5 (C7). This corresponds to a 93% drop in just four months on route C3.

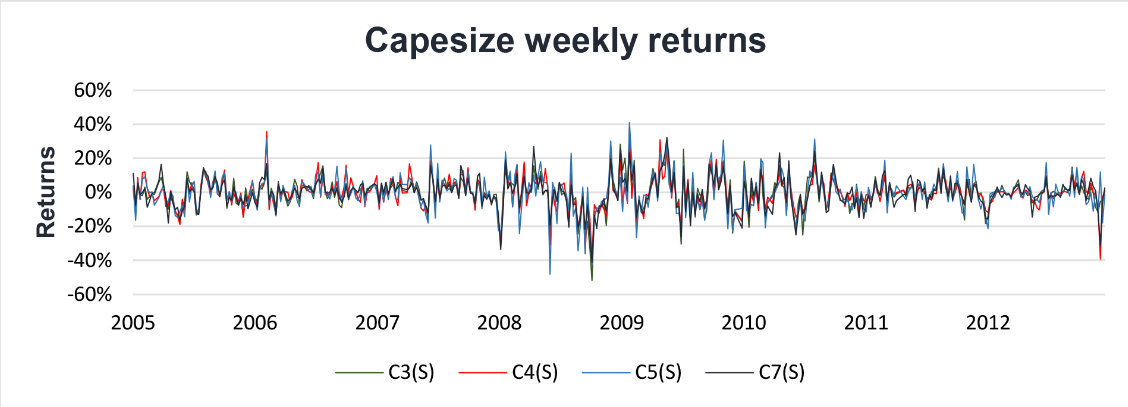

Figure 3.2: *Weekly returns on Capesize spot freight rates from july 2005 to december 2012.*

Figure 3.2 presents a plot of weekly returns for Capesize spot freight rates from January 2005 to December 2012. Weekly returns ranged between -52% to 32% for C3, -39% to 38% for C4, -48% to 41% for C5 and -41% to 32% for C7. The plot also illustrates the high correlation between the Capesize routes in table 3.2. Average weekly log returns turned out to be -0.20%, -0.28%, -0.20% and -0.22%, respectively. The plot shows that the period between 2008 and 2010 was characterized by high volatility. It seems like the volatility dropped after 2009. This is supported by the figure below.

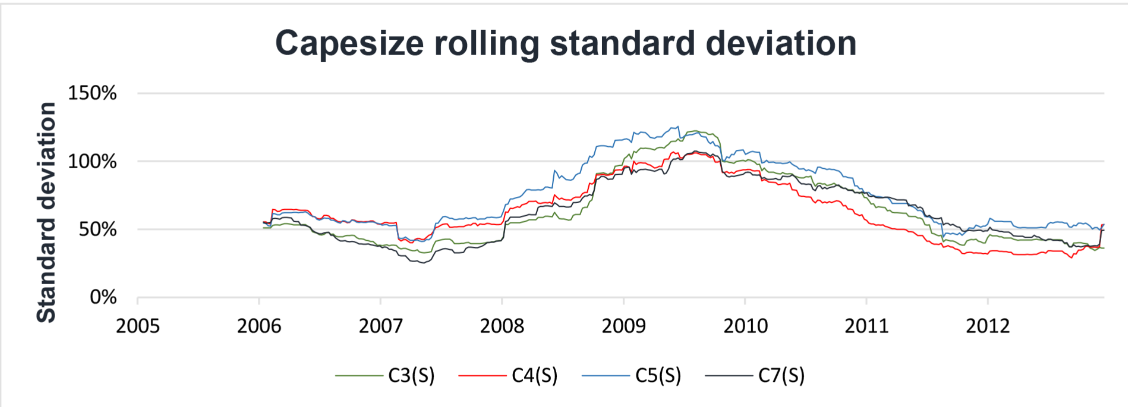

Figure 3.3: *52-week rolling standard deviation of Capesize spot freight rate return from january 2005 to december 2012.*

To illustrate how the dynamics of volatility vary over the sample period, we have estimated rolling standard deviation for investigated routes. Figure 3.3 plots the calculated 52-week rolling standard deviation on selected routes in the Capesize market. There are differences in volatility levels between the contracts, but they follow a similar path. We observe that the volatility vary significantly over the sample period. In C3 and C4, volatility ranges between a minimum of 32% and 29% to a maximum of 122% and 106%. In C5 and C7, volatility range between a minimum 40% and 25% to a maximum of 125% and 107%. Volatility peaked in period 2009, before it slowly decreased down to pre-financial crisis levels. Rolling standard deviation assigns equal weights to observations and thereby ignores that recent events may have greater impact than distant past events. We therefore estimated exponentially weighted standard deviation.

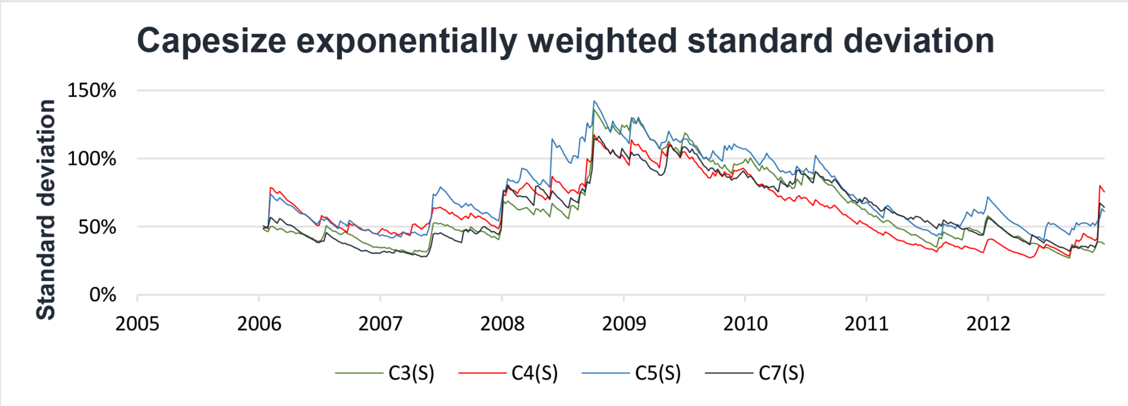

Figure 3.4: *52-week exponentially weighted standard deviation on Capesize spot freight rates from January 2005 to December 2012 using annualized weekly returns.*

Figure 3.4 shows a similar dynamic to those observed in figure 3.1.2 when a simple rolling variance method was used to estimate time-varying volatility. The volatility increases sharply and declines slowly, which means that there seems to be a degree of persistence after a increase in volatility. Again, there are differences between the contracts, and we can observe that the volatility vary significantly over the sample period. In C3 and C4, it ranges from a minimum 26% and 27% to a maximum 136% and 117%. In C5 and C7, volatility range from a minimum 39% and 27% to a maximum of 142% and 116%.

	FFACUR	FFA+1	FFA+2	FFA+3
2005-2012				
C3(S)	0,80	0,85	0,85	
C4(S)	0,78	0,78	0,74	0,73
C5(S)	0,93	0,88	0,82	
C7(S)	0,76	0,77	0,77	0,74
2007-2009				
C3(S)	0,81	0,87	0,88	
C4(S)	0,82	0,82	0,81	0,79
C5(S)	0,83	0,91	0,90	
C7(S)	0,81	0,82	0,82	0,80

Table 3.3: *Return correlations between Capesize freight spot routes and associated FFAs*

Another important statistical feature is the return correlations between Forward Freight Agreements (FFA) and spot freight rates. As shown in table 3.3, return correlations between the spot freight rates and FFAs are strong. There correlations apperas to be stable also for contracts with longer maturity. This means that there is evidence of a common trend that drives the prices. We expect the high correlations between the spot freight rates and FFAs to generate high hedge efficiencies.

3.3. Panamax

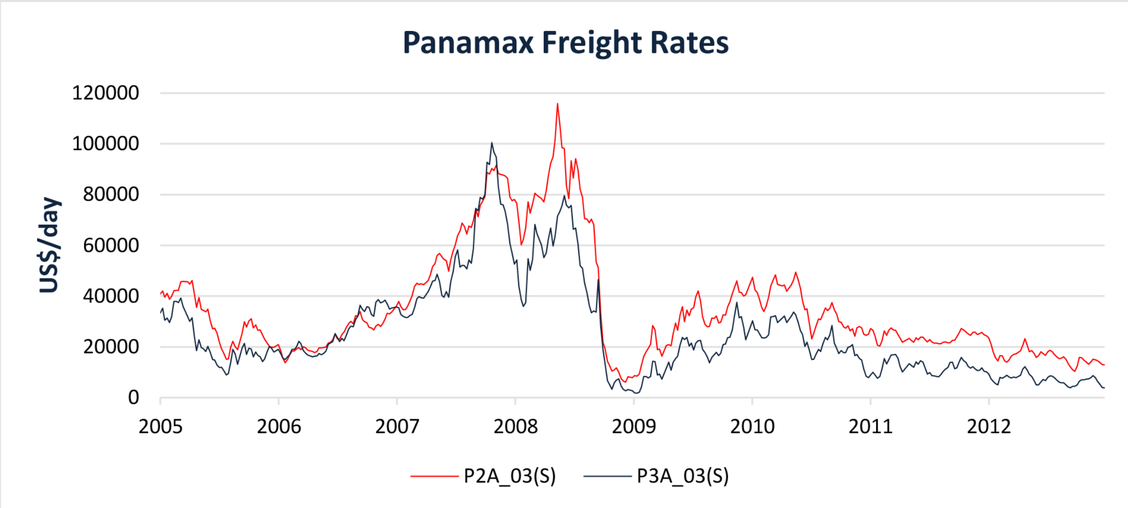

Figure 3.5: *Freight rates ($ per day) on route P2A_03 and P3A_03 from January 2005 - December 2012 using weekly observations.*

Figure 3.5 shows the spot freight rate development for Panamax vessels. Spot freight rates increased steadily from the second quarter in 2006, most likely due to increased commodity trade and economic growth. The freight rates peaked in October 2007 at 90,000 US$/day for P2A_03 and 100,548 US$/day for P3A_03. The subsequent period until mid-2008 was characterized by falling rates, likely triggered by large deliveries of ships on to the market and the financial crisis. Exports of grains was relatively stable in the period, so the demand downturn in the Panamax market was also likely influenced by a drop in Asian steel demand. The Panamax market experienced a double dip, with a peak at the end of the second quarter in 2008 before it dropped again. The P2A_03 freight rates peaked at 115,850 US$/day in June 2008 and dropped to a record low 6,078 US$/day in December 2008. P3A_03 peaked at 79,588 US$/day and dropped to 1,700 US$/day in January 2009.

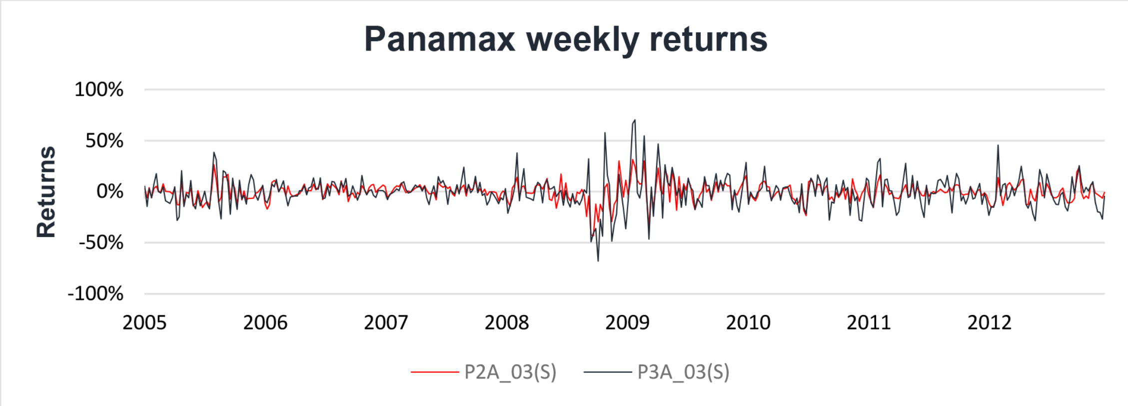

Figure 3.6: *Weekly returns on Panamax spot freight rates from july 2005 to december 2012.*

Figure 3.6 presents a plot of weekly returns for Panamax spot freight rates from July 2005 to December 2012. The plot shows that the spot freight rate at route P3A have larger revenue fluctuations compared to the P2A route. P2A_03 weekly return range from a minimum of -43% to a maximum of 31%. P3A_03 range from a minimum of -67% to a maximum of 70%. Similar to the Capesize, it shows that the period between 2008 and 2010 was characterized by high volatility. It seems like the volatility dropped after 2009. This is supported by the figure 3.7 Average weekly returns for the P2A_03 and P3A_03 freight rate over the sample period was -0.54% and -0.29%, respectively.

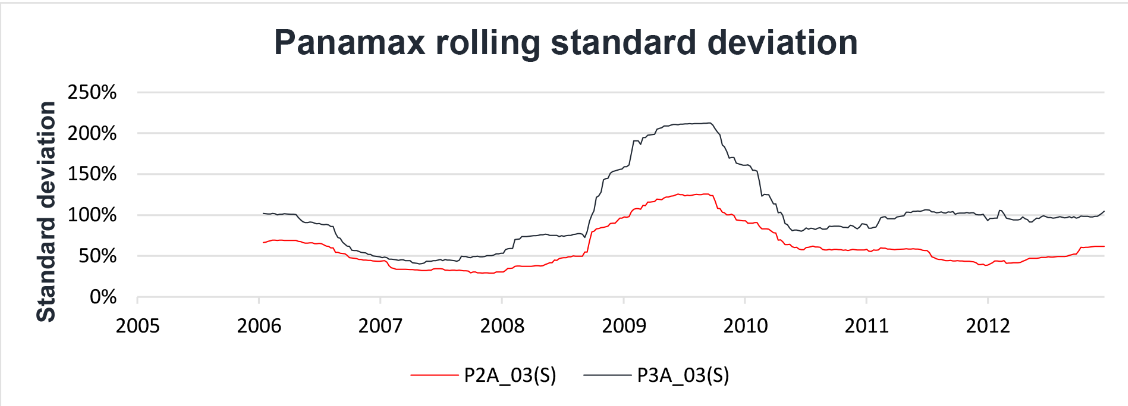

Figure 3.7: *52 week rolling standard deviation turned in to annualised standard deviation over the period january 2005 to december 2012.*

Figure 3.7 plots the estimated rolling standard deviation for P2A_03 and P3A_03. There are differences between the contracts, and we can observe that the volatilities vary significantly over the sample period. In P2A_03, 52-week standard deviation range from a minimum 28% to a maximum 125%. In P3A_03, standard deviation range from a minimum 40% to a maximum of 212%. In the global financial crisis period, when spot freight rate dropped, volatility in Panamax weekly returns increased significantly.

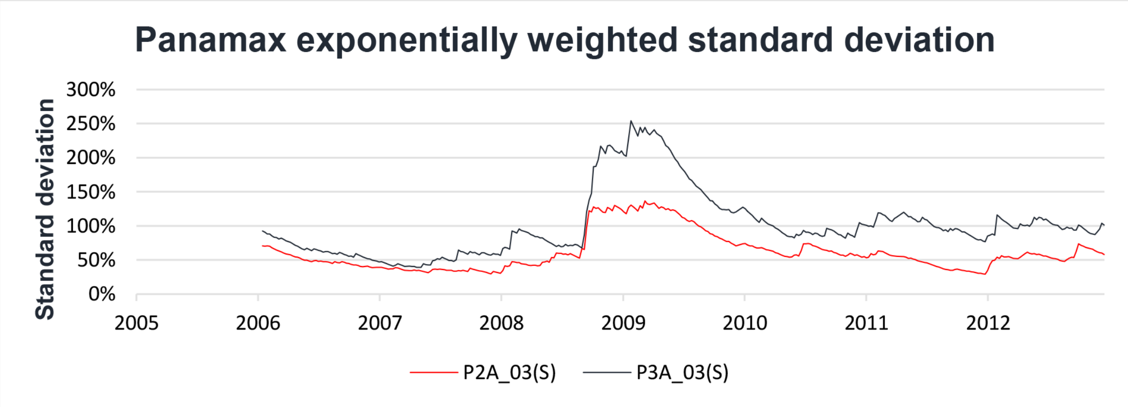

Figure 3.8: *Exponentially weighted time warying volatilities over the period january 2005 to december 2012. Annualised based on weekly data.*

Exponentially weighted standard deviation for Panamax returns are shown in figure 3.8. The standard deviation ranges from 29% to 136% (P2A_03) and 38% to 253% (P3A_03). Figure 3.8 have many of the same characteristics as figure 3.7 with route P3A volatility considerably higher than P2A volatility, especially in the period between 2008 and 2009.

	FFACUR	FFA+1	FFA+2	FFA+3	FFA+4	FFA+5
2005-2012						
P2A_03	0,79	0,76	0,73	0,72	0,71	0,71
P3A-03	0,82	0,79	0,78	0,75	0,75	0,74
2007-2009						
P2A_03	0,82	0,80	0,79	0,79	0,77	0,76
P3A-03	0,82	0,83	0,82	0,79	0,78	0,77

Table 3.4: *Returns correlations between Panamax spot freight routes and associated FFAs*

Table 3.4 shows the co-movement between return on freight rate routes and return on FFAs. The degree of co-movement between TC5 and associated FFAs can are high with correlations around 0.80. Panamax FFAs with longer maturates offer slightly lower return correlations than FFAs with maturity in the near future. Hedge ratio is highly dependent of correlation. We expect the high correlations between the spot freight rates and FFAs to generate high hedge efficiencies.

3.4. Clean product tankers

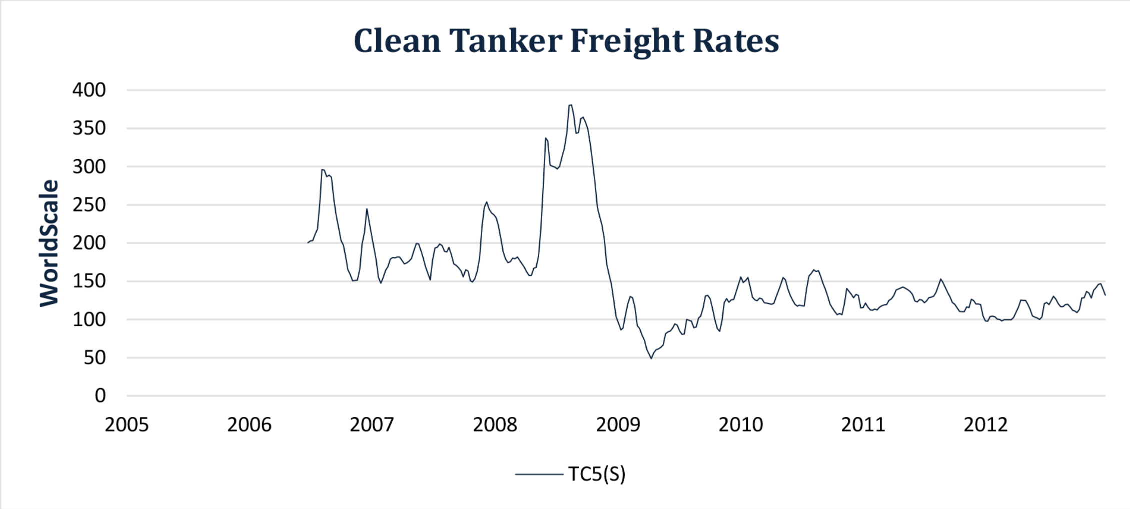

Figure 3.9: *Freight rates (Worldscale) on route TC5 from June 2006 to December 2012 using weekly observations.*

The maximum freight rate, quoted in worldscale points rate reached 380,77 in August 2008. After this the freight rate dropped significantly to a record low of 48 WS in April 2009. This period was characterised by low demand after oil products and deliveries of new vessels to the market. In recent years overcapacity of tankers has led to a low freight rate for the TC5 contract.

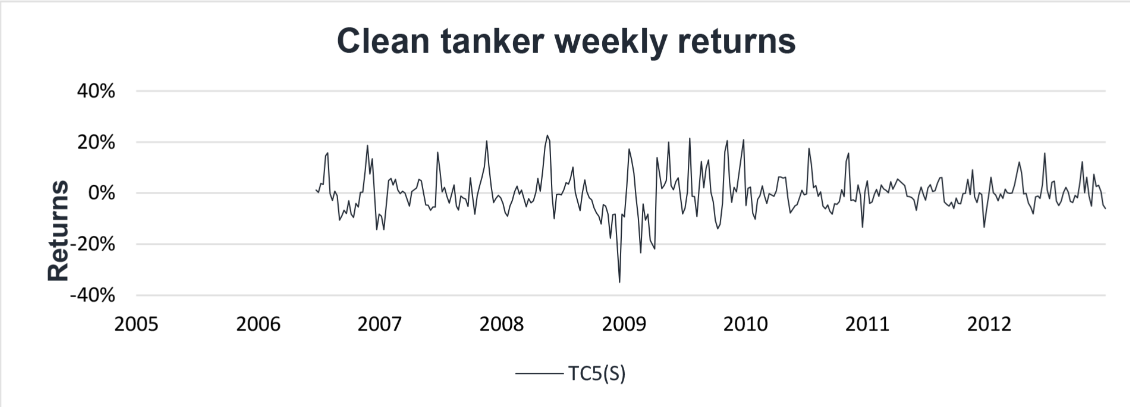

Figure 3.10: *Weekly returns of spot freight rates for TC5 from July 2006 to December 2012.*

Weekly spot freight rate returns on route TC5 ranged from a minimum of -34% to a maximum of 22%, with weekly mean of -0.13%. Period July 2006 to December 2012 exhibits higher volatility relative to period January 2010 to December 2012, but the increase was not as significant as in the Capesize and Panamax segments. Weekly mean return equals 8.73% and 5.30%, respectively.

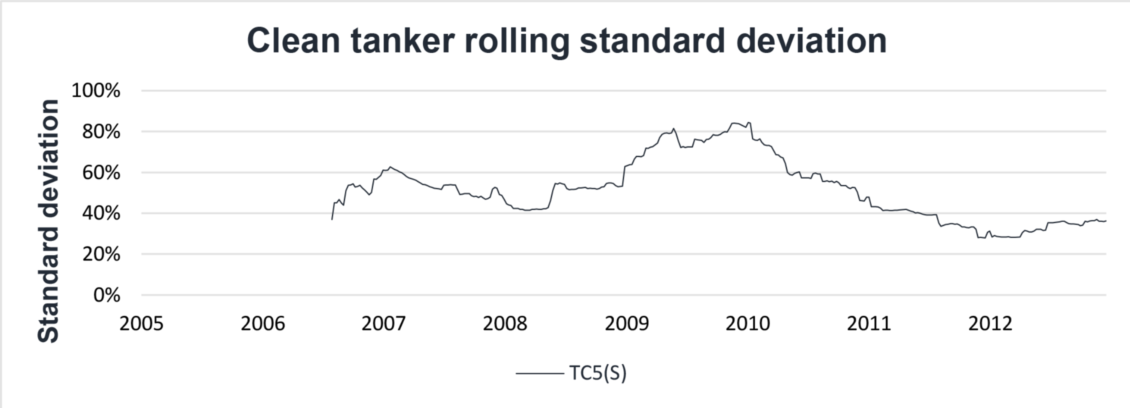

Figure 3.11: *52 week rolling standard deviation turned in to annualized standard deviation over the period july 2006 to december 2012.*

Figure 3.11 plots the estimated 52-week rolling standard deviation for TC5. The Clean tanker volatility varied from a minimum of 27% to a maximum of 84%. The annual mean was 51%. In period 2011 to 2012 52-week annualised standard deviation is low and stable, relative to prevailing period. We can see that the volatility do not increased as much as in the Panamax and Capesize segments during the financial crisis.

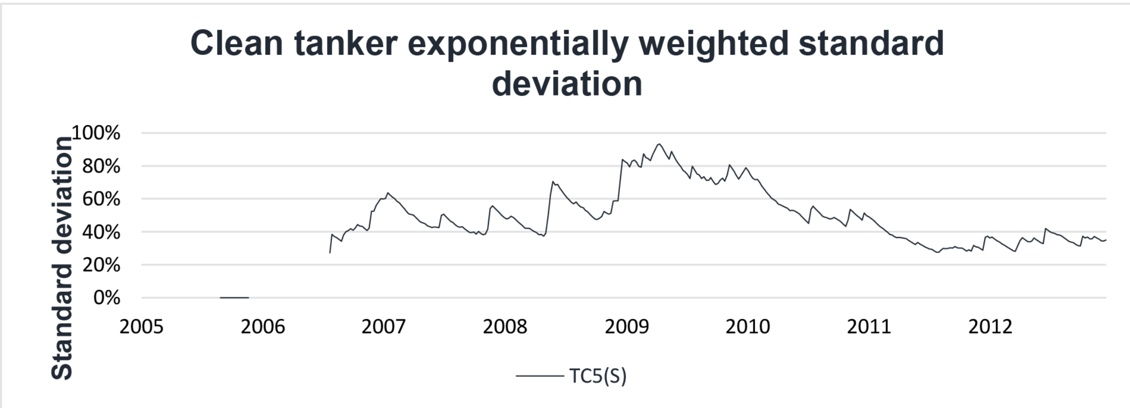

Figure 3.12: *52 week exponentially weighted time warying standard deviations turned into annualised form over the period july 2006 to december 2012. Annualised based on weekly data.*

Figure 3.12 illustrate similar dynamics to those observed in figure 3.11 when a simple rolling variance method was used to estimate time-varying. The EMWA-curve is somewhat smoother and it seems to be a degree of persistence in volatilities. The 52-week exponentially weighted annualised standard deviation range from a minimum 27,21% to a maximum 93,25%, with annualised mean of 49,98%.

	FFACUR	FFA+1	FFA+2	FFA+3	FFA+4	FFA+5
2005-2012						
TC5(S)	0,63	0,44	0,31	0,33	0,31	0,30
2007-2009						
TC5(S)	0,67	0,48	0,32	0,35	0,34	0,40

Table 3.5: *Return correlations between Clean tanker spot freight route and associated FFAs*

Table 3.5 shows the correlations between the TC5 spot freight rate returns and the associated FFA returns. The correlations appears to medium, and decreases when maturity increases. We expect hedge efficiencies to be medium for contracts with short maturity like CUR and +1 contracts.

3.5. Dirty tankers

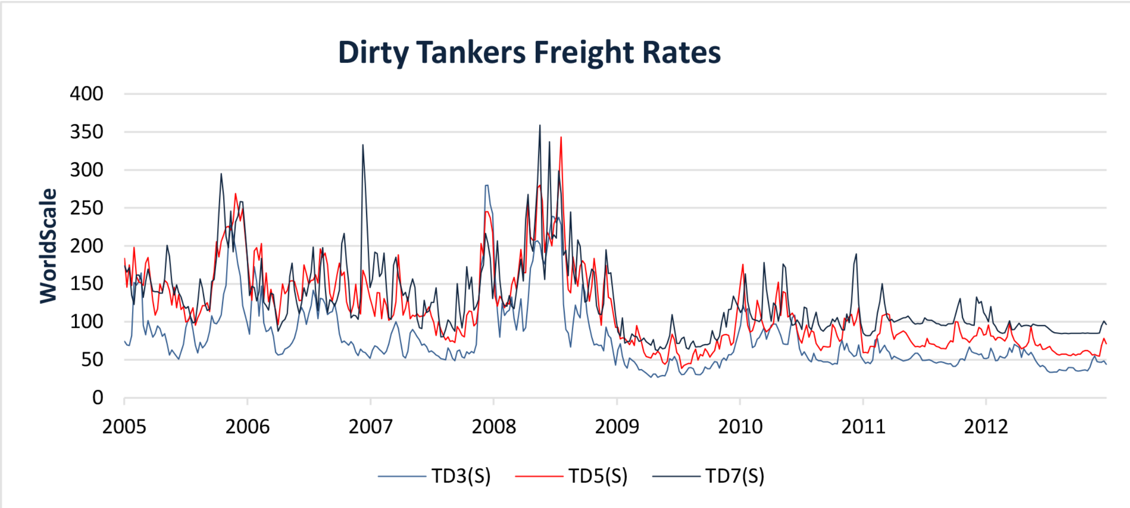

Table 3.13: *Freight rates (Worldscale) on route TD3, TD5 and TD7 from January 2005 to December 2012 using weekly observations.*

The dirty tanker freight rates (quoted in worldscale points) peaked in 2008, reaching 279 WS for TD3, 343 WS for TD5 and 359 WS for TD7. The average freight rate for the TD3, TD5 and TD7 route was 78 WS, 114 WS and 127 WS, respectively. Rates was likely pushed up by a record high oil price, low global oil inventories and increased imports. TD3 fluctuated within a range of 252 WS, while TD5 and TD7 fluctuated within a range of 343 WS and 297 WS. The Dirty tanker market can be defined as a high volatility market, confirmed by weekly mean standard deviation equal to 45 WS points in route TD3, 52 WS points in TD5 and 48 WS points in TD7.

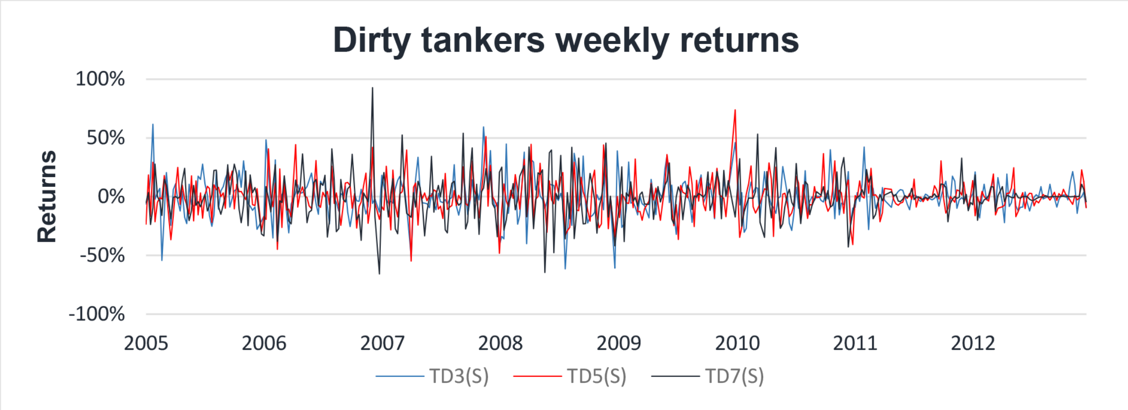

Figure 3.14: *Weekly returns of spot freight rates (Worldscale points) for route TD3, TD5 and TD7 from January 2005 to December 2012.*

Figure 3.14 presents a plot of weekly returns for Dirty tanker spot freight rates from July 2005 to December 2012. The figure shows that the returns from week to week has been very high. In periods as high as 92%, 73% and 61% on TD7, TD5, TD3, respectively.

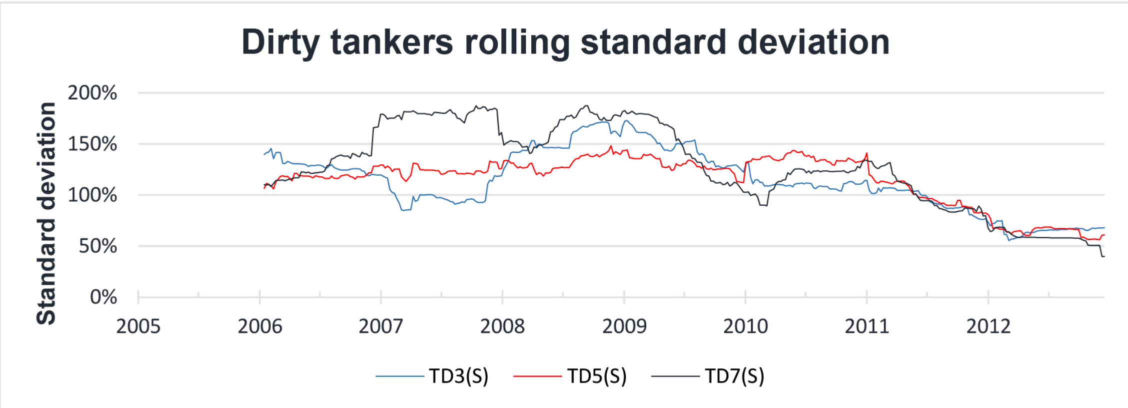

Figure 3.15: *52-week annualized rolling standard deviation for dirty tanker routes from January 2005 to December 2012.*

Figure 3.15 plots the estimated 52-week annualised rolling standard deviation for TD3, TD5 and TD7. There are differences between the contracts, and we can observe that the tanker volatilities vary significantly over the sample period. Volatility range between 55% and 173%(TD3), 56% and 148% in TD5, and 39% and 187% in TD7. In period 2011 to 2012, 52-week annualised rolling standard deviation drops and stabilizes, relative to prevailing period.

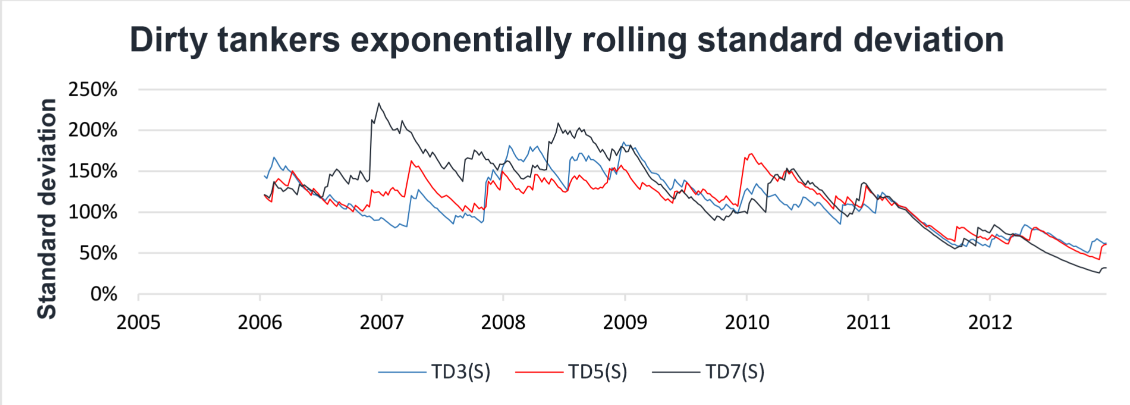

Figure 3.16: *52-week exponentially weighted time varying annualized standard deviation from January 2005 to December 2012.*

Figure 3.16 illustrates similar dynamics to those observed in figure 3.15, when a simple rolling variance method was used to estimate time-varying volatilities. There are some differences between the contracts, and again we can observe that the tanker volatilities vary significantly over the sample period. In TD3 volatility range from a minimum 50% to a maximum 185% with annualised mean of 111%. In TD5 and TD7 the volatility range from a minimum 41% and 25% to a maximum of 171% and 233% with annualized mean of 113% and 124%. Further on, we observe that the volatility in first half of 2007, second half of 2008 and first half of 2009, exhibit higher volatility levels than in the period 2010 to 2012. Some of this volatility increase can be explained by fat tails and high kurtosis in log returns. This means that more of its volatility can be explained by extreme events. Both rolling annualised standard deviation and exponentially annualised standard deviation illustrates the uncertainty and risk underlying the return process in this industry.

	FFACUR	FFA+1	FFA+2	FFA+3	FFA+4	FFA+5
2005-2012						
TD3(S)	0,68	0,55	0,42	0,34	0,28	0,39
TD5(S)	0,63	0,49	0,41	0,30	0,23	0,25
TD7(S)	0,68	0,62	0,46	0,33	0,23	0,26
2007-2009						
TD3(S)	0,66	0,54	0,43	0,33	0,24	0,43
TD5(S)	0,62	0,44	0,41	0,27	0,22	0,28
TD7(S)	0,68	0,64	0,53	0,43	0,30	0,30

Table 3.6: *Return correlations between Dirty tanker spot freight routes and associated FFAs*

Returns correlations between Dirty tanker spot freight rates and and FFA returns indicate that the FFA do not follow spot closely in the Dirty tanker market. FFAs with longer maturity have a lower degree of co-movement with the underlying spot contract. We note that correlation in the Dirty tanker market were somewhat lower than in the Capesize and Panamax market. We expect the low correlations between the spot and FFA contracts to have negative impact on hedge performance and efficiency in the Dirty segment.

4. Methodology for freight rate hedging and forecasting

4.1. Minimum Variance Hedge Ratio

The objective of hedging is to control or reduce the impact of large price changes on the company‘s cash flow. The hedger decides a hedge ratio, i.e. the number of futures contracts to buy or sell for each unit of spot commodity on which he bears price risk. The hedger may choose a naive one-to-one hedge strategy, which assume that the price on the underlying asset and futures move closely together. This approach fails to recognize that the correlation is less than perfect, and does not consider the stochastic nature of futures resulting in time variations in hedge ratios. Minimum variance hedge ratio (MVHR) was proposed by Johnson (1960) and Stein (1961). It was developed by Ederington (1979) and takes into account the imperfect correlation between spot and futures markets. It argues that the objective of hedging is to minimize the variance of portfolio returns. The hedge ratio that generates the minimum portfolio variance should be equal to the optimal hedge ratio, also known as the minimum variance hedge ratio. As an example, consider a shipowners portfolio, consisting of spot positions in the freight market and positions in forward contracts. Change in portfolio depends on the hedge ratio (h), and changes in spot- ($\triangle S_t = lnS_t - lnS_{t-1}$) and futures positions ($\triangle F_t = lnF_t - lnF_{t-1}$).

$$\triangle P_t = \triangle S_t - h \triangle F_t \tag{4.1}$$

Using the formula for the portfolio variance of two risky assets, the variance of the returns of the hedged portfolio is given by:

$$Var(\triangle P_t) = Var(\triangle S_t) - 2hCov(\triangle S_t, \triangle F_t) + h^2 Var(\triangle F_t) \tag{4.2}$$

The MVHR can be expressed as the ratio between the unconditional covariance between spot and futures changes, and the unconditional variance of futures price changes:

$$h^* = \frac{Cov(\triangle S_t, \triangle F_t)}{Var(\triangle F_t)} \tag{4.3}$$

where h^* is the optimal hedge ratio. The MVHR hedge ratio can also be estimated by the $h*$ in the following regression:

$$\triangle S_t = \alpha + h^* \triangle F_t + \varepsilon_t \tag{4.4}$$

This method is criticised by among others Myers and Thompson (1989) and Kroner and Sultan (1993) for the implicit assumption that risk in spot and futures markets is constant over time. Empirical evidence in different markets indicate that this assumption is too restrictive due to time varying distributions in cash and futures prices. Park & Bera (1987) showed that the OLS model is inappropriate to estimate hedge ratios. Since conditional moments change, as new information arrives the market, the hedge ratio changes over time. The efficiency of the hedge is defined as the proportion of risk eliminated compared to the unhedged position. The larger degree of reduction in unhedged variance, the higher hedge effectiveness. This can be measured through the coefficient of determination (R^2) when estimating model 4.4 using OLS. In line with several papers on risk management using FFAs, including Kavussanos and Viskvis (2010), we define the risk reduction as:

$$1 - \frac{Var(\triangle S_t - h^* \triangle F_t)}{Var(\triangle S_t)} \tag{4.5}$$

We assume that the hedger manage risk exposure by selling a Forward Freight Agreement equivalent to total delivery obligation. At the end of each month, FFA is rolled forward into another one-month contract. This is referred to as “stack-and-roll”. In other words, contracts are rolled over the 13. each month. When the 13. falls on a weekend, we have used the first available trading day in advance.

4.2. Forecasting using forward freight agreements

There are two popular ways to define forward prices (Fama & French, 1987). For storable commodities like oil and metals, the forward prices can be explained by the cost of carry, also called the theory of storage. It states that the forward price for an asset equals the spot price plus all costs related to holding the asset until maturity. The costs associated with holding the asset can be divided into four categories: storage, insurance, transport and finance (Kolb & Overdahl, 2007). The cost of carry may be expressed as:

$$F_t^i = S_t + C_t^i \tag{4.6}$$

where F_t is the price of the forward contract today for delivery of a commodity in the future, S_t is the spot price today and C is the costs of carrying the commodity forward in time. Deviations from the relationship will be restored in the market by investors performing cash and carry or reverse cash and carry strategies (Gray, 1990). When considering non-storable commodities like freight and electricity, the cost of carry model breaks down in terms of pricing the futures contract (Geman, 2005). The spot and forward price for a non-storable commodity are not linked through arbitrage, but determined by supply and demand expectations (Kavussanos et al., 2004). Mathematically this can by expressed as:

$$F_t^i = E_t(S_{t+i}) + RP_t \tag{4.7}$$

If long hedge demand is exactly balanced by short hedge demand, the forward price will be equal to the expected spot price. In case of unbalanced hedge demand, the forward price will deviate from the expected spot price corresponding to the size of the risk premium (Gjolberg & Brattested, 2011). The risk premium may be positive, negative or zero. According to the unbiasedness hypothesis, forward prices should be equal to subsequent spot prices under the assumption of no risk premium and rational use of information (Geman, 2008). If this holds it can help market participants to forecast subsequent spot prices using forward prices. The normal approach is to compare the forward price at time t with the spot price at $t + i$ and define the difference as a forecast error. The latter may consist of a risk premium, non-rational expectations or market inefficiencies. In its purest form the unbiasedness hypothesis states that the futures price should be equal expected spot prices. This involves that the mean difference between the forward price at time t and associated spot price at time $t + i$ is zero. This can be tested using a null hypotheses where the constant (α) is equal to zero. Unbiased forecast are associated with a β equal to unity, which involves testing a null hypothesis where the β is equal to one. The unbiasedness hypothesis can be tested by applying the parameter restrictions $\alpha = 0$ and $\beta = 1$ on formula 8 or 9:

$$S_{t+i} = \alpha + \beta F_t^i + u_{t+i} \tag{4.8}$$

$$lnS_{t+i} = \alpha + \beta lnF_t^i + u_{t+i} \tag{4.9}$$

where in this thesis S_{t+i} is the settlement price (average spot price current month) at time $t+i$, F_t^i is the spot price the first day of the month at time t for delivery at time $t+i$, u_{t+i} is a white noise error process and ln is the natural log. The slope coefficient β in model 8 measures the rate of change in the (conditional) mean spot freight rate per unit change in the FFA price.The slope coefficientβ in model 9 on the other hand, measures the elasticity of the spot freight rate, with respect to the FFA price. In other words it measures the percentage change in spot freight rate for a given percentage change in FFA price. When using OLS to estimate the parameters in model 4.8 and 4.9, we are likely to run into problems with non-stationary variables. The use of conventional regression analysis implicitly assumes that the underlying variables are stationary. If non-stationary variables are used in the regression the t-ratios and F-ratios will not follow the t-distribution and f-distribution, respectively. The estimated coefficients may appear statistically significant even when there is no true relationship between the explained and explanatory variables. This means we cannot perform valid hypothesis tests on the parameters. The variables are stationary if they contain a unit root. The Dickey-Fuller and augmented Dickey-Fuller[1] test can be used for this purpose. If tests imply non-stationary variables, one can choose between different solutions to get around this problem. One of them is to transform the variable so that it becomes stationary by estimating change in spot price as a function of the basis. The model, proposed by Fama (1984) can be expressed as:

$$(S_{t+i} - S_t) = \alpha + \beta(F_t^i - S_t) + \varepsilon_{t+i} \tag{4.10}$$

[1]ADF test: $\triangle Y_t = \beta 1 + \beta 2_t + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \triangle Y_{t-i} + \epsilon_t$

$$(lnS_{t+i} - lnS_t) = \alpha + \beta(lnF_t^i - lnS_t) + \varepsilon_{t+i} \tag{4.11}$$

where in this thesis S_{t+i} is the settlement price (average spot price entire month) at time $t + i$. S_t is the spot price and F_t the FFA price, both at the first day of the month at time t. Model 4.16 and 4.17 are specified with the aforementioned variables in absolute terms and logs, respectively. Another problem that often occurs is autocorrelation and heteroscedasticity in the error term. One solution is to still use OLS for the regression, but correct the standard error for autocorrelation with the Newey-West method (Gujarati, 2003). This method corrects the standard error so that it becomes heteroscedasticity- and autocorrelation-consistent.


STENA SUPERIOR

5. Econometric hedging results

In this chapter we present the hedge efficiency of Forward Freight Agreements (FFA) when the model described in the methodology chapter is used to calculate optimal hedge ratios. These ratios are calculated over the in-sample period. We then analyse the results before we investigate the hedge effectiveness of holding the hedge ratio estimated in-sample through an out-of-sample period. The purpose is to find out whether the econometric based hedging strategy is robust out of sample. This strategy will also be compared to a naive hedge strategy, both in and out-of-sample. This is be done by comparing the variance from holding a portfolio consisting of positions in the spot market and positions in forward contracts, with an unhedged position in the freight market. We perform two-sample F-tests for variances. If the F-value computed exceeds the critical F-value at 5% level of significance, we reject the null hypothesis of equality in variance. Significant results indicate that the econometric based strategy offer a lower portfolio variance than the unhedged position. Preliminary AR and ARCH tests discovered that the majority of the residuals are homoscedastic and not serial correlated. 24-month rolling hedge ratios, covariances and variances are calculated to support our findings.

5.1. In-sample hedge performance

Capesize

Table 5.1 presents in-sample results for the Capesize market. Results indicate hedge ratios above one for all contracts ($h^* > 1$). We reject the null hypothesis of a hedge ratio equal to zero($h = 0$). Contracts with longer maturity exhibit higher minimum variance hedge ratio(h^*) than contracts with short maturity. At the same time we note, that higher h^* leads to lower variance reduction. $h^* > 1$ implies that investors and hedgers need more contracts to hedge their spot risk. In other words, higher ratio result in higher cost for improving the hedging performance.

Capesize: In-sample portfolio variances and hedgning effectiveness

$$Variance\ Reduction(VR) = 1 - \frac{Var(\Delta S_t - h^*\Delta F_t)}{Var(\Delta S_t)}$$

Route/FFA	h*	t-value (h*)	Var (S)	Var (h*)	Var (h=1)	VR (h*)	VR (h=1)
C3:			0.068				
FFACUR	1.03	27.0		0.006	0.006	91 %	91 %
FFA+1	1.10	25.0		0.007	0.007	90 %	89 %
FFA+2	1.13	21.6		0.009	0.009	87 %	86 %
C4:			0.052				
FFACUR	1.03	34.5		0.003	0.003	94 %	94 %
FFA+1	1.12	22.1		0.007	0.008	86 %	85 %
FFA+2	1.15	15.7		0.012	0.013	76 %	75 %
FFA+3	1.15	12.9		0.015	0.016	71 %	69 %
C5:			0.073				
FFACUR	1.10	23.8		0.008	0.008	89 %	89 %
FFA+1	1.20	22.2		0.009	0.011	88 %	86 %
FFA+2	1.21	17.1		0.014	0.016	81 %	79 %
C7:			0.069				
FFACUR	1.10	26.7		0.007	0.007	90 %	90 %
FFA+1	1.25	19.6		0.011	0.014	84 %	80 %
FFA+2	1.32	16.6		0.015	0.018	78 %	74 %
FFA+3	1.36	13.9		0.018	0.022	74 %	68 %

Table 5.1: *Capesize FFA in sample hedging effectiveness from January 2005 to July 2011. Minimum variance hedge ratio(h*) is the OLS regressor from model 4.7, and h=1 represents a naive hedge. Var(h*) and Var(h=1) denotes the variance of a portfolio calculated using formula 4.3 with continuously compounded returns.*

Variance reduction when using h^* show that owners of Capesize vessels can remove a large share of the freight rate risk. Average hedge effectiveness using h^* is 75%, and we note that the FFAs closest to maturity offer somewhat higher variance reduction than in the FFAs with longer maturity. Using traditional theory of a naive hedge with an implied $h = 1$, average hedge effectiveness become 72%. F ratios and critical F-values in table A.2.1 imply that hedging using econometric based strategy offer no significant lower portfolio variances compared to portfolio variances in a naive hedge. The F-test also implies that both econometric based strategy and naive strategy offer significant lower portfolio variance relative to an unhedged position in the spot market. The in-sample results, is above the variance reduction Kavussanos & Visvikis (2010) found in contract C4. Their results showed a variance reduction between 56% and 60%. Difference could be attributed to frequency in the data. Kavussanos & Visvikis (2010) used weekly observations. Our hedge analysis is based on monthly data.

Panamax

The Panamax market show similar results as the Capesize market. h^* is above one for all FFAs and are significant different from zero. Again, FFAs with longer maturity exhibit higher h^* than FFAs with short maturity.

Panamax: In-sample portfolio variances and hedgning effectiveness

$$Variance\ Reduction(VR) = 1 - \frac{Var(\Delta S_t - h^*\Delta F_t)}{Var(\Delta S_t)}$$

Route/FFA	h*	t-value (h*)	Var (S)	Var (h*)	Var (h=1)	VR (h*)	VR (h=1)
P2A_03:			0.066				
FFACUR	1.05	34.9		0.004	0.004	94 %	94 %
FFA+1	1.08	17.5		0.013	0.013	80 %	80 %
FFA+2	1.10	14.2		0.018	0.018	73 %	72 %
FFA+3	1.11	12.4		0.022	0.022	67 %	66 %
FFA+4	1.12	10.9		0.025	0.026	62 %	61 %
FFA+5	1.14	10.3		0.027	0.028	59 %	58 %
P3A_03:			0.139				
FFACUR	1.16	41.9		0.006	0.008	96 %	94 %
FFA+1	1.26	17.9		0.027	0.031	81 %	78 %
FFA+2	1.33	15.8		0.031	0.038	77 %	73 %
FFA+3	1.35	12.6		0.045	0.051	68 %	63 %
FFA+4	1.41	10.8		0.054	0.062	61 %	56 %
FFA+5	1.43	10.1		0.059	0.067	57 %	52 %

Table 5.2: *Panamax FFA in sample hedging performance from January 2005 to July 2011. Minimum variance hedge ratio(h*) is the OLS regressor from model 4.7, and h=1 represents a naive hedge. Var(h*) and Var(h=1) denotes the variance of a portfolio calculated using formula 4.3 with continuously compounded returns.*

In-sample results in both P2A_03 and P3A_03 show that owners of Panamax vessels can remove a large share of the freight rate risk using FFA for hedging purposes. This can be achieved by hedging with both econometric based hedging(h^*) and a naive hedging($h = 1$). Variance reduction range between 58% and 94% in FFAs written on P2A_03 and 52% and 94% written on P3A_03. We also observe that variance reduction decrease when contracts with maturity in distant future are used. F-test two-sample for variances in table A.2.2 indicate that portfolio variance in the econometric based hedge and the naive hedge are significant and lower relative to an unhedged position in the spot market. Further on, results indicate that the hedger do not recieve significant lower portfolio variance in a econometric based hedge compared to a naive hedge. Finally, note that the ratio of the variance of the hedged position and the variance of the unhedged position is equal to $1 - VR$. The square root of this ratio gives the ratio of the volatility of the hedged position and the volatility of the unhedged position. If we use $VR(h^*) = 0.80$ in contract +1 written on P2A_03, the square root of $1 - 0.80$ is equal to 0.44. Consequently, the volatility of the hedged position is 44 percent of the volatility of the unhedged position. Through hedging, a shipping company can eliminate 56 percent of the volatility of the unhedged position.

Clean tanker

The clean tanker market exhibit lower h^* compared to the Capesize and Panamax market. Except from the CUR contract, t-values for the h^* is low and decreasing with longer maturity. All hedge ratios are significant and different from zero, and we reject the null hypothesis of equality.

Clean tankers: In-sample portfolio variances and hedgning effectiveness

$$Variance\ Reduction(VR) = 1 - \frac{Var(\Delta S_t - h^* \Delta F_t)}{Var(\Delta S_t)}$$

Route/FFA	h*	t-value (h*)	Var (S)	Var (h*)	Var (h=1)	VR (h*)	VR (h=1)
TC5:			0.055				
FFACUR	1.09	46.6		0.001	0.002	97 %	97 %
FFA+1	0.98	9.4		0.022	0.022	60 %	60 %
FFA+2	0.86	5.6		0.036	0.036	35 %	34 %
FFA+3	0.95	5.6		0.036	0.036	35 %	35 %
FFA+4	1.03	5.3		0.037	0.037	33 %	33 %
FFA+5	0.93	4.0		0.043	0.043	22 %	21 %

Table 5.3: *Clean tankers FFA in sample hedging performance from July 2006 to July 2011. Minimum variance hedge ratio(h^*) is the OLS regressor from model 4.7, and h=1 represents a naive hedge. Var(h^*) and Var(h=1) denotes the variance of a portfolio calculated using formula 4.3 with continuously compounded returns.*

In-sample results for the Clean tanker market show that owners can remove a large share of the variance by hedging with the CUR and +1 contract. The F-test in table A.2.3 in appendix show that the hedger can reduce a significant amount of the variance using both econometric based hedging and a naive hedging relative to an unhedged position in the spot market in the two contracts. All other FFAs offer low variance reduction and are not significant lower than spot variance. The F-test also indicate that the hedger cannot obtain significant lower portfolio variance using econometric based hedge relative to a naive hedge. The null hypothesis of equality are not rejected on 5% significance level. Further on, the low variance reduction in contract +2, +3, +4 and +5 can be related to low covariance and return correlations between spot and FFA. Previous studies show that out-of-sample hedge efficiency will be lower than in-sample hedge efficiency due to changes in dynamics between variables. By this, we assume that the Clean tanker market will suffer from somewhat lower variance reduction out-of-sample.

Dirty tankers

From descriptive statistics in section 3.5, we found low return correlations between spot and FFAs. Contracts with maturity far away indicated a low degree of co-movement with the underlying spot contract. In-sample hedge results indicate low hedge efficiency in contracts with maturity far away, which is in line with previous assumptions in section 3.5. Looking at h^*, we note that this range between 0.33 and 1.65. h^* in contract +3, +4 and +5 associated with route TD7, and contract +5 associated with route TD5, is not significant different from zero and we cannot reject the null hypothesis of equality. All other FFA offer significant h^* different from zero, and we reject the null hypothesis of equality.

Dirty tankers: In-sample portfolio variances and hedgning effectiveness

$$Variance\ Reduction(VR) = 1 - \frac{Var(\Delta S_t - h^* \Delta F_t)}{Var(\Delta S_t)}$$

Route/FFA	h*	t-value (h*)	Var (S)	Var (h*)	Var (h=1)	VR (h*)	VR (h=1)
TD3:			0.157				
FFACUR	1.20	36.5		0.008	0.013	94 %	91 %
FFA+1	1.29	12.7		0.050	0.056	66 %	62 %
FFA+2	1.19	6.9		0.097	0.098	34 %	33 %
FFA+3	1.02	4.8		0.120	0.120	18 %	18 %
FFA+4	1.06	4.5		0.115	0.115	22 %	22 %
FFA+5	1.19	4.9		0.109	0.110	26 %	25 %
TD5:			0.093				
FFACUR	1.27	26.6		0.009	0.013	91 %	87 %
FFA+1	1.26	7.8		0.051	0.053	47 %	45 %
FFA+2	1.03	4.9		0.070	0.070	28 %	28 %
FFA+3	0.80	3.3		0.081	0.082	17 %	16 %
FFA+4	0.85	3.1		0.085	0.086	12 %	12 %
FFA+5	0.54	1.9		0.092	0.096	5 %	1 %
TD7:			0.112				
FFACUR	1.42	23.9		0.013	0.022	88 %	81 %
FFA+1	1.65	7.2		0.067	0.074	41 %	35 %
FFA+2	1.14	3.9		0.094	0.094	17 %	16 %
FFA+3	0.62	1.9		0.107	0.109	5 %	3 %
FFA+4	0.33	0.8		0.118	0.123	-5 %	-9 %
FFA+5	0.73	1.7		0.114	0.115	-2 %	-2 %

Table 5.4: *Dirty tankers FFA in sample hedging performance from January 2005 to July 2011. Minimum variance hedge ratio(h*) is the OLS regressor from model 4.7, and h=1 represents a naive hedge. Var(h*) and Var(h=1) denotes the variance of a portfolio calculated using formula 4.3 with continuously compounded returns.*

As in the Capesize, Panamax -and Clean tanker markets there are small differences in variance reduction between econometric based hedging and naive hedging. However, we note that the spread between the two approaches is somewhat higher in the Dirty Tanker market. The F-test two-sample for variances in table A2.4 indicate significant lower portfolio variance using econometric based hedging compared to naive hedging in FFACUR associated with route TD3 and TD7. Further on, CUR, +1, +2 contracts associated with route TD3, indicate significant lower portfolio variance using econometric based hedging compared to an unhedged position in the spot market. CUR and +1 associated with route TD5 and TD7 yield similar results. Some of the FFAs written on TD7 indicate negative variance reduction. This is due to the fact that portfolio variance($Var(h^*)$, $Var(h = 1)$) is higher than spot variance($Var(S)$). Finally, traditional naive hedge strategy with an implied hedge ratio of one, are only significant lower than spot variance for CUR, +1 and +2 contracts associated with route TD3, and CUR and +1 contracts associated with routes TD5 and TD7.

5.2. Out-of-sample hedge performance

Capesize

Portfolio risk, derivative pricing and hedging, and trading strategies are all forward looking. Out-of-sample testing is therefore essential. We have taken a fixed size estimation window and estimated realized variance reduction for all contracts in the in-sample analysis. The time series period range from August 2011 to December 2012. $Var(h^*)$ is calculated using formula 7 in section 4.1 and $h^*$is the minimum variance hedge ratio found in the in-sample analysis through formula 4.

Capesize: Out-of-sample portfolio variances and hedgning effectiveness

$$Variance\ Reduction(VR) = 1 - \frac{Var(\Delta S_t - h^* \Delta F_t)}{Var(\Delta S_t)}$$

Route/FFA	Var (S)	Var (h*)	Var (h=1)	VR (h*)	VR (h=1)
C3:	0.028				
FFACUR		0.002	0.002	92 %	92 %
FFA+1		0.001	0.002	95 %	94 %
FFA+2		0.005	0.006	81 %	78 %
C4:	0.035				
FFACUR		0.005	0.005	87 %	86 %
FFA+1		0.005	0.006	87 %	84 %
FFA+2		0.016	0.018	50 %	53 %
FFA+3		0.021	0.022	53 %	50 %
C5:	0.037				
FFACUR		0.003	0.003	92 %	91 %
FFA+1		0.008	0.008	80 %	78 %
FFA+2		0.013	0.014	64 %	62 %
C7:	0.031				
FFACUR		0.005	0.006	83 %	81 %
FFA+1		0.004	0.006	88 %	80 %
FFA+2		0.013	0.015	59 %	53 %
FFA+3		0.016	0.018	49 %	43 %

Table 5.5: *Capesize FFA out-of-sample hedging performance from August 2011 to December 2012. Var(h*) and Var(h=1) denotes the variance of a portfolio calculated using formula 4.3 with continuously compounded returns. The minimum variance hedge ratio(h*) is the OLS regressor from model 4.7 calculated from the in sample period 2005-2011(7), and h=1 represents a naive hedge.*

Out-of-sample results for the Capesize market show somewhat similar results relative to the in-sample analysis. High and medium variance reduction for all FFA show that owners of Capesize vessels would have reduced a significant amount of the price risk using both econometric based hedge strategy computed in-sample, and the traditional naive hedge with an implied hedge ratio of one. However, we note that the difference in variance reduction between the minimum variance hedge ratio approach and the naive approach is somewhat larger out-of-sample. F-test two-sample for variances in table A.3.1 indicate that none of the portfolio variances found, using econometric based hedge strategy are significant lower than portfolio variances found using a naive approach. This means that econometric based hedge strategy does not outperform naive strategy. Further on, contract +2 and +3 associated with route C4, and the +3 contract associated with route C7, does not exhibit significant lower h^* porfolio variance than spot variance and we cannot reject the null hypothesis of equality. All other FFAs are significant and lower than spot variance.

Even though the significance of the variance reduction holds for the majority of the contracts, we wish to check for instability in hedge ratio. Figure 5.1 presents a plot of Capesize 24-month rolling hedge ratios. Estimation window range from January 2005 to December 2012.

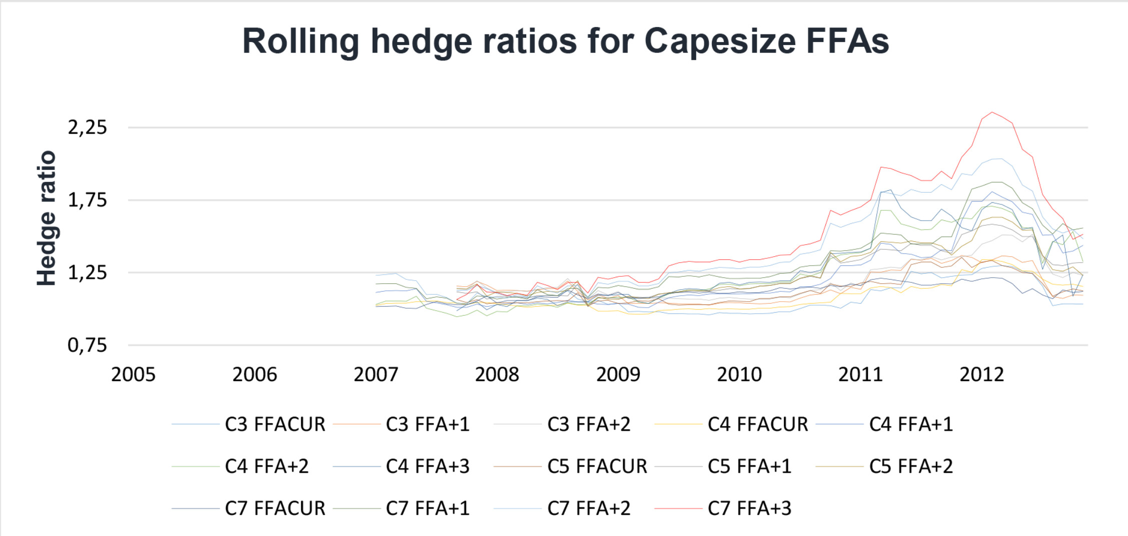

Figure 5.1: *Plot of Capesize 24-month rolling minimum variance hedge ratios (h*) from January 2005 to December 2012, calculated by using formula 2.5.*

24-month rolling hedge ratios for FFAs indicate a stable environment in period 2007 to 2009. The subsequent period is characterized by increasing hedge ratios for all contracts. All contratcs reach a turning point in third quarter 2012. The plot also indicate that hedge ratio for FFAs with maturity far ahead, tend to move further away from one relative to FFAs with shorter maturity. The most extreme variable appears to be FFA+3 written on route C7. For deeper insight into what causes the path of the hedge ratio for FFA+5, we track the 24-month rolling covariance and variance in the figure below.

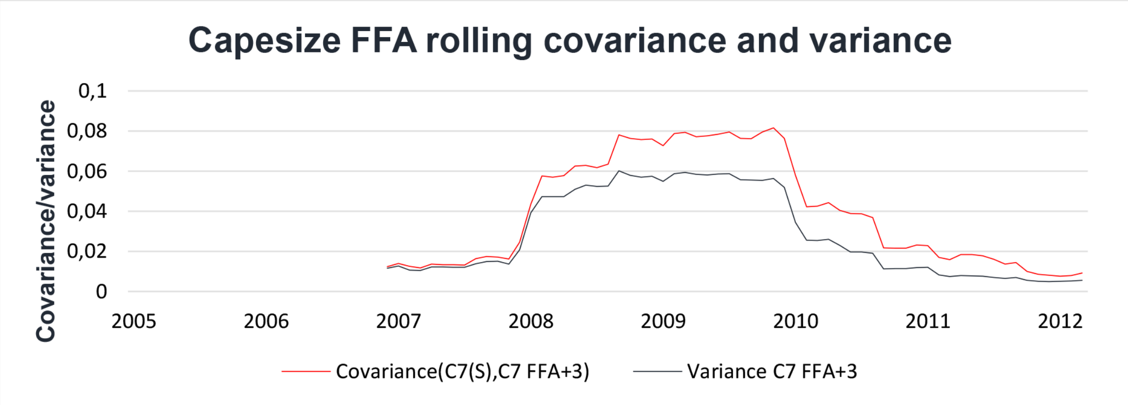

Figure 5.2: *Plot of Capesize 24-month rolling covariance between C7 and FFA+3, and variance in FFA+3 from January 2005 to December 2012.*

Figure 5.2 plots the 24-month rolling covariance of the change in the spot freight rate with the change in FFA price and variance of the change in the FFA price. From model 4.3 in section 4.1 we conclude that when the spread between covariance and variance is close to zero, hedge ratio is close to one. This property can be observed in time period 2007 to late 2008, by comparing figure 5.1 and 5.2. If covariance increases and all other variables are held constant, the hedge ratio increases. When both covariance and variance is close to zero, the hedge ratio becomes more sensitive to a change in one of the variables. This can be observed by comparing rolling covariance and variance in figure 5.2, against rolling hedge ratio in figure 5.1. Low covariance and variance in period 2011 to 2012 results in higher hedge ratio than in the prevailing period 2008 to 2010 were covariance and variance exhibit higher values. Hedge ratio in period 2008 and through the first quarter in 2010, reach a maximum of 1.34. In the subsequent period when covariance and variance approaches zero, hedge ratio increases and peak at 2.35 in march 2012. Also note that spread is somewhat smaller.

Panamax

In-sample results for the Panamax market indicated high and medium variance reduction for all FFA. Contratcs with maturity far ahead offered lower efficiency than contratcs with short maturity. Table 5.6 presents out-of-sample hedge efficiency for FFAs associated with Panamax routes P2A_03 and P3A_03.

Panamax: Out-of-sample portfolio variances and hedgning effectiveness

$$Variance\ Reduction(VR) = 1 - \frac{Var(\Delta S_t - h^{*}\Delta F_t)}{Var(\Delta S_t)}$$

Route/FFA	Var (S)	Var (h*)	Var (h=1)	VR (h*)	VR (h=1)
P2A_03:	0.020				
FFACUR		0.007	0.007	67 %	67 %
FFA+1		0.019	0.019	5 %	7 %
FFA+2		0.020	0.020	2 %	4 %
FFA+3		0.019	0.019	7 %	8 %
FFA+4		0.015	0.016	24 %	24 %
FFA+5		0.017	0.017	17 %	17 %
P3A_03:	0.089				
FFACUR		0.006	0.008	93 %	91 %
FFA+1		0.024	0.028	73 %	68 %
FFA+2		0.038	0.045	57 %	49 %
FFA+3		0.060	0.063	33 %	29 %
FFA+4		0.059	0.063	34 %	30 %
FFA+5		0.042	0.051	53 %	43 %

Table 5.6: *Panamax FFA out-of-sample hedging performance from August 2011 to December 2012. Var(h*) and Var(h=1) denotes the variance of a portfolio calculated using formula 4.3 with continuously compounded returns. The minimum variance hedge ratio(h*) is the OLS regressor from model 4.7 calculated from the in sample period 2005-2011(7), and h=1 represents a naive hedge.*

Use of FFAs associated with route P3A_03 results in variance reduction between 29% and 91%, depending on which contract used. The CUR, +1 and +2 contratcs range from 49% to 91% and, can be said to have medium and high hedge efficiency. Contract +3, +4 and +4 indicate low hedge efficiency. A significant reduction in freight revenue variability using econometric based hedging can only be obtained through contract CUR, +1 and +2. Similar results occur for contract CUR and +1 when naive approach is used. Moreover, econometric based hedging does not provide shipping companies with significant lower portfolio variance relative to a naive hedge. FFAs in P2A_03 perform poorly out-of-sample. The CUR contract is the only FFA with significant variance reduction relative to spot variance. It seems strange that contract +1, +2, and +3 offer lower variance reduction than contract

+4 and +5, especially when P2A_03 and P3A_03 indicated similar dynamics in the in-sample analysis. Examination of the data confirms that minimum variance using econometric based hedging for contracts +1, +2 and +3 are close to the spot variance. From formula 7 in section 4.1 we conclude that this results in a variance reduction close to zero. Further on, we check for instability in hedge ratio by plotting 24-week rolling hedge ratios over the sample period 2005 to 2012. This will contribute to define constant hedging as a good or bad strategy for shipping companies.

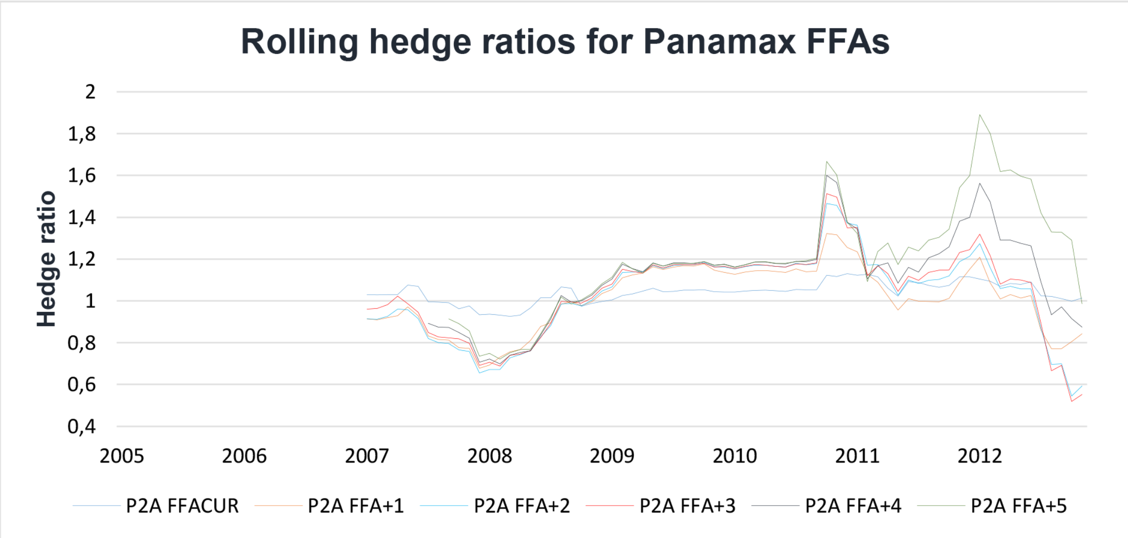

Figure 5.3: *Plot of Panamax (P2A_02) 24-month rolling minimum variance hedge ratios (h^*) from January 2005 to December 2012, calculated by using formula 2.5.*

We clearly observe that hedge ratio over a 24-month period are unstable in period 2007 to 2008 and from the fourth quarter in 2012 and throughout 2012. Hedge ratio volatility is most significant in the +5 contract associated with route P2A_03. 24-month hedge ratio range between 0.98 and 1.89 in period November 2011 to december 2012. For further insight on what causes this volatility in rolling hedge ratio in contract +5 associated with route P2A_03, we have estimated 24-month rolling covariance and variance in table 5.2.3.

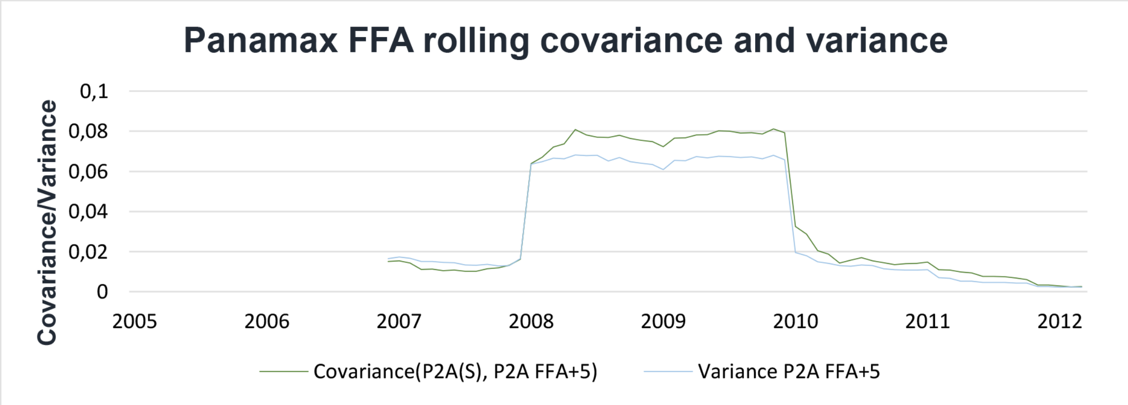

Figure 5.4: *Plot of Panamax 24-month rolling covariance between P2A_03 and FFA+5, and variance in FFA+5 from January 2005 to December 2012.*

Period 2008 to 2010 was characterized by a high and stable covariance between P2A_03 and FFA+5 contract, and variance in FFA+5. Same period also indicate a stable spread between the two, leading to a relatively constant hedge ratio above one. In November 2010 and December 2011 hedge ratio experience a significant increase over a short time period before it declined to same levels as in the prevailing period. For further explanation and insight we look at our data set and table 5.4. Both indicate that covariance and variance approaches zero while the spread remains the same, which in turn results in an increased hedge ratio reaching a maximum of 1.66 and 1.89, respectively. In period March 2012 until December 2012, covariance and variance stabilizing while the spread approaches zero, resulting in decreased hedge ratio.

Clean tankers

Variance reduction in-sample for FFAs in the Clean tanker route, varied between 22% and 97% using econometric based hedging. Similar results were found when using a naive approach. We also observed that portfolio variance in contract +2, +3, +4 and +5 was not significant lower than spot variance.

Clean tankers: Out-of-sample portfolio variances and hedgning effectiveness

$$Variance\ Reduction(VR) = 1 - \frac{Var(\Delta S_t - h^* \Delta F_t)}{Var(\Delta S_t)}$$

Route/FFA	Var (S)	Var (h*)	Var (h=1)	VR (h*)	VR (h=1)
TC5:	0.012				
FFACUR		0.000	0.000	98 %	97 %
FFA+1		0.013	0.013	-8 %	-9 %
FFA+2		0.014	0.015	-16 %	-22 %
FFA+3		0.010	0.010	13 %	13 %
FFA+4		0.013	0.013	-9 %	-8 %
FFA+5		0.015	0.015	-24 %	-27 %

Table 5.7: *Clean tankers FFA out-of-sample hedging performance from August 2011 to December 2012. Var(h*) and Var(h=1) denotes the variance of a portfolio calculated using formula 4.3 with continuously compounded returns. The minimum variance hedge ratio(h*) is the OLS regressor from model 4.7 calculated from the in sample period 2006-2011(7), and h=1 represents a naive hedge.*

Table 5.7 presents out-of-sample hedge efficiency. We observe extreme values in both portfolio variance and variance reduction in the Clean Tanker FFAs. If a shipping company followed a constant econometric based hedge strategy or a traditionally naive hedge in contract +1, +2, +4 and +5 , this would have resulted in greater risk compared to an unhedged position in the spot freight market. The +3 contract offer a small variance reduction, but the contract are not significant lower than spot variance. Econometric based hedging ourperform naive hedge only i the CUR contract. Out-of-sample hedge efficiency in the Clean tanker market clearly indicate that econometric based -and naive strategy is not robust out-of-sample. Further on, since extreme values appears, a check for hedge ratio instability are conducted. Examination of 24-month rolling hedge ratios during the period suggests that FFA hedging strategies would be somewhat susceptible to swings in performance. Hedge ratio instability does appear to have substantial impact on the hedge performance.

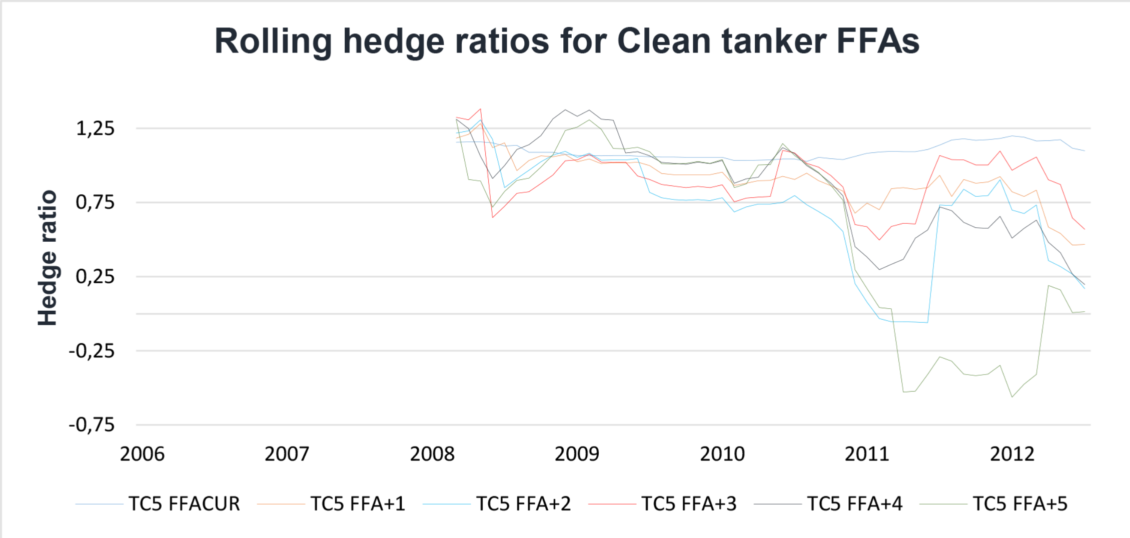

Figure 5.5: *Plot of Clean tankers 24-month rolling minimum variance hedge ratios (h*) from July 2006 to December 2012, calculated by using formula 2.5.*

Only the CUR contract seem to perfom well under the assumption that the joint distribution are constant over the sample period. Contracts +2, +4 and +5 fluctuates the most and exhibit a hedge ratio range of 1.36, 1.17 and 1.87, respectively. From the figure we observe that contract +2 and +5 provide negative hedge ratio in period 2011 to 2012 reaching a minimum of -0.06 and -0.56, respetively. For further insight we calculate 24-month rolling covariance between spot TC5 and FFA+5, and variance in FFA+5 in Figure 5.6

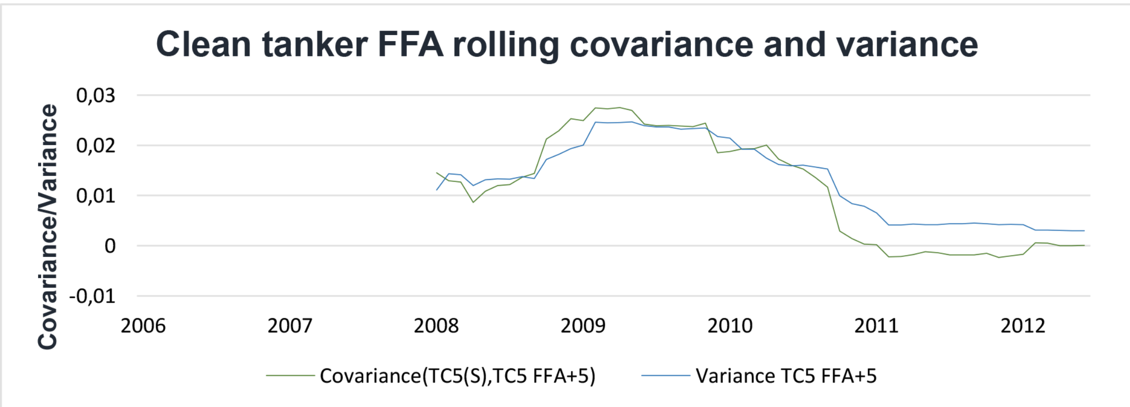

Figure 5.6: *Plot of Clean tanker 24-month rolling covariance between TC5 and FFA+5, and variance in FFA+5 from January 2005 to December 2012.*

The figure shows that 24-month rolling covariance and variance exhibit negative values in period August 2011 to July 2012. Hedge ratio become negative, which in in turn leads to negative hedge efficiency. It is clear that hedge ratio variability is a result of time variation in covariance and variance. A constant econometric based hedge strategy do appear to be insufficient in providing a significant reduction in freight rate variability in the Clean tanker freight market.

Dirty tankers

In-sample analysis for the Dirty tanker market indicated varying hedge efficiency within the investigated routes. FFAs in TD3 perform well in-sample relative to FFAs in TD5 and TD7. Except from the CUR contract in TD7 we could not reject the null hypothesis of equality between econometric based hedge -and naive hedge strategy. At the same time, shipping companies could only reduce a significant amount of the freight rate variability through FFAs with maturity in near future.

Dirty tankers: Out-of-sample portfolio variances and hedgning effectiveness

$$Variance\ Reduction(VR) = 1 - \frac{Var(\Delta S_t - h^* \Delta F_t)}{Var(\Delta S_t)}$$

Route/FFA	Var (S)	Var (h*)	Var (h=1)	VR (h*)	VR (h=1)
TD3:	0.024				
FFACUR		0.001	0.001	96 %	96 %
FFA+1		0.019	0.014	20 %	39 %
FFA+2		0.023	0.022	4 %	8 %
FFA+3		0.018	0.018	22 %	23 %
FFA+4		0.020	0.020	14 %	14 %
FFA+5		0.027	0.024	-14 %	-2 %
TD5:	0.025				
FFACUR		0.003	0.005	88 %	80 %
FFA+1		0.029	0.026	-14 %	-2 %
FFA+2		0.015	0.015	39 %	39 %
FFA+3		0.036	0.038	-44 %	-51 %
FFA+4		0.030	0.031	-20 %	-23 %
FFA+5		0.027	0.029	-5 %	-15 %
TD7:	0.027				
FFACUR		0.002	0.005	92 %	80 %
FFA+1		0.034	0.030	-23 %	-8 %
FFA+2		0.023	0.023	17 %	17 %
FFA+3		0.029	0.030	-5 %	-10 %
FFA+4		0.028	0.031	-3 %	-12 %
FFA+5		0.027	0.027	3 %	3 %

Table 5.8: *Dirty tankers FFA out-of-sample hedging performance from August 2011 to December 2012. Var(h*) and Var(h=1) denotes the variance of a portfolio calculated using formula 4.3 with continuously compounded returns. The minimum variance hedge ratio(h*) is the OLS regressor from model 4.7 calculated from the in sample period 2005-2011(7), and h=1 represents a naive hedge.*

Out-of-sample hedge efficiency deviates significantly from the in-sample hedge efficiencies. In a real-world situation, reduction in freight rate variability could only be obtained using the CUR contract written on TD7. Further on, the CUR contract are also the only FFA that would have resulted in a significant lower portfolio variance compared naive portfolio variance, and spot variance. Some of the effectiveness measures exhibit negative variance reduction, which means that freight rate risk actually increases compared to an unhedged position in the spot freight rate market. Since the out-of-sample analysis indicates extreme values on hedge efficiency, we investigate 24-month rolling hedge ratio in FFA associated with route TD7 to check for time varying hedge ratios.

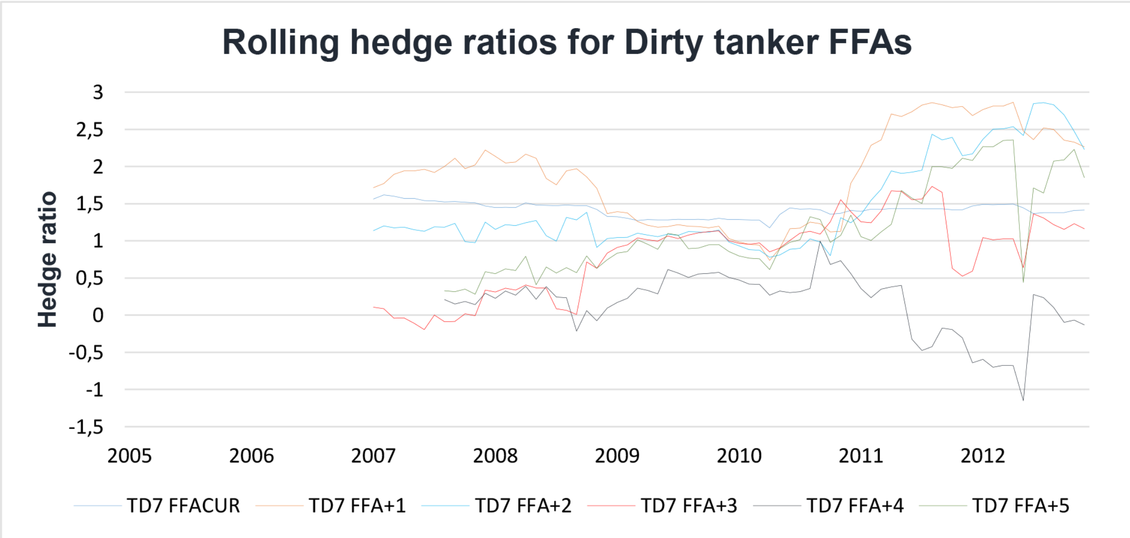

Figure 5.7: *Plot of dirty tankers (TD5) 24-month rolling minimum variance hedge ratios (h*) from January 2005 to December 2012, calculated by using formula 2.5.*

If the assumption that a static hedge should provide robust out-of-sample results, hedge ratio must be time invariant over the sample period. As we can observe from table 5.2.7, hedge ratio for FFAs written on route TD7 indicate significant fluctuations. 24-month rolling hedge ratio for contract +1, +2 and +5 range between 0.73, 0.77 and 0.28 to 2.86, 2.85 and 2.35, respectively. Standard deviations over the sample period are 62%, 61% and 59%, respectively. Clearly, time varying hedge ratio do appear to have substantial impact on the hedge performance. FFA+4 written on route TD7 provide the lowest minimum hedge ratio. Hedge ratio reaches -1.15 in June 2012. For further explanation of the hedge ratio instability a plot of 24-months rolling covariance between spot freight rate contract TD7 and variance in FFA+4 is calculated table 5.8.

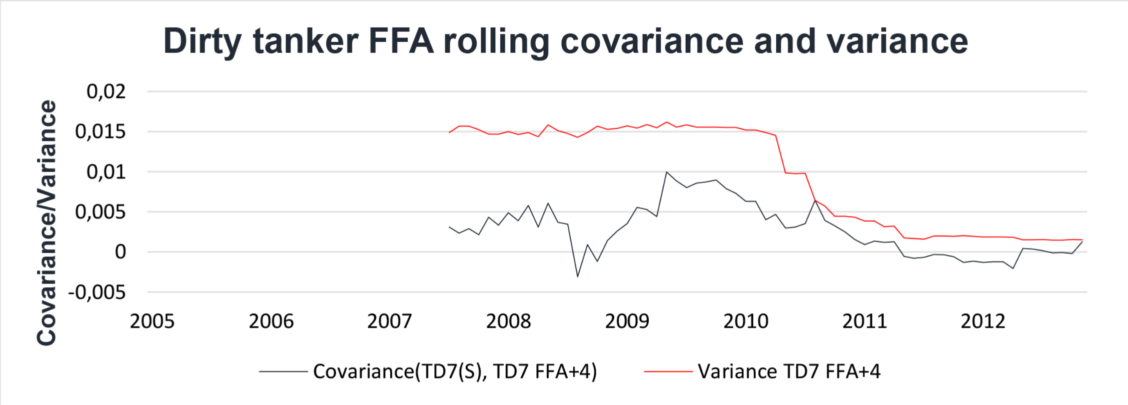

Figure 5.8: *Plot of Dirty tanker 24-month rolling covariance between TD7 and FFA+4, and variance in FFA+4 from January 2005 to December 2012.*

In figure 5.2, 24-month rolling covariance between C7 spot and FFA+3 and variance for FFA+3 was presented. The plot indicated that hedge ratio was higher than one if $covariance(\triangle C7(S)_t, \triangle C7FFA{+}3_t > variance(\triangle C7FFA{+}3_t)$. Opposite result is shown in figure 5.8 and results in a hedge ratio below one over the entire sample period. We also note negative covariance between TD7 and associated FFA+4 resulting in negative hedge ratio, which in turn lead to negative hedge efficiency. Overall, the cause for lower out-of-sample hedging effectiveness appears to be hedge ratio -and covariance variability.

5.3. Summary

In-sample analysis

- Results for the Capesize -and Panamax market indicate that shipping companies can reduce a significant amount of the freight rate variability using FFAs. All contracts exhibit significant lower portfolio variance compared to an unhedged position in the spot market. Results also indicate that FFAs with long maturities offers a lower risk reduction compared to contracts with short maturities. Only the CUR and +1 contract in the Clean tanker market gave significant lower portfolio variance compared to spot variance using econometric based hedge. Similar results was shown for the CUR, +1 and +2 contracts associated with route TD3, and CUR and +1 contracts associated with route TD5 and TD7 in the Dirty tanker market.
- In the Capesize, Panamax -and Clean tanker market it is shown that econometric based hedging strategies does not outperform naive strategy. In the Dirty tanker market, econometric based hedging outperform naive hedge only in FFACUR associated to route TD3 and TD7. In all other FFAs the null hypothesis of equality holds.
- The estimated minimum variance hedge ratio(h^*) is significant different from zero for all FFAs in the Capesize, Panamax and Clean segments. Dirty tanker +3, +4 and +5 contracts associated with route TD7 are not significantly different from zero. We also note that when hedge ratio approaches zero, the variance reduction decreases.

Out-of-sample analysis

- Holding the minimum variance hedge ratio estimated in-sample through the out-of-sample period indicate that econometric based hedge strategy are not robust for the majority of the FFAs. We observe that Capesize FFAs resulted in significant lower portfolio variance relative to an unhedged position in the spot freight market. The CUR contract associated within the other segments yield similar result.
- In the majority of the FFAs we observed that econometric based hedge strategy do not outperform naive strategy.

- Comparison of hedge efficiency measures clearly shows a discrepancy between in -and out-of-sample performance. Lower out-of-sample hedge efficiency appears to be caused by hedge ratio variability. Examination of 24-month rolling hedge ratios over the sample period suggests that FFA hedging strategies would be somewhat susceptible to swings in performance. Time varying covariance and variance, and time varying hedge ratio do appear to have substantial impact on the hedge performance. Low and negative covariance for log returns indicate that dynamics are independent in some periods.

6. Econometric forecasting results

In this chapter we discuss Forward Freight Agreements (FFA) as a freight rate forecasting tool using models from the methodology chapter. The most important findings are summarized in tables and figures, while the complete overview can be found in the appendix. First we estimated the the models using OLS. Then we tested the residuals for autocorrelation and heteroscedasticity. AR and ARCH tests revealed heteroscedastic and autocorrelated residuals in the majority of the cases. We therefore applied the Newey-West method of adjusting standard errors. In turn this means that reported standard errors and t-values are heteroskedastic and autocorrelation consistent (HAC). The forecasting horizon depends on the contract. Spot freight rates and FFA prices at time t are observed the first day of the month. Spot freight rates at time $t + i$ are the average spot prices current month, also called the settlement price. This means that the CUR, +1 and +2 contracts have a forecasting horizon of 30, 60 and 90 days, respectively.

6.1. Forecasting performance of FFA prices

This section contains results from regressing the spot freight rates at time $t+1$ on FFA prices at time t using monthly data from 2005 to 2012 . We use two different models, one where the variables are in absolute terms (model 4.8) and one where the variables are in logs (model 4.9). First we performed a series of Augmented Dickey Fuller tests (ADF) on the spot freight rates and FFA prices. The tests shows that the spot prices in all segments contains a unit-root and are thus nonstationary. The results from the ADF tests also shows that Capesize and Panamax FFA prices are stationary, while nine of the Clean and Dirty tanker FFA prices are stationary. As mentioned, nonstationary variables implies that we cannot perform valid hypothesis tests on the parameters. We can interpret the results if we chose to ignore this problem, but must be careful not to jump to any hasty conclusions.

Forecasting performance of FFAs using the linear model

$$S_{t+i} = \alpha + \beta F_t^i + \mu_{t+i}$$

Route	FFA contract	α	t-value (α)	β	SE (B)	t-value (β)	Adj. R2
				Panamax			
P2A	FFA+5	18382	2.16*	0.53	0.33	-1.40	0.21
P3A	FFA+3	6370	1.99*	0.75	0.18	-1.37	0.49
	FFA+4	9208.37	2.35*	0.67	0.23	-1.48	0.37
	FFA+5	11399.30	2.44*	0.59	0.26	-1.59	0.27
				Clean tanker			
TC5	FFACUR	-10.19	-2.14*	1.07	0.03	2.06*	0.96
				Dirty tanker			
TD3	FFA+3	28.65	2.15*	0.64	0.21	-1.74	0.18
	FFA+4	36.31	2.63**	0.52	0.22	-2.21*	0.12
	FFA+5	37.10	2.49*	0.51	0.24	-2.04*	0.10

Table 6.1: *Estimation results using model 4.8 with monthly observations from 2005 to 2012. T-values are heteroskedastic and autocorrelation consistent (T-HACE). H0: $\alpha = 0$, $\beta = 1$. "*" and "**" denotes significance at the 0.05 and 0.01 level, respectively.*

We start with the estimation results from model 4.8. In the Capesize segment, our findings(A.5) suggests that all betas are not significantly different from unity, and that all alphas are significantly different from zero. This means that the hypothesis that FFA prices provides unbiased forecasts of subsequent spot freight rates can not be rejected. The CUR contract written on route C3 has the highest coefficient of determination, R^2, at 0.94. The +3 contract associated with route C7 has the lowest R^2 at 0.33. In other words, the variation in the +3 contract price only explains about one third of the variation in the subsequent C7 spot freight rate. The explanatory power seems to decrease when we increase the forecasting horizon. Average R^2in the investigated FFAs in the Capesize market is equal 0.67. One should note that the maximum forecasting horizon of investigated contracts in this segment is three calender months (FFA+3). Table 6.1 present the contracts where the FFA prices are biased estimators of subsequent spot prices. Within the Panamax segment, none of the estimated beta values are significantly different from unity. Alpha values of +3, +4 and +5 contracts written on route P3A, in addition to +1 and +5 contracts on route P2A are significantly different from zero. This means that the unbiasedness hypothesis does not hold for these contracts. These results are similar to the findings of Kavussanos et al. (2004) and Grober (2010). The contract with the highest explanatory power is the CUR contract written on route P2A with a R^2 at 0.96. This contract has a relative short forecasting horizon of 30 days. To visualize the relationship we plotted the P2A spot freight rate against the price of the CUR contract and obtained the scattergram shown in figure 6.1.

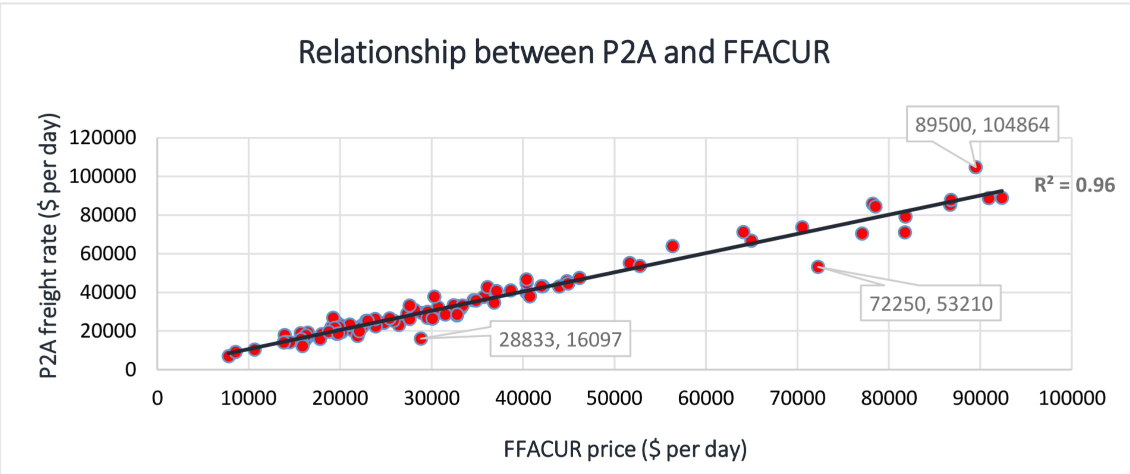

Figure 6.1: *FFACUR price as predictor of subsequent spot freight rate ($ per day) on route P2A from January 2005 to December 2012. Monthly observations.*

The relationship between the CUR price and the P2A spot freight rate appears to be linear and strong with only minor deviations. The first and second number in the scattergram labels denotes the FFA price and the subsequent spot freight rate, respectively. Results imply that the explanatory power of Panamax FFAs seems to decrease when forecasting horizon is increased. In the Clean tanker segment, findings indicate that the CUR contract has a beta significantly different from unity, and a significantly different from zero alpha. This means that the unbiasedness hypothesis holds for the Clean tankers FFAs, except the current month contract. Although the hypothesis does not hold, as much as 96% of the variation in the TC5 spot freight rate can be explained by 1.07 times the CUR price. The average explanatory power for the six Clean tankers contracts can be defined as medium, with R^2 equal to 0.52. In the Dirty tanker segment, we find that the +3, +4 and +5 contracts associated with route TD3 all have significantly different from zero alphas. The +4 and +5 contracts associated with the same route also exhibit significant betas different from unity. This means that the unbiasedness hypothesis does not hold for the +3, +4 and +5 contracts written on route TD3. Contracts written on all three Dirty tanker routes exhibit high R^2, when the forecasting horizon is short. Like in the other investigated segments, the explanatory contracts drops for each month of increase in horizon. The average explanatory power for the Dirty tankers contracts is medium, with R^2 equal to 0.42.

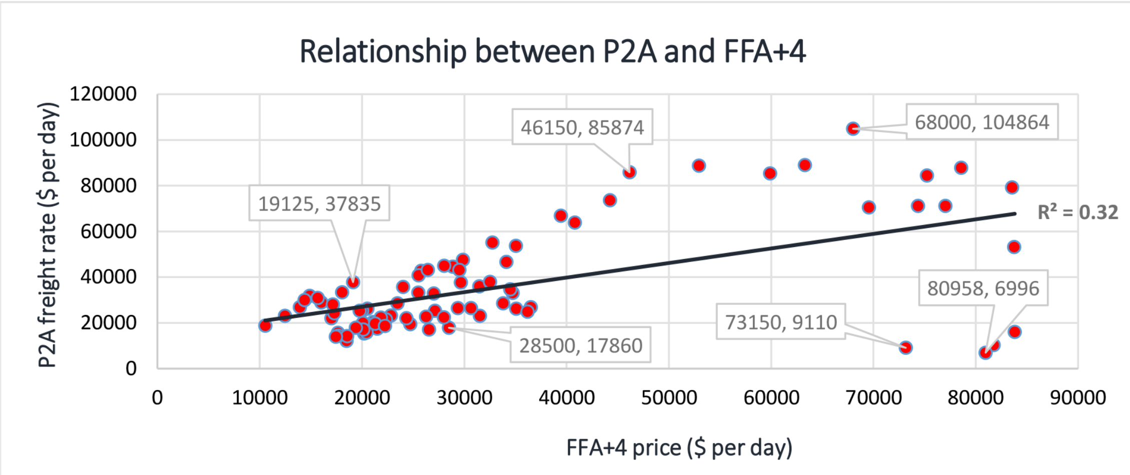

Figure 6.2: *FFA+5 price as predictor of subsequent spot freight rate ($ per day) on route P2A from January 2005 to December 2012.*

Our results shows that when model 4.8 is applied, 42 of 50 contracts across the four segments appear to be unbiased predictors of the respective freight rates. Unbiased contracts does not necessarily mean that they are good forecast of the subsequent spot freight rate. In figure 6.2 the price on the +4 contract is plotted against the subsequent spot freight rate on route P2A. The scattergram reflects some important points. First of all, if we compare figure 6.1 with 6.2, we see that the forecast beome unstable when we expand forecasting horizon by means of a contract with longer maturity. At the same time we observe that even though the unbiasedness hypothesis holds for the +4 contract, it is not a very precise forecast of the subsequent freight rates. In addition, it seems like the deviations are larger when the P2A freight rate and +5 FFA prices are high, compared to when they are low .

Forecasting performance of FFAs using the log-linear model							
$lnS_{t+i} = \alpha + \beta lnF_t^i + \mu_{t+i}$							
Route	**FFA contract**	**α**	**t-value (α)**	**β**	**SE (B)**	**t-value (β)**	**Adj. R2**
Clean tanker							
TD3	FFA+5	1.47	2.00*	0.64	0.18	-1.96	0.23

Table 6.2: *Estimation results using model 4.9 with monthly observations from 2005 to 2012. T-values are heteroskedastic and autocorrelation consistent (T-HACE). H0: $\alpha = 0$, $\beta = 1$. "*" and "**" denotes significance at the 0.05 and 0.01 level, respectively.*

Results when estimating model 4.9 (variables in log) are similar to results eatimated in model 4.8 (variables in absolute terms) in terms of R^2. The main difference is that the unbiasedness hypothesis holds for a higher number of contracts in model 4.9 compared to model 4.8. All estimated betas are not significantly different from unity, and only one alpha value is significant and different from zero. This applies to all contracts and segments. This means that all contracts except the +3 contract written on route TD3 appear to be unbiased predictors of subsequent spot prices. The results from model 4.8 conflicts with the results from model 4.9 in terms of the unbiasedness hypothesis in seven of the contracts. On the other hand, our results from the two models agrees on that the unbiasedness hypothesis holds for 42 of the 50 FFAs during the period. Although the variables in model 4.8 and model 4.9 is not on the same form and strictly speaking not directly comparable, they are approximately the same. With regard to stability, the log-linear model (4.9) have much in common with the linear model (4.8). The CUR and partly +1 contracts are stable, and the forecasts seems to become unstable when we increase the forecasting horizon using contracts with longer maturity.

6.2. Forecast performance of basis

To avoid the problem of nonstationary variables we estimate models in which the spot freight rate change is estimated as a function of the basis (the difference between the FFA price and the spot freight rate at time t). This specification means that the variables become stationary, which in turn means that we can perform valid hypothesis tests on the parameters. Like in section 6.1, we have used two models. One where spot freight rates and FFA prices are in absolute terms (model 4.10), and one in logs (model 4.11).

Forecasting performance of FFAs using the basis model

$$(S_{t+i} - S_t) = \alpha + \beta(F_t^i - S_t) + \varepsilon_{t+i}$$

Route	FFA contract	α	t-value (α)	β	SE (B)	t-value (β)	Adj. R2
				Capesize			
C3	FFACUR	-0.39	-0.60	-0.35	0.56	-2.42*	0.00
C5	FFACUR	3.32	5.78**	-0.58	0.49	-3.21**	0.01
C7	FFACUR	-0.11	-0.32	-0.05	0.36	-2.89**	-0.01
				Panamax			
P2A	FFACUR	389.51	0.69	0.22	0.23	-3.41**	0.00
P3A	FFACUR	517.76	1.07	0.23	0.37	-2.10*	0.00
				Clean tanker			
TC5	FFACUR	0.45	0.27	0.92	0.17	-0.48	0.42
	FFA+1	-0.89	-0.18	0.99	0.21	-0.03	0.32
	FFA+2	3.09	-0.41	0.86	0.25	-0.56	0.29
	FFA+3	-5.29	-0.57	0.91	0.33	-0.27	0.33
	FFA+4	-5.75	-0.58	1.09	0.27	0.35	0.45
	FFA+5	-3.69	-0.38	1.32	0.19	1.70	0.59
				Dirty tanker			
TD5	FFA+5	3.34	0.57	0.99	0.22	-0.03	0.48
TD7	FFA+1	8.11	1.81	0.35	0.24	-2.68**	0.05
	FFA+3	6.65	1.06	0.55	0.21	-2.11*	0.16

Table 6.3: *Estimation results using model 4.10 with monthly observations from 2005 to 2012. T-values are heteroskedastic and autocorrelation consistent (T-HACE). H0:* $\alpha = 0$, $\beta = 1$. *"*" and "**" denotes significance at the 0.05 and 0.01 level, respectively.*

Our results from estimating model 4.10 and 4.11 indicate that the basis is an imprecise forecast of subsequent spot freight rate changes in the Capesize and Panamax segments, with R^2 ranging from 0.00 to 0.12 (A.7, A.8). Capesize FFA estimation results implies that CUR contracts written on route C3, C5 and C7 have betas significantly different from unity, and a significantly different from zero alpha on the CUR contract associated with C5. This means that the hypothesis that basis is unbiased predictors of subsequent spot freight rate changes can not be rejected. This applies to all Capesize FFAs except for the CUR contracts on routes C3, C5 and C7. In the Panamax segment, all estimated betas are significantly different from unity except the CUR contracts written on route P2A and P3A. None of the alphas are significantly different from zero. This means that the unbiasedness hypothesis holds for the majority of the contracts in the Capesize and Panamax segment.

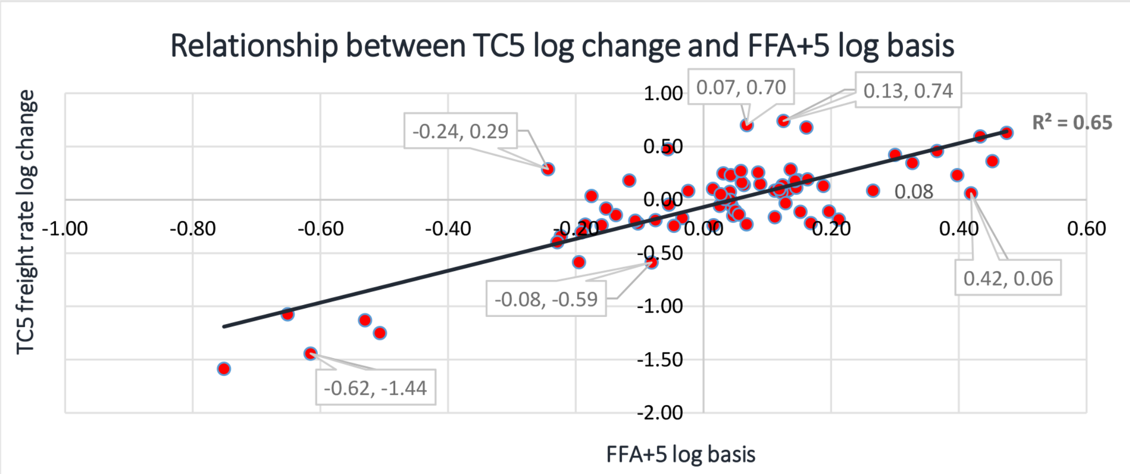

Figure 6.3: *Relationship between TC5 log change and the FFA+5 log basis (model 4.11) from January 2005 to December 2012.*

The most interesting results from estimating model 4.10 and 4.11 can be found in the Clean and Dirty tanker segments. The results exhibit almost twice as high explanatory power in the +5 contracts compared to the CUR contracts written on TC5 and TD5. The explanatory power seems to increase when we increase the forecasting horizon in both the Clean and Dirty tanker segments. The +5 contract written on TC5 has the highest R^2 at 0.65. Figure 6.3 shows the relationship between the TC5 spot freight rate change in logs ($lnS_{t+i} - lnS_t$) and the difference between the FFA price and the spot freight rate in logs ($lnF_t^i - lnS_t$). The scattergram shows that the relationship is relatively strong, but deviations occurs on individual observations. The two models disagree on the if the beta value on the +5 contract is significance of beta significantly different from unity or not. They agree on that the remaining four contracts are unbiased.

Forecasting performance of FFAs using the log basis model

$$(lnS_{t+i} - lnS_t) = \alpha + \beta(lnF_t^i - lnS_t) + \varepsilon_{t+i}$$

Route	FFA contract	α	t-value (α)	β	SE (B)	t-value (β)	Adj. R2
Capesize							
C3	FFACUR	0.00	0.14	-0.44	0.44	-3.31**	0.02
C5	FFACUR	0.21	8.84**	0.37	0.30	-2.07*	0.00
C7	FFACUR	0.00	0.22	0.12	0.27	-3.25**	-0.01
Panamax							
P2A	FFACUR	0.01	1.05	0.18	0.26	-3.21**	0.00
P3A	FFACUR	0.02	1.21	0.46	0.25	-2.17*	0.06
Clean tanker							
TC5	FFACUR	-0.01	-0.60	0.85	0.14	-1.09	0.34
	FFA+1	-0.02	-0.88	1.05	0.16	0.33	0.37
	FFA+2	-0.04	-0.92	0.92	0.16	-0.48	0.34
	FFA+3	-0.05	-1.06	0.96	0.24	-0.16	0.35
	FFA+4	-0.07	-1.26	1.23	0.24	0.99	0.51
	FFA+5	-0.07	-1.33	1.50	0.22	2.27*	0.65
Dirty tanker							
TD5	FFA+2	0.00	-0.05	0.78	0.15	-1.49	0.40
	FFA+3	0.00	-0.10	0.85	0.17	-0.90	0.43
	FFA+4	0.00	-0.09	0.94	0.19	-0.31	0.47
	FFA+5	0.01	0.21	1.13	0.18	0.72	0.58
TD7	FFA+1	0.04	1.36	0.58	0.18	-2.32*	0.18
	FFA+2	0.04	0.92	0.63	0.16	-2.26*	0.24

Table 6.4: *Estimation results using model 4.11 with monthly observations from 2005 to 2012. T-values are heteroskedastic and autocorrelation consistent (T-HACE). H0: $\alpha = 0$, $\beta = 1$. "*" and "**" denotes significance at the 0.05 and 0.01 level, respectively.*

In the dirty segment, none of the alphas are significantly different from zero. All estimated betas that are significantly different from unity, except the +1 -and +2 contracts associated with route TD7. The unbiasedness hypothesis holds for the rest of the contracts. The highest contract with the highest explanatory power in this model is +5 contract written on route TD5, with R^2 at 0.58. In general the results from model 4.10 (variables in log) are similar to model 4.8 (variables in absolute terms) both in terms of the unbiasedness hypothesis and explanatory power. The results indicate that the basis is unbiased predictor of subsequent spot freight rate changes in 42 of the 50 contracts across all four segments.

6.3. Summary

Forecasting performance of FFA prices

- Spot freight rates are not stationary in absolute terms. This means that the results from model 4.8 and 4.9 must be interpreted with caution.
- Variation in the CUR and +1 contract price explains a large portion of the variation in subsequent spot freight rates. The forecasting performance decreases rapidly when we increase the forecasting horizon by using contracts with longer maturity. This accounts for all four segments.
- there is small difference in forecasting performance between specifying the model on absolute form (model 4.8) compared to the same model in logarithmic form (model 4.9).
- FFA prices are unbiased predictors of subsequent spot freight rates in 42 of 50 total contracts across the four segments.

Forecast performance of basis

- The basis is not a stable tool for forecasting Capesize and Panamax spot freight rate changes, with R^2 ranging from 0.00 to 0.12. For the majority of the contracts, the basis provides biased forecasts of spot freight rate changes in the Capesize and Panamax segment.
- The explanatory power of the basis is low to medium in Clean- and Dirty tanker segments. The R^2 increases when we increase the forecasting horizon by using contracts with longer maturities.
- The basis on +5 contracts written on TC5 and TD5 has a relatively high R^2 at 0.65 and 0.58, respectively.
- Basis is unbiased predictors of the subsequent spot freight rate change in 42 out of 50 contracts across the four segments.

7. Main conclusions

We find that the hedge ratios estimated with the conventional method offer high hedge efficiency for the majority of the FFAs during the in-sample period. By holding these hedge ratios through an out-of-sample period we find that the hedge efficiency is not robust for the majority of the contracts. We find robust results in the majority of the FFAs in the Capesize market and in route P3A_03 in the Panamax market. The CUR contract associated with the other segments yield similar result. The tanker market seems to provide low reduction in freight rate variability in - and out-of-sample when considering contracts with maturity far away. Some of the FFAs give negative variance reduction, which indicate that shipping companies would have exposed themselves to excessive risk relative to an unhedged position in the spot freight rate market. Finally, econometric based hedge strategy does not offer significant lower portfolio variance compared to portfolio variance in a naive hedge. In chapter five we also investigate 24-month rolling hedge ratio, covariance and variance. We observe that the majority of the contracts investigated exhibit stable variance and covariance between spot freight rates -and FFA returns over the in-sample period, while the out-of-sample time period indicate time varying variance and covariance. One can assume that the hedger would be better of choosing a dynamic strategy based on models that can account for the time-variation in the joint-distribution. Further studies on this matter should be extended to finding optimal hedge ratios making allowances for time varying conditional variances and the covariance of spot freight rates and FFA returns.

Our results shows that FFA prices are unbiased predictors of subsequent spot freight rates in 42 of 50 contracts we investigate across the four segments. FFA prices are good forecasts of subsequent spot freight rates when considering contracts with short forecasting horizons, for instance CUR and +1 contracts. The forecasts gets rapidly more unstable when we increase the forecasting horizon by one month, although that the unbiasedness hypothesis still holds for the majority of the contracts. This applies to all four segments, and both model 4.8 and 4.9. Unit root tests reveals that the spot freight rates in absolute terms are not stationary. This means that the results from model 4.8 and 4.9 must be interpreted with caution. To get around the problem with nonstationary variables we estimated models in which the spot freight rate change is estimated as a function of the basis (the difference between the FFA price and the spot freight rate at time t). Our findings indicate that the basis is not a stable tool for forecasting Capesize and Panamax spot freight rate changes. For the majority of the contracts, the basis provides biased forecasts of spot freight rate changes in the. The explanatory power of the basis is much higher in the Clean- and Dirty tanker segments, low to medium in. The explanatory power increases when we increase the forecasting horizon by using contracts with longer maturities. The basis is relatively suited for forecasting spot freight rate changes in some routes, for instance TC5 and TD5. The +5 contract basis for this contracts has a relatively high R^2 at around 0.60. In total the basis is unbiased predictors of the subsequent spot freight rate change in 42 out of 50 contracts across the four segments.

Bibliography

A. Alizadeh & N. Nomikos (2009). *Shipping Derivatives and Risk Management.* Palgrave Macmillian, London.

K. Cullinane (1991). 'Who's using Biffex? Results from a survey of shipowners'. *Maritime Policy & Management* **18**.

J. Dinwoodie, J. Morris (2003). 'Tanker forward freight agreements: the futures for freight futures.'. *Maritime Pol* **30**:45–58.

L. Ederington (1979). 'The Hedging Performance of the New Futures Markets'. *The Journal of Finance* **34**(1):157–170.

E. F. Fama (1984). 'Forward and spot exchange rates'. *Journal of Monetary Economics* **14**(3):319 – 338.

E. F. Fama & K. R. French (1987). 'Commodity Futures Prices: Some Evidence on Forecast Power, Premiums, and the Theory of Storage'. *Journal of Business* **60**:55–73.

H. Geman (2005). *Commodities and Commodity Derivatives.* John Wilay & Sonds Ltd, Chichester.

H. Geman (2008). *Risk Management in Commodity Markets : From shipping to agricuturals and energy.* Wiley.

O. Gjolberg & T. Brattested (2011). 'The biased short term futures price at Nord Pool: can it really be a risk premium?'. *Journal of Energy Markets* **4**:1–20.

J. Gray (1990). *Shipping Futures.* LLoyd's of London Press LTD, London.

P. Grober (2010a). 'Forecasting Shipping Freight Rates' .

P. Grober (2010b). 'Is the forward freight market efficient?' .

P. Grober (2010c). 'The lead-lag relationshiip between spot prices and FFA's in international shipping markets' .

D. N. Gujarati (2003). *Basic Econometrics.* McGraw-Hill, fourth edition edn.

M. S. Haigh (2000). 'Cointegration, unbiased expectations and forecasting in the BIFFEX freight futures market'. *Journal of Futures Markets* **20**(6):545 – 571.

M. S. Haigh, et al. (2004). 'Integration and Causality in International Freight Markets: Modeling with Error Correction and Directed Acyclic Graphs'. *Southern Economic Journal* **71**(1):145–162.

S. Harrington & G. Niehaus (2003). *Risk management and insurance*. Mcgraw-Hill, London.

J. Hull (2012). *Options, Futures and other Derivatives*. Pearson Education Limited, Edinburgh.

L. L. Johnson (1960). 'The Theory of Hedging and Speculation in Commodity Futures'. *The Review of Economic Studies* **27**(3):139–151.

M. Kavussanos, et al. (2004). 'The Unbiasedness Hypothesis in the Freight Forward Market: Evidence from Cointegration Tests' **7**:241–266.

M. G. Kavussanos & N. K. Nomikos (1999). 'The forward pricing function of the shipping freight futures market'. *Journal of Futures Markets* **19**(3):353 – 376.

M. G. Kavussanos & N. K. Nomikos (2000). 'Futures hedging when the structure of the underlying asset changes: The case of the BIFFEX contract' **20**:775–801.

M. G. Kavussanos & I. D. Visvikis (2006). 'Shipping freight derivatives: a survey of recent evidence' **33**:233–255.

M. G. Kavussanos & I. D. Visvikis (2010). *International Handbook of Maritime Business*. Edwar Elgar Publishing Limited.

S. Koekebakker, et al. (2006). 'Are Spot Freight Rates Stationary?'. *Journal of Transport Economics and Policy* **40**(3):449–472.

R. Kolb & J. Overdahl (2007). *Futures, Options and Swaps*. Blackwell Publishing, Oxford.

K. F. Kroner & J. Sultan (1993). 'Time-Varying Distributions and Dynamic Hedging with Foreign Currency Futures.'. *Journal of Financial & Quantitative Analysis* **28**(4):535 – 551.

R. J. Myers & S. R. Thompson (1989). 'Generalized Optimal Hedge Ratio Estimation'. *American Journal of Agricultural Economics* **71**(4):858–868.

D. Oakley (2008). 'Freight futures surge as funds seek refuge'.

H. Park & A. Bera (1987). 'Interest-Rate Volatility, Basis Risk and Heteroskedasticity in Hedging Mortgages'. *AREUEA Journal,* **5**:79–97.

J. L. Stein (1961). 'The Simultaneous Determination of Spot and Futures Prices'. *The American Economic Review* **51**(5):1012–1025.

M. Stopford (2009). *Maritime Economics*. Routledge, London.

L. T. Thuong & S. L. Visscher (1990). 'The Hedging Effectiveness of Dry-Bulk Freight Rate Futures.'. *Transportation Journal (American Society of Transportation & Logistics Inc)* **29**(4):58 – 65.

J. Tvedt (2003). 'A new perspective on price dynamics of the dry bulk market'. *Maritime Policy & Management* **30**(3):221–230.

A. Appendix

A.1. Normality tests

Jarque-Bera test on weekly returns for spot and FFA $JB = \frac{T}{6} * (Skew^2 + \frac{EKurt^2}{4})$						
Route	**FFACUR**	**FFA+1**	**FFA+2**	**FFA+3**	**FFA+4**	**FFA+5**
Capesize						
C3						
227,90	706,43	518,12	649,41	-	-	-
C4						
162,69	190,30	124,62	138,75	304,06	-	-
C5						
93,91	450,39	280,82	377,89	-	-	-
C7:						
71,15	417,38	419,24	470,21	694,48	-	-
Panamax						
P2A						
167,12	93,83	165,25	310,61	415,83	607,82	1125,00
P3A						
241,98	1826,09	321,60	409,19	261,44	380,48	487,20
Clean Tanker						
TC5						
90,08	1024,89	435,26	7012,65	4500,36	3476,59	4250,43
Dirty Tankers						
TD3						
77,46	572,34	55,39	116,12	686,65	388,57	986,34
TD5						
64,43	1057,71	60,63	648,99	2444,56	745,98	5785,18
TD7						
126,58	288,01	121,83	625,73	1402,47	4966,94	7225,34

Table A.1.1: *Jarque-Bera test of log returns in Capesize, Panamax, Clean tanker and Dirty tanker spot freight rate routes. Based on weekly observations. For a definition of time series period see section 3.1 in chapter 3. Exel has a built-in correction that will give kurtosis equal to zero for a normal distribution.*

A.2. F-test two-sample for variances in-sample

An F-test two sample for variance has been conducted. We wish to check for equality between variances in two variables. F-ratios has been calculated using formula $F = \frac{\sigma_1^2}{\sigma_2^2}$. The larger of the two estimated variances is the numerator. By comparing the F-value against critical F, we can decide to reject or not reject the null hypothesis of equality in variancesGujarati (2003). The F-test two-sample for variances in -and out-of-sample, have three null hypothesis:

- $H_0 = \frac{Var(S)}{Var(h^*)} = 1$, variance spot is equal to variance in minimum variance hedge ratio portfolio.
- $H_0 = \frac{Var(h=1)}{Var(h^*)} = 1$, variance using naive portfolio is equal to variance in minimum variance hedge ratio portfolio.
- $H_0 = \frac{Var(S)}{Var(h=1)} = 1$, variance spot is equal to variance in naive portfolio.

In-Sample hedging: F-Test Two-Sample for Variances						
	Var(S)/Var(h*)	t-critical	Var(h=1)/Var(h*)	t-critical	Var(S)/Var(h=1)	t-critical
C3:						
FFACUR	11.71	1.49	1.01	1.49	11.58	1.49
FFA+1	10.21	1.49	1.08	1.49	9.47	1.49
FFA+2	7.86	1.49	1.09	1.49	7.24	1.49
C4:						
FFACUR	16.64	1.46	1.01	1.46	16.43	1.46
FFA+1	7.40	1.46	1.08	1.46	6.87	1.46
FFA+2	4.23	1.46	1.05	1.46	4.01	1.46
FFA+3	3.42	1.49	1.04	1.49	3.27	1.49
C5:						
FFACUR	9.30	1.49	1.07	1.49	8.70	1.49
FFA+1	8.26	1.49	1.19	1.49	6.92	1.49
FFA+2	5.29	1.49	1.12	1.49	4.70	1.49
C7:						
FFACUR	10.38	1.46	1.08	1.46	9.57	1.46
FFA+1	6.07	1.46	1.20	1.46	5.06	1.46
FFA+2	4.62	1.46	1.21	1.46	3.81	1.46
FFA+3	3.78	1.49	1.20	1.49	3.15	1.49

Table A.2.1: *Capesize in-sample F-test two-sample for variances. Minimum variance hedge ratio(h*) is the OLS regressor from model 4.3, and h=1 represents a naive hedge. Var(h*) and Var(h=1) denotes the variance of a portfolio calculated using formula 4.1 with continuously compounded returns.*

In-Sample hedging: F-Test Two-Sample for Variances						
	Var(S)/Var(h*)	t-critical	Var(h=1)/Var(h*)	t-critical	Var(S)/Var(h=1)	t-critical
P2A_03:						
FFACUR	16.84	1.51	1.02	1.51	16.47	1.51
FFA+1	5.01	1.46	1.02	1.46	4.92	1.46
FFA+2	3.64	1.46	1.02	1.46	3.57	1.46
FFA+3	3.01	1.46	1.02	1.46	2.95	1.46
FFA+4	2.63	1.48	1.02	1.48	2.58	1.48
FFA+5	2.43	1.49	1.02	1.49	2.38	1.49
P3A_03:						
FFACUR	24.86	1.46	1.41	1.46	17.67	1.46
FFA+1	5.21	1.46	1.17	1.46	4.46	1.46
FFA+2	4.42	1.46	1.21	1.46	3.66	1.46
FFA+3	3.09	1.46	1.14	1.46	2.72	1.46
FFA+4	2.56	1.48	1.14	1.48	2.25	1.48
FFA+5	2.34	1.49	1.13	1.49	2.06	1.49

Table A.2.2: *Panamax in-sample F-test two-sample for variances. Minimum variance hedge ratio(h*) is the OLS regressor from model 4.3, and h=1 represents a naive hedge. Var(h*) and Var(h=1) denotes the variance of a portfolio calculated using formula 4.1 with continuously compounded returns.*

In-Sample hedging: F-Test Two-Sample for Variances						
	Var(S)/Var(h*)	t-critical	Var(h=1)/Var(h*)	t-critical	Var(S)/Var(h=1)	t-critical
TC5:						
FFACUR	38.50	1.54	1.24	1.54	31.11	1.54
FFA+1	2.52	1.54	1.00	1.54	2.51	1.54
FFA+2	1.54	1.54	1.01	1.54	1.52	1.54
FFA+3	1.54	1.54	1.00	1.54	1.54	1.54
FFA+4	1.49	1.54	1.00	1.54	1.49	1.54
FFA+5	1.28	1.54	1.00	1.54	1.27	1.54

Table A.2.3: *Clean Tanker in-sample F-test two-sample for variances. Minimum variance hedge ratio(h*) is the OLS regressor from model 4.3, and h=1 represents a naive hedge. Var(h*) and Var(h=1) denotes the variance of a portfolio calculated using formula 4.1 with continuously compounded returns.*

In-Sample hedging: F-Test Two-Sample for Variances						
	Var(S)/Var(h*)	t-critical	Var(h=1)/Var(h*)	t-critical	Var(S)/Var(h=1)	t-critical
TD3:						
FFACUR	18.54	1.46	1.50	1.46	12.40	1.46
FFA+1	3.12	1.46	1.11	1.46	2.81	1.46
FFA+2	1.62	1.46	1.02	1.46	1.60	1.46
FFA+3	1.31	1.46	1.00	1.46	1.31	1.46
FFA+4	1.37	1.49	1.00	1.49	1.37	1.49
FFA+5	1.44	1.49	1.01	1.49	1.43	1.49
TD5:						
FFACUR	10.34	1.46	1.42	1.46	7.31	1.46
FFA+1	1.80	1.46	1.03	1.46	1.74	1.46
FFA+2	1.32	1.46	1.00	1.46	1.32	1.46
FFA+3	1.15	1.46	1.01	1.46	1.14	1.46
FFA+4	1.09	1.49	1.00	1.49	1.08	1.49
FFA+5	1.01	1.49	1.04	1.49	0.97	1.49
TD7:						
FFACUR	8.54	1.46	1.65	1.46	5.16	1.46
FFA+1	1.69	1.46	1.11	1.46	1.53	1.46
FFA+2	1.20	1.46	1.00	1.46	1.20	1.46
FFA+3	1.03	1.46	1.02	1.46	1.03	1.46
FFA+4	0.95	1.49	1.04	1.49	0.91	1.49
FFA+5	0.98	1.49	1.01	1.49	0.98	1.49

Table A.2.4: *Dirty Tankers in-sample F-test two-sample for variances. Minimum variance hedge ratio(h*) is the OLS regressor from model 4.3, and h=1 represents a naive hedge. Var(h*) and Var(h=1) denotes the variance of a portfolio calculated using formula 4.1 with continuously compounded returns.*

F-test two-sample for variances out-of-sample

Out-of-Sample hedging: F-Test Two-Sample for Variances						
	Var(S)/Var(h*)	t-critical	Var(h=1)/Var(h*)	t-critical	Var(S)/Var(h=1)	t-critical
C3:						
FFACUR	13.31	2.33	1.03	2.33	12.86	2.33
FFA+1	18.61	2.33	1.08	2.33	17.17	2.33
FFA+2	5.22	2.33	1.13	2.33	4.60	2.33
C4:						
FFACUR	7.44	2.33	1.08	2.33	6.91	2.33
FFA+1	7.74	2.33	1.27	2.33	6.08	2.33
FFA+2	2.13	2.33	1.08	2.33	1.98	2.33
FFA+3	1.71	2.33	1.05	2.33	1.62	2.33
C5:						
FFACUR	12.89	2.33	1.14	2.33	11.32	2.33
FFA+1	4.90	2.33	1.10	2.33	4.46	2.33
FFA+2	2.77	2.33	1.05	2.33	2.64	2.33
C7:						
FFACUR	5.82	2.33	1.13	2.33	5.16	2.33
FFA+1	8.47	2.33	1.68	2.33	5.04	2.33
FFA+2	2.44	2.33	1.15	2.33	2.13	2.33
FFA+3	1.95	2.33	1.11	2.33	1.75	2.33

Table A.2.5: *Capesize out-of-sample F-test two-sample for variances. Var(h*) and Var(h=1) denotes the variance of a portfolio calculated using formula 4.1 with continuously compounded returns.*

Out-of-Sample hedging: F-Test Two-Sample for Variances						
	Var(S)/Var(h*)	t-critical	Var(h=1)/Var(h*)	t-critical	Var(S)/Var(h=1)	t-critical
P2A_03:						
FFACUR	3.02	2.33	0.98	2.33	3.07	2.33
FFA+1	1.05	2.33	0.97	2.33	1.08	2.33
FFA+2	1.02	2.33	0.98	2.33	1.04	2.33
FFA+3	1.08	2.33	0.99	2.33	1.09	2.33
FFA+4	1.32	2.33	1.01	2.33	1.31	2.33
FFA+5	1.21	2.33	1.01	2.33	1.20	2.33
P3A_03:						
FFACUR	14.32	2.33	1.22	2.33	11.75	2.33
FFA+1	3.68	2.33	1.16	2.33	3.17	2.33
FFA+2	2.33	2.33	1.19	2.33	1.96	2.33
FFA+3	1.49	2.33	1.05	2.33	1.42	2.33
FFA+4	1.52	2.33	1.07	2.33	1.42	2.33
FFA+5	2.13	2.33	1.22	2.33	1.74	2.33

Table A.3.6: *Panamax out-of-sample F-test two-sample for variances. Var(h*) and Var(h=1) denotes the variance of a portfolio calculated using formula 4.1 with continuously compounded returns.*

Out-of-Sample hedging: F-Test Two-Sample for Variances						
	Var(S)/Var(h*)	t-critical	Var(h=1)/Var(h*)	t-critical	Var(S)/Var(h=1)	t-critical
TC5:						
FFACUR	53.17	2.33	1.59	2.33	33.48	2.33
FFA+1	0.93	2.33	1.01	2.33	0.92	2.33
FFA+2	0.86	2.33	1.05	2.33	0.82	2.33
FFA+3	1.15	2.33	1.01	2.33	1.14	2.33
FFA+4	0.92	2.33	0.99	2.33	0.93	2.33
FFA+5	0.81	2.33	1.03	2.33	0.79	2.33

Table A.2.7: *Clean Tanker out-of-sample F-test two-sample for variances. Var(h*) and Var(h=1) denotes the variance of a portfolio calculated using formula 4.1 with continuously compounded returns.*

Out-of-Sample hedging: F-Test Two-Sample for Variances						
	Var(S)/Var(h*)	t-critical	Var(h=1)/Var(h*)	t-critical	Var(S)/Var(h=1)	t-critical
TD3:						
FFACUR	26.25	2.33	0.98	2.33	26.67	2.33
FFA+1	1.26	2.33	0.77	2.33	1.64	2.33
FFA+2	1.05	2.33	0.97	2.33	1.08	2.33
FFA+3	1.28	2.33	1.00	2.33	1.29	2.33
FFA+4	1.16	2.33	0.99	2.33	1.17	2.33
FFA+5	0.87	2.33	0.90	2.33	0.98	2.33
TD5:						
FFACUR	8.24	2.33	1.65	2.33	5.00	2.33
FFA+1	0.88	2.33	0.89	2.33	0.98	2.33
FFA+2	1.64	2.33	1.01	2.33	1.63	2.33
FFA+3	0.69	2.33	1.05	2.33	0.66	2.33
FFA+4	0.83	2.33	1.02	2.33	0.81	2.33
FFA+5	0.95	2.33	1.09	2.33	0.87	2.33
TD7:						
FFACUR	11.80	2.33	2.36	2.33	4.99	2.33
FFA+1	0.81	2.33	0.88	2.33	0.92	2.33
FFA+2	1.21	2.33	1.00	2.33	1.20	2.33
FFA+3	0.95	2.33	1.05	2.33	0.91	2.33
FFA+4	0.97	2.33	1.09	2.33	0.89	2.33
FFA+5	1.03	2.33	1.00	2.33	1.03	2.33

Table A.2.8: *Dirty Tankers out-of-sample F-test two-sample for variances. Var(h*) and Var(h=1) denotes the variance of a portfolio calculated using formula 4.1 with continuously compounded returns.*

A.3. Unit-root tests

Augmented Dickey and Fuller test(ADF): Data: Settlement, spot and FFA prices in model:	$1: S_{t+i} = \alpha + \beta F_t^i + u_{t+i}$	$ADF = \Delta y_t = \omega y_{t-1} + \sum_{i=1}^{P} \alpha_i \Delta y_{t-1} + u_t$					
	Capesize ADF tests: T=74		Constant;	5%=-2.90	1%=-3.52		
	D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
C3	2	-2.146	0.911	7.466	-0.700	0.487	4.073	0.492
FFACUR	2	-2.088	0.910	7.848	-0.636	0.527	4.173	0.632
FFA+1	2	-2.101	0.908	7.775	-0.270	0.788	4.154	0.591
FFA+2	2	-2.115	0.909	7.521	-0.323	0.748	4.088	0.519
C4	2	-1.939	0.920	4.033	-0.917	0.362	2.841	0.458
FFACUR	2	-1.97	0.914	4.278	0.333	0.740	2.960	0.759
FFA+1	2	-1.873	0.926	3.789	0.548	0.586	2.717	0.953
FFA+2	2	-1.861	0.932	3.413	0.246	0.806	2.508	0.763
FFA+3	2	-1.875	0.932	3.271	0.375	0.709	2.423	0.957
C5	2	-2.103	0.894	3.705	0.019	0.985	2.672	0.737
FFACUR	2	-1.907	0.901	3.719	-0.028	0.978	2.680	0.158
FFA+1	2	-1.783	0.907	3.603	0.061	0.951	2.616	0.053
FFA+2	2	-1.775	0.909	3.404	0.198	0.844	2.502	0.038
C7	2	-2.278	0.894	4.603	-0.820	0.415	3.106	0.257
FFACUR	2	-2.121	0.905	4.400	-0.311	0.756	3.016	0.891
FFA+1	2	-1.999	0.916	4.059	0.180	0.858	2.854	0.677
FFA+2	2	-1.973	0.920	3.790	0.109	0.913	2.717	0.530
FFA+3	2	-1.947	0.923	3.612	0.040	0.968	2.621	0.469
	Panamax ADF tests: T=74		Constant;	5%=-2.90	1%=-3.52			
P2A	2	-2.347	0.911	7269.000	2.175	0.033	17.840	0.223
FFACUR	2	-2.017	0.922	7278.000	0.881	0.381	17.840	0.941
FFA+1	2	-1.983	0.925	7004.000	0.755	0.453	17.760	0.792
FFA+2	2	-1.943	0.927	6843.000	0.483	0.631	17.710	0.846
FFA+3	2	-1.967	0.926	6709.000	0.487	0.628	17.670	0.786
FFA+4	2	-1.972	0.927	6385.000	0.260	0.796	17.580	0.625
FFA+5	2	-1.989	0.928	6140.000	0.203	0.839	17.500	0.553
P3A	2	-1.798	0.926	7139.000	-0.456	0.650	17.800	0.787
FFACUR	2	-1.772	0.929	6954.000	-0.761	0.449	17.750	0.638
FFA+1	2	-1.753	0.933	6639.000	-0.642	0.523	17.650	0.552
FFA+2	2	-1.737	0.938	6103.000	-0.987	0.327	17.490	0.601
FFA+3	2	-1.773	0.937	5930.000	-0.897	0.373	17.430	0.352
FFA+4	2	-1.778	0.938	5736.000	-1.003	0.319	17.360	0.259
FFA+5	2	-1.777	0.939	5549.000	-0.964	0.339	17.300	0.219

Table A.3.1: *Capesize and Panamax: Augmented Dickey and Fuller(ADF) test. Computed for time series used in the linear model(4.8) under section 6.1 in chapter 6. D-lag = number of lagged differences, t-adf=t value on the lagged level, beta Y_1=coefficient on the lagged level, $\hat{\sigma}$ =standard error, t prob=significance of the longest lag, AIC=Akaike criterion, F-prob=significance level of the F-test on the lags dropped up to that point.*

Augmented Dickey and Fuller test(ADF): $ADF = \Delta y_t = \omega y_{t-1} + \sum_{i=1}^{P} \alpha_i \Delta y_{t-1} + u_t$								
Data: Settlement, spot and FFA prices in model: 1: $S_{t+i} = \alpha + \beta F_t^i + u_{t+i}$								
	Clean tankers ADF tests: T=74			Constant;	5%=-2.90	1%=-3.52		
	D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
TC5	2	-2.557	0.848	29.570	0.301	0.764	6.826	0.392
FFACUR	2	-2.673	0.824	30.230	1.426	0.158	6.871	0.743
FFA+1	2	-2.779	0.820	26.850	1.041	0.301	6.633	0.444
FFA+2	2	**-2.974***	0.809	24.890	1.285	0.203	6.482	0.413
FFA+3	2	-2.787	0.858	18.740	0.458	0.649	5.914	0.294
FFA+4	2	-2.45	0.873	18.160	2.700	0.009	5.851	0.350
FFA+5	2	-2.034	0.898	16.280	0.218	0.828	5.633	0.321
	Dirty tankers ADF tests: T=74			Constant;	5%=-2.90	1%=-3.52		
TD3	2	-2.687	0.750	29.790	0.133	0.894	6.841	0.564
FFACUR	2	-2.47	0.809	21.920	0.278	0.782	6.227	0.904
FFA+1	2	**-2.970***	0.805	15.950	1.177	0.243	5.592	0.916
FFA+2	2	**-3.043***	0.811	14.250	1.119	0.267	5.366	0.275
FFA+3	2	**-3.234***	0.816	12.510	2.188	0.032	5.106	0.712
FFA+4	2	-2.774	0.863	10.210	-0.095	0.924	4.699	0.728
FFA+5	2	-2.685	0.831	12.480	0.962	0.339	5.101	0.231
TD5	2	-2.121	0.840	27.630	0.203	0.840	6.690	0.824
FFACUR	2	-2.1	0.872	20.270	0.064	0.949	6.071	0.361
FFA+1	2	-2.593	0.872	14.650	0.318	0.751	5.422	0.727
FFA+2	2	-2.747	0.856	15.140	0.510	0.612	5.487	0.374
FFA+3	2	-2.74	0.862	13.800	0.748	0.457	5.302	0.996
FFA+4	2	-2.651	0.883	11.420	0.350	0.728	4.923	0.616
FFA+5	2	-1.885	0.900	12.770	0.425	0.672	5.147	0.425
TD7	2	-2.348	0.809	26.160	0.840	0.404	6.581	0.580
FFACUR	2	-2.106	0.852	16.790	0.248	0.805	5.694	0.874
FFA+1	2	**-3.527****	0.821	11.250	1.982	0.051	4.893	0.003
FFA+2	2	**-3.445***	0.822	11.110	-0.308	0.759	4.869	0.558
FFA+3	2	**-3.342***	0.815	11.320	2.588	0.012	4.906	0.158
FFA+4	2	**-3.042***	0.836	10.030	0.095	0.925	4.664	0.380
FFA+5	2	**-2.956***	0.810	11.140	1.709	0.092	4.873	0.567

Table A.3.2: *Clean -and Dirty tanker: Augmented Dickey and Fuller(ADF) test. Computed for time series used in the linear model(4.8) under section 6.1 in chapter 6. D-lag = number of lagged differences, t-adf=t value on the lagged level, beta Y_1=coefficient on the lagged level, $\hat{\sigma}$ =standard error, t prob=significance of the longest lag, AIC=Akaike criterion, F-prob=significance level of the F-test on the lags dropped up to that point.*

A.4. Residual tests

Tests for autocorrelation and heteroscedasticity in residuals

1: $S_{t+i} = \alpha + \beta F_t^i + u_{t+i}$ 2: $lnS_{t+i} = \alpha + \beta lnF_t^i + \mu_{t+i}$ 3: $(S_{t+i} - S_t) = \alpha + \beta(F_t^i - S_t) + \varepsilon_{t+i}$ 4: $(lnS_{t+i} - lnS_t) = \alpha + \beta(lnF_t^i - lnS_t) + \varepsilon_{t+i}$

Route	FFA	1:AR1-6	1:ARCH1-6	2:AR1-6	2:ARCH1-6	3:AR 1-2	3:ARCH1-1	4:AR1-2	4:ARCH1-1
	Critical Values→	*F(6.78)*	*F(6.74)*	*F(2.83)*	*F(1.85)*	*F(2.81)*	*F(1.83)*	*F(2.82)*	*F(1.84)*
C3	FFACUR	3.42	5.87	9.77	11.31	1.86	5.94	5.61	10.86
	FFA+1	13.47	5.41	36.40	27.50	23.84	18.69	33.19	24.86
	FFA+2	46.64	22.54	95.89	55.74	111.26	66.76	89.81	59.84
C4	FFACUR	4.63	3.18	7.72	7.05	2.96	3.41	3.17	5.17
	FFA+1	13.09	5.71	32.76	28.56	23.10	23.94	25.11	24.92
	FFA+2	36.80	15.19	102.73	58.81	108.09	61.19	87.23	54.12
	FFA+3	54.55	25.59	128.28	91.44	134.09	114.78	113.12	104.52
C5	FFACUR	3.24	7.13	2.83	15.97	17.13	7.90	6.90	2.74
	FFA+1	7.42	3.82	17.88	18.60	11.56	13.49	14.42	18.42
	FFA+2	27.72	13.29	66.77	32.11	77.45	52.01	62.28	33.59
C7	FFACUR	5.13	7.99	9.42	38.44	2.07	6.29	4.68	9.64
	FFA+1	12.06	4.93	38.06	33.23	20.68	10.82	29.34	25.40
	FFA+2	43.75	19.85	102.33	57.74	121.95	62.38	90.58	56.24
	FFA+3	44.11	16.92	122.74	75.65	107.40	96.57	112.13	93.20
P2A	FFACUR	4.28	6.14	10.82	2.30	3.19	8.66	2.06	4.05
	FFA+1	9.95	1.81	36.12	25.19	17.58	5.47	16.48	6.00
	FFA+2	35.95	18.87	110.39	86.05	88.54	59.96	75.10	59.95
	FFA+3	49.66	17.60	136.87	90.97	63.08	52.02	101.36	77.81
	FFA+4	71.60	38.94	205.82	118.67	177.73	156.68	165.86	135.90
	FFA+5	101.42	38.80	237.49	145.61	181.25	204.55	237.38	191.56
P3A	FFACUR	2.70	3.89	0.51	1.67	2.04	24.97	1.49	8.75
	FFA+1	11.18	3.82	23.17	30.31	16.32	13.90	11.92	22.01
	FFA+2	46.37	13.32	93.99	124.61	73.87	30.51	57.32	72.73
	FFA+3	57.80	26.69	117.46	104.51	88.71	38.85	74.41	126.74
	FFA+4	85.91	28.37	138.21	83.52	90.79	41.21	76.45	126.91
	FFA+5	81.03	53.25	191.96	93.61	110.32	104.75	168.18	128.59
TC5	FFACUR	0.65	7.41	0.77	2.86	0.53	11.14	1.07	4.42
	FFA+1	2.42	4.05	3.88	2.34	3.16	1.07	3.66	2.63
	FFA+2	15.40	10.74	26.01	15.15	31.74	21.65	27.31	9.79
	FFA+3	21.45	19.08	36.63	28.04	44.69	33.70	32.20	15.15
	FFA+4	26.48	16.39	52.47	44.90	47.81	69.32	37.87	36.96
	FFA+5	28.93	22.49	58.65	70.10	47.09	97.20	34.50	48.73
TD3	FFACUR	3.48	2.18	0.83	1.66	1.66	18.14	0.34	3.55
	FFA+1	4.31	2.67	7.72	2.67	1.53	0.40	3.10	0.03
	FFA+2	10.14	3.53	31.40	14.21	19.83	5.69	20.15	7.58
	FFA+3	12.99	4.09	37.38	14.61	18.18	6.87	28.35	9.17
	FFA+4	13.31	4.59	44.61	23.01	22.92	5.50	36.46	13.65
	FFA+5	13.21	5.06	46.37	29.66	24.69	6.76	35.48	32.79
TD5	FFACUR	1.14	4.35	0.46	0.56	0.66	2.53	0.02	0.03
	FFA+1	3.23	4.09	6.99	3.62	1.80	0.85	2.21	0.00
	FFA+2	8.98	3.80	23.10	13.42	14.10	3.40	15.58	3.07
	FFA+3	13.32	4.61	35.28	12.83	22.11	4.24	25.29	4.76
	FFA+4	15.08	5.60	34.43	19.96	29.77	10.07	29.99	14.83
	FFA+5	18.50	7.06	47.83	25.51	36.54	13.08	40.86	32.64
TD7	FFACUR	2.55	3.47	4.22	11.00	4.88	12.18	3.76	8.19
	FFA+1	5.41	5.64	7.70	12.00	3.42	16.80	2.21	5.90
	FFA+2	8.94	11.97	15.17	31.30	7.26	13.70	9.80	14.35
	FFA+3	11.93	16.14	23.88	55.20	19.64	39.52	19.55	38.04
	FFA+4	14.13	18.10	30.14	78.06	27.47	51.54	27.59	54.63
	FFA+5	17.11	25.15	36.87	113.36	50.79	85.73	45.45	108.49

Table A.4.1: *Autocorrelation and hetroscedasticity test of residuals computed for time series used in chapter 6. The table include all investigated routes.*

A.5. Forecasting using the linear model

Forecasting performance of Capesize FFAs prices using the linear model

$$S_{t+i} = \alpha + \beta F_t^i + \mu_{t+i}$$

Route	FFA contract	α	t-value (α)	β	SE (B)	t-value (β)	Adj. R2
C3:	FFACUR	1.09	1.00	0.97	0.05	-0.69	0.94
	FFA+1	4.80	1.69	0.87	0.12	-1.08	0.72
	FFA+2	9.04	1.89	0.75	0.20	-1.25	0.51
C4:	FFACUR	0.36	0.65	0.97	0.04	-0.64	0.94
	FFA+1	1.74	1.22	0.90	0.11	-0.90	0.75
	FFA+2	3.45	1.46	0.80	0.19	-1.04	0.56
	FFA+3	5.21	1.60	0.71	0.26	-1.12	0.41
C5:	FFACUR	0.36	0.81	0.99	0.05	-0.32	0.92
	FFA+1	1.87	1.58	0.89	0.12	-0.90	0.70
	FFA+2	3.03	1.56	0.82	0.20	-0.91	0.53
C7:	FFACUR	0.34	0.49	0.98	0.05	-0.35	0.93
	FFA+1	2.42	1.35	0.88	0.13	-0.90	0.69
	FFA+2	4.72	1.62	0.76	0.21	-1.12	0.49
	FFA+3	7.08	1.85	0.65	0.28	-1.26	0.33

Table A.5.1: *Capesize: Estimation results using model 4.8 with monthly observations from 2005 to 2012. T-values are heteroskedastic and autocorrelation consistent (T-HACE). H0:* $\alpha = 0$, $\beta = 1$.

Forecasting performance of Panamax FFAs using the linear model

$$S_{t+i} = \alpha + \beta F_t^i + \mu_{t+i}$$

Route	FFA contract	α	t-value (α)	β	SE (B)	t-value (β)	Adj. R2
P2A:	FFACUR	681	0.72	0.99	0.03	-0.16	0.96
	FFA+1	9492	4.97	0.99	0.10	-0.05	0.78
	FFA+2	6449	1.44	0.84	0.18	-0.91	0.62
	FFA+3	10468	1.72	0.73	0.24	-1.15	0.43
	FFA+4	14333	1.92	0.64	0.30	-1.23	0.32
	FFA+5	18382	2.16	0.53	0.33	-1.40	0.21
P3A	FFACUR	-37	-0.13	1.00	0.01	0.37	0.94
	FFA+1	1199	1.00	0.95	0.95	-0.06	0.78
	FFA+2	3628	1.61	0.85	0.13	-1.11	0.67
	FFA+3	6370	1.99	0.75	0.18	-1.37	0.49
	FFA+4	9208	2.35	0.67	0.23	-1.48	0.37
	FFA+5	11399	2.44	0.59	0.26	-1.59	0.27

Table A.5.2: *Panamax: Estimation results using model 4.8 with monthly observations from 2005 to 2012. T-values are heteroskedastic and autocorrelation consistent (T-HACE). H0:* $\alpha = 0$, $\beta = 1$.

Forecasting performance of Clean tanker FFAs using the linear model

$$S_{t+i} = \alpha + \beta F_t^i + \mu_{t+i}$$

Route	FFA contract	α	t-value (α)	β	SE (B)	t-value (β)	Adj. R2
TC5:	FFACUR	-10.19	-2.14	1.07	0.03	2.06	0.96
	FFA+1	1.01	0.06	0.99	0.14	-0.09	0.70
	FFA+2	21.81	0.82	0.84	0.21	-0.77	0.49
	FFA+3	38.50	1.35	0.72	0.22	-1.27	0.36
	FFA+4	40.99	1.52	0.70	0.21	-1.43	0.32
	FFA+5	31.74	1.21	0.77	0.21	-1.09	0.31

Table A.5.3: *Clean tanker: Estimation results using model 4.8 with monthly observations from 2005 to 2012. T-values are heteroskedastic and autocorrelation consistent (T-HACE). H0:* $\alpha = 0$, $\beta = 1$.

Forecasting performance of Dirty tanker FFAs using the linear model

$$S_{t+i} = \alpha + \beta F_t^i + \mu_{t+i}$$

Route	FFA contract	α	t-value (α)	β	SE (B)	t-value (β)	Adj. R2
TD3:	FFACUR	-4.06	-1.05	1.06	0.06	0.92	0.81
	FFA+1	12.18	1.21	0.86	0.16	-0.86	0.39
	FFA+2	20.63	1.67	0.75	0.20	-1.27	0.26
	FFA+3	28.65	2.15	0.64	0.21	-1.74	0.18
	FFA+4	36.31	2.63	0.52	0.22	-2.21	0.12
	FFA+5	37.10	2.49	0.51	0.24	-2.04	0.10
TD5:	FFACUR	-3.60	-0.78	1.03	0.05	0.63	0.89
	FFA+1	5.71	0.70	0.98	0.09	-0.25	0.64
	FFA+2	12.13	1.14	0.93	0.12	-0.60	0.53
	FFA+3	15.21	1.18	0.90	0.14	-0.67	0.47
	FFA+4	25.38	1.94	0.80	0.15	-1.36	0.36
	FFA+5	21.13	1.52	0.84	0.16	-0.97	0.35
TD7:	FFACUR	-2.91	-0.29	1.06	0.09	0.62	0.73
	FFA+1	6.57	0.50	0.99	0.12	-0.10	0.53
	FFA+2	18.88	1.12	0.89	0.15	-0.73	0.39
	FFA+3	22.72	1.19	0.86	0.16	-0.83	0.35
	FFA+4	33.79	1.88	0.75	0.15	-1.59	0.24
	FFA+5	27.02	1.53	0.81	0.16	-1.17	0.25

Table A.5.4: *Dirty tankers: Estimation results using model 4.8 with monthly observations from 2005 to 2012. T-values are heteroskedastic and autocorrelation consistent (T-HACE). H0:* $\alpha = 0$, $\beta = 1$.

A.6. Forecasting using the log-linear model

Forecasting performance of Capesize FFAs using the log-linear model

$$lnS_{t+i} = \alpha + \beta lnF_t^i + \mu_{t+i}$$

Route	FFA contract	α	t-value (α)	β	SE (B)	t-value (β)	Adj. R2
C3:	FFACUR	0.17	1.36	0.95	0.04	-1.34	0.92
	FFA+1	0.61	1.92	0.82	0.10	-1.77	0.64
	FFA+2	1.11	1.91	0.68	0.18	-1.75	0.40
C4:	FFACUR	0.02	0.24	0.99	0.03	-0.39	0.94
	FFA+1	0.20	0.90	0.92	0.09	-0.93	0.73
	FFA+2	0.46	1.13	0.82	0.16	-1.10	0.54
	FFA+3	0.66	1.11	0.75	0.24	-1.05	0.41
C5:	FFACUR	0.09	1.17	0.97	0.03	-1.06	0.91
	FFA+1	0.36	1.63	0.86	0.10	-1.44	0.65
	FFA+2	0.60	1.48	0.76	0.18	-1.31	0.46
C7:	FFACUR	0.04	0.43	0.99	0.03	-0.49	0.92
	FFA+1	0.35	1.36	0.87	0.10	-1.28	0.65
	FFA+2	0.74	1.53	0.73	0.19	-1.42	0.42
	FFA+3	1.03	1.47	0.63	0.27	-1.35	0.29

Table A.6.1: *Dirty tankers: Estimation results using model 4.9 with monthly observations from 2005 to 2012. T-values are heteroskedastic and autocorrelation consistent (T-HACE). H0:* $\alpha = 0$, $\beta = 1$.

Forecasting performance of Panamax FFAs using the log-linear model

$$lnS_{t+i} = \alpha + \beta lnF_t^i + \mu_{t+i}$$

Route	FFA contract	α	t-value (α)	β	SE (B)	t-value (β)	Adj. R2
P2A:	FFACUR	0.18	0.75	0.98	0.02	-0.71	0.95
	FFA+1	0.99	1.31	0.90	0.08	-1.27	0.75
	FFA+2	2.38	1.60	0.77	0.15	-1.56	0.51
	FFA+3	3.88	1.72	0.62	0.22	-1.67	0.31
	FFA+4	4.93	1.69	0.52	0.29	-1.64	0.20
	FFA+5	6.07	1.90	0.41	0.32	-1.84	0.12
P3A	FFACUR	0.01	0.04	1.00	0.03	-0.10	0.94
	FFA+1	0.43	0.65	0.95	0.04	-1.11	0.76
	FFA+2	1.38	1.17	0.86	0.12	-1.19	0.56
	FFA+3	2.70	1.45	0.72	0.19	-1.44	0.37
	FFA+4	3.62	1.38	0.63	0.27	-1.35	0.26
	FFA+5	4.45	1.46	0.55	0.32	-1.43	0.18

Table A.6.2: *Dirty tankers: Estimation results using model 4.9 with monthly observations from 2005 to 2012. T-values are heteroskedastic and autocorrelation consistent (T-HACE). H0:* $\alpha = 0$, $\beta = 1$.

Forecasting performance of Clean tanker FFAs using the log-linear model

$$lnS_{t+i} = \alpha + \beta lnF_t^i + \mu_{t+i}$$

Route	FFA contract	α	t-value (α)	β	SE (B)	t-value (β)	Adj. R2
TC5:	FFACUR	-0.32	-1.65	1.06	0.04	1.66	0.95
	FFA+1	0.05	0.10	0.99	0.10	-0.15	0.73
	FFA+2	0.55	0.80	0.88	0.14	-0.84	0.57
	FFA+3	0.95	1.20	0.80	0.16	-1.23	0.46
	FFA+4	0.99	1.23	0.79	0.16	-1.27	0.42
	FFA+5	0.89	1.09	0.81	0.17	-1.12	0.37

Table A.6.3: *Dirty tankers: Estimation results using model 4.9 with monthly observations from 2005 to 2012. T-values are heteroskedastic and autocorrelation consistent (T-HACE). H0:* $\alpha = 0$, $\beta = 1$.

Forecasting performance of Dirty tanker FFAs using the log-linear model

$$lnS_{t+i} = \alpha + \beta lnF_t^i + \mu_{t+i}$$

Route	FFA contract	α	t-value (α)	β	SE (B)	t-value (β)	Adj. R2
TD3:	FFACUR	-0.05	-0.31	1.01	0.04	0.22	0.87
	FFA+1	0.40	0.95	0.90	0.10	-0.95	0.57
	FFA+2	0.73	1.35	0.82	0.13	-1.33	0.45
	FFA+3	1.00	1.66	0.76	0.15	-1.63	0.37
	FFA+4	1.32	1.92	0.68	0.17	-1.88	0.28
	FFA+5	1.47	2.00	0.64	0.18	-1.96	0.23
TD5:	FFACUR	-0.03	-0.22	1.01	0.03	0.16	0.92
	FFA+1	0.12	0.41	0.98	0.06	-0.37	0.75
	FFA+2	0.30	0.79	0.94	0.08	-0.73	0.67
	FFA+3	0.33	0.74	0.93	0.10	-0.68	0.62
	FFA+4	0.58	1.11	0.88	0.12	-1.04	0.52
	FFA+5	0.44	0.77	0.91	0.13	-0.72	0.51
TD7:	FFACUR	-0.22	-0.75	1.05	0.06	0.79	0.78
	FFA+1	0.00	0.01	1.00	0.10	0.04	0.61
	FFA+2	0.33	0.61	0.94	0.11	-0.56	0.49
	FFA+3	0.42	0.68	0.92	0.13	-0.63	0.44
	FFA+4	0.82	1.21	0.83	0.14	-1.17	0.33
	FFA+5	0.71	0.96	0.85	0.16	-0.92	0.31

Table A.6.4: *Dirty tankers: Estimation results using model 4.9 with monthly observations from 2005 to 2012. T-values are heteroskedastic and autocorrelation consistent (T-HACE). H0:* $\alpha = 0$, $\beta = 1$.

A.7. Forecasting using the basis model

Forecasting performance of Capesize FFAs using the basis model

$$(S_{t+i} - S_t) = \alpha + \beta(F_t^i - S_t) + \varepsilon_{t+i}$$

Route	FFA contract	α	t-value (α)	β	SE (B)	t-value (β)	Adj. R2
C3:	FFACUR	-0.39	-0.60	-0.35	0.56	-2.42	0.00
	FFA+1	-0.43	-0.22	-0.08	0.89	-1.22	-0.01
	FFA+2	-0.13	-0.04	0.33	0.84	-0.80	-0.01
C4:	FFACUR	-0.06	-0.19	0.47	0.36	-1.44	0.04
	FFA+1	0.07	0.08	0.91	0.45	-0.20	0.08
	FFA+2	0.14	0.10	0.90	0.52	-0.19	0.07
	FFA+3	0.30	0.17	1.02	0.56	0.04	0.08
C5:	FFACUR	3.32	5.78	-0.58	0.49	-3.21	0.01
	FFA+1	0.56	0.69	1.29	0.55	0.53	0.12
	FFA+2	0.63	0.59	1.07	0.42	0.16	0.08
C7:	FFACUR	-0.11	-0.32	-0.05	0.36	-2.89	-0.01
	FFA+1	-0.11	-0.10	0.07	0.59	-1.57	-0.01
	FFA+2	0.11	0.10	0.58	0.63	0.02	0.03
	FFA+3	0.51	0.29	1.01	0.61	0.26	0.08

Table A.7.1: *Dirty tankers: Estimation results using model 4.10 with monthly observations from 2005 to 2012. T-values are heteroskedastic and autocorrelation consistent (T-HACE). H0:* $\alpha = 0$, $\beta = 1$.

Forecasting performance of Panamax FFAs using the basis model

$$(S_{t+i} - S_t) = \alpha + \beta(F_t^i - S_t) + \varepsilon_{t+i}$$

Route	FFA contract	α	t-value (α)	β	SE (B)	t-value (β)	Adj. R2
P2A:	FFACUR	389.51	0.69	0.22	0.23	-3.41	0.00
	FFA+1	519.33	0.30	0.42	0.45	-1.30	0.01
	FFA+2	500.22	0.18	0.36	0.54	-1.20	0.00
	FFA+3	-186.52	-0.06	-0.92	1.00	-1.92	0.04
	FFA+4	1667.44	0.54	0.76	0.84	-0.29	0.02
	FFA+5	2652.83	0.80	0.95	0.92	-0.06	0.03
P3A	FFACUR	517.76	1.07	0.23	0.37	-2.10	0.00
	FFA+1	456.31	0.37	0.16	0.80	-1.05	-0.01
	FFA+2	366.69	0.18	0.10	0.94	-0.96	-0.01
	FFA+3	262.77	0.09	-0.09	0.84	-1.29	-0.01
	FFA+4	263.62	0.09	-0.02	0.81	-1.26	-0.01
	FFA+5	-188.87	-0.05	-0.22	0.67	-1.81	-0.01

Table A.7.2: *Dirty tankers: Estimation results using model 4.10 with monthly observations from 2005 to 2012. T-values are heteroskedastic and autocorrelation consistent (T-HACE). H0:* $\alpha = 0$, $\beta = 1$.

Forecasting performance of Clean tanker FFAs using the basis model

$$(S_{t+i} - S_t) = \alpha + \beta(F_t^i - S_t) + \varepsilon_{t+i}$$

Route	FFA contract	α	t-value (α)	β	SE (B)	t-value (β)	Adj. R2
TC5:	FFACUR	0.45	0.27	0.92	0.17	-0.48	0.42
	FFA+1	-0.89	-0.18	0.99	0.21	-0.03	0.32
	FFA+2	3.09	-0.41	0.86	0.25	-0.56	0.29
	FFA+3	-5.29	-0.57	0.91	0.33	-0.27	0.33
	FFA+4	-5.75	-0.58	1.09	0.27	0.35	0.45
	FFA+5	-3.69	-0.38	1.32	0.19	1.70	0.59

Table A.7.3: *Dirty tankers: Estimation results using model 4.10 with monthly observations from 2005 to 2012. T-values are heteroskedastic and autocorrelation consistent (T-HACE). H0:* $\alpha = 0$, $\beta = 1$.

Forecasting performance of Dirty tanker FFAs using the basis model

$$(S_{t+i} - S_t) = \alpha + \beta(F_t^i - S_t) + \varepsilon_{t+i}$$

Route	FFA contract	α	t-value (α)	β	SE (B)	t-value (β)	Adj. R2
TD3:	FFACUR	0.49	0.29	0.53	0.32	-1.48	0.12
	FFA+1	0.43	0.10	0.64	0.29	-1.23	0.16
	FFA+2	-0.37	-0.06	0.62	0.24	-1.59	0.18
	FFA+3	-1.18	-0.17	0.71	0.19	-1.59	0.23
	FFA+4	-1.14	-0.16	0.68	0.30	-1.07	0.21
	FFA+5	-0.03	0.00	0.78	0.39	-0.56	0.25
TD5:	FFACUR	0.02	0.01	0.83	0.18	-0.91	0.37
	FFA+1	0.13	0.04	0.60	0.24	-1.71	0.23
	FFA+2	0.38	0.07	0.71	0.19	-1.51	0.32
	FFA+3	0.31	0.05	0.76	0.20	-1.22	0.34
	FFA+4	0.25	0.04	0.79	0.23	-0.91	0.35
	FFA+5	3.34	0.57	0.99	0.22	-0.03	0.48
TD7:	FFACUR	7.16	1.97	0.68	0.22	-1.45	0.09
	FFA+1	8.11	1.81	0.35	0.24	-2.68	0.05
	FFA+2	6.30	1.17	0.60	0.22	-1.81	0.12
	FFA+3	6.65	1.06	0.55	0.21	-2.11	0.16
	FFA+4	5.77	0.84	0.69	0.24	-1.33	0.21
	FFA+5	6.03	0.85	0.85	0.26	-0.59	0.29

Table A.7.4: *Dirty tankers: Estimation results using model 4.10 with monthly observations from 2005 to 2012. T-values are heteroskedastic and autocorrelation consistent (T-HACE). H0:* $\alpha = 0$, $\beta = 1$.

A.8. Forecasting performance of the log basis model

Forecasting performance of Capesize FFAs using the log basis model

$$(lnS_{t+i} - lnS_t) = \alpha + \beta(lnF_t^i - lnS_t) + \varepsilon_{t+i}$$

Route	FFA contract	α	t-value (α)	β	SE (B)	t-value (β)	Adj. R2
C3:	FFACUR	0.00	0.14	-0.44	0.44	-3.31	0.02
	FFA+1	0.00	0.07	0.48	0.61	-0.85	0.00
	FFA+2	0.01	0.12	1.09	0.56	0.16	0.04
C4:	FFACUR	0.00	-0.08	0.39	0.22	-2.82	0.03
	FFA+1	-0.01	-0.25	0.72	0.30	-0.95	0.07
	FFA+2	-0.01	-0.22	0.80	0.30	-0.68	0.08
	FFA+3	-0.02	-0.23	0.75	0.28	-0.90	0.06
C5:	FFACUR	0.21	8.84	0.37	0.30	-2.07	0.00
	FFA+1	0.02	0.34	0.88	0.34	-0.34	0.06
	FFA+2	0.02	0.31	1.08	0.28	0.27	0.10
C7:	FFACUR	0.00	0.22	0.12	0.27	-3.25	-0.01
	FFA+1	0.00	0.00	0.69	0.40	-0.78	0.06
	FFA+2	0.00	0.04	0.90	0.34	-0.30	0.09
	FFA+3	0.00	0.03	0.87	0.26	-0.48	0.09

Table A.8.1: *Dirty tankers: Estimation results using model 4.11 with monthly observations from 2005 to 2012. T-values are heteroskedastic and autocorrelation consistent (T-HACE). H0:* $\alpha = 0$, $\beta = 1$.

Forecasting performance of Panamax FFAs using the log basis model

$$(lnS_{t+i} - lnS_t) = \alpha + \beta(lnF_t^i - lnS_t) + \varepsilon_{t+i}$$

Route	FFA contract	α	t-value (α)	β	SE (B)	t-value (β)	Adj. R2
P2A:	FFACUR	0.01	1.05	0.18	0.26	-3.21	0.00
	FFA+1	0.02	0.38	1.08	0.81	0.10	0.03
	FFA+2	0.01	0.08	0.31	0.47	-1.46	0.00
	FFA+3	0.01	0.07	0.43	0.45	-1.27	0.01
	FFA+4	0.02	0.23	0.74	0.47	-0.55	0.03
	FFA+5	0.04	0.35	0.92	0.55	-0.14	0.05
P3A	FFACUR	0.02	1.21	0.46	0.25	-2.17	0.06
	FFA+1	0.00	-0.01	0.54	0.49	-0.94	0.05
	FFA+2	-0.01	-0.12	0.41	0.51	-1.16	0.02
	FFA+3	-0.02	-0.19	0.47	0.47	-1.14	0.02
	FFA+4	-0.01	-0.14	0.46	0.42	-1.27	0.03
	FFA+5	-0.04	-0.26	0.73	0.48	-0.57	0.06

Table A.8.2: *Dirty tankers: Estimation results using model 4.11 with monthly observations from 2005 to 2012. T-values are heteroskedastic and autocorrelation consistent (T-HACE). H0:* $\alpha = 0$, $\beta = 1$.

Forecasting performance of Clean tanker FFAs using the log basis model

$$(lnS_{t+i} - lnS_t) = \alpha + \beta(lnF_t^i - lnS_t) + \varepsilon_{t+i}$$

Route	FFA contract	α	t-value (α)	β	SE (B)	t-value (β)	Adj. R2
TC5:	FFACUR	-0.01	-0.60	0.85	0.14	-1.09	0.34
	FFA+1	-0.02	-0.88	1.05	0.16	0.33	0.37
	FFA+2	-0.04	-0.92	0.92	0.16	-0.48	0.34
	FFA+3	-0.05	-1.06	0.96	0.24	-0.16	0.35
	FFA+4	-0.07	-1.26	1.23	0.24	0.99	0.51
	FFA+5	-0.07	-1.33	1.50	0.22	2.27	0.65

Table A.8.3: *Dirty tankers: Estimation results using model 4.11 with monthly observations from 2005 to 2012. T-values are heteroskedastic and autocorrelation consistent (T-HACE). H0:* $\alpha = 0$, $\beta = 1$.

Forecasting performance of Dirty tanker FFAs using the log basis model

$$(lnS_{t+i} - lnS_t) = \alpha + \beta(lnF_t^i - lnS_t) + \varepsilon_{t+i}$$

Route	FFA contract	α	t-value (α)	β	SE (B)	t-value (β)	Adj. R2
TD3:	FFACUR	0.00	-0.18	0.62	0.20	-1.87	0.14
	FFA+1	-0.02	-0.40	0.59	0.24	-1.71	0.14
	FFA+2	-0.03	-0.50	0.65	0.21	-1.71	0.19
	FFA+3	-0.05	-0.65	0.74	0.20	-1.30	0.24
	FFA+4	-0.05	-0.63	0.87	0.28	-0.47	0.30
	FFA+5	-0.04	-0.54	1.04	0.33	0.11	0.38
TD5:	FFACUR	-0.01	-0.54	0.79	0.14	-1.47	0.33
	FFA+1	0.00	-0.03	0.73	0.17	-1.57	0.33
	FFA+2	0.00	-0.05	0.78	0.15	-1.49	0.40
	FFA+3	0.00	-0.10	0.85	0.17	-0.90	0.43
	FFA+4	0.00	-0.09	0.94	0.19	-0.31	0.47
	FFA+5	0.01	0.21	1.13	0.18	0.72	0.58
TD7:	FFACUR	0.04	1.87	0.69	0.17	-1.81	0.13
	FFA+1	0.04	1.36	0.58	0.18	-2.32	0.18
	FFA+2	0.04	0.92	0.63	0.16	-2.26	0.24
	FFA+3	0.03	0.69	0.70	0.18	-1.61	0.28
	FFA+4	0.02	0.42	0.84	0.20	-0.78	0.34
	FFA+5	0.02	0.37	0.97	0.21	-0.14	0.41

Table A.8.4: *Dirty tankers: Estimation results using model 4.11 with monthly observations from 2005 to 2012. T-values are heteroskedastic and autocorrelation consistent (T-HACE). H0:* $\alpha = 0$, $\beta = 1$.