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Can You Hedge Ship Price Risk Using Freight Derivatives?

A Study of the Dry Bulk Market

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Abstract

This thesis investigates the possibility of reducing ship price risk in the dry bulk sector using freight derivatives. We establish a theoretical linkage between ship prices and FFA prices and empirically test this relationship. Based on this relationship, we construct a time-weighted FFA portfolio whose aim is to reflect the future operational earnings of a vessel. The static hedge ratios are calculated using the OLS model, while the dynamic hedge ratios are generated from a dynamic conditional correlation GARCH (1,1) model. We find that the hedging efficiency of an FFA portfolio on ship price risk is, in general, very good. However, there are variations among vessels of different vintages and sizes: (i) the hedging efficiency is negatively correlated with age; and (ii) the hedging efficiency is higher for the smaller vessel sizes. We also find that the static hedge ratio outperforms the dynamic hedge ratio in all ship categories. Thus, we conclude that an FFA portfolio can be used for ship price risk management in the dry bulk sector. Ship owners should apply a static hedging strategy and adjust the hedge ratio in accordance with the age and size composition of their fleets.

Preface

This thesis is written as a concluding part of our Master of Science in Economics and Business Administration, within our Major in Finance, at NHH - Norwegian School of Economics.

We would like to thank our supervisor, Roar Os Ådland, for valuable discussions and constructive feedback throughout the process. His insights in the field of maritime economics have been invaluable for the outcome of this thesis.

We hope that our thesis will prove to be interesting for its readers, relevant for market participants in the dry bulk sector and that it can serve as a basis for further research.

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1. Introduction

Due to the volatile nature of shipping markets, risk management plays an important role in this competitive industry. Volatility of ship prices has a significant impact on the market players' businesses, where ship owners, banks, investors and shipyards are affected the most (Kavussanos & Visvikis, 2006a). As ships are used as collateral in financial transactions, any changes in ship value will affect the creditworthiness of ship owners as well as the financial investors' credit risk. Volatility of ship prices affects the balance sheet of ship owners, which also impacts investors' portfolios.

Modigliani and Miller (1958) have found that, assuming a fixed investment policy and no contracting costs or taxes, a firm's corporate financing strategy is irrelevant. This implies that the firm's value is unaffected by its hedging strategy; In fact, transaction costs related to hedging actually reduce shareholder wealth. If a firm's hedging policy affects its value, it does so through taxes, contracting costs or by impacting the investment policy (Smith & Stulz, 1985). Based on this, there are several reasons why ship owners should hedge. For instance, it is a sector characterized by capital intensive investments, which suggests extensive debt financing where capital costs affect profits. Thus, creditors will reward ship owners who reduce risk through lower interest rates. Additionally, expected transaction costs of bankruptcy can be lowered through risk management since ships are used as collateral in debt financing (Smith & Stulz, 1985). Other effects, such as potential higher after-tax income[1] and lower share price volatility for public firms should also be considered. For private or family owned shipping companies especially, hedging can be a solution if the owners are not able to diversify their portfolio themselves.

One must also consider the drawbacks of futures hedging. For example, avoiding the potential loss from decreasing asset prices also implies no possible profit will be gained from market upturns. Often, such asset gains can be greater than those attained from the operation of the vessel itself, which is why many ship owners rely on vessel transactions to make a profit in this sector (Kavussanos & Visvikis, 2006a). Under such circumstances, hedging is counterproductive.

[1] Dependent on the structure of the tax code, see e.g. Smith and Stulz (1985) for further discussions.

While there exists a highly liquid and functioning futures markets for freight, interest rates and currency, as well as derivatives for bunkers, the vessel value risk in bulk shipping is the only risk that currently cannot be managed through the use of financial tools. However, this risk is perhaps the most important risk to ship owners in terms of dollar exposure (Adland et al., 2004).

Traditionally, asset diversification has been the primary tool used to manage fluctuations in the balance sheet due to volatile ship prices. Portfolios can be diversified by including ships of different sizes, ages and types. The diversification will have an effect if the prices of the different ships are not perfectly correlated. It has also been shown that smaller vessels have more flexibility over which routes to operate, and therefore their ship prices are less volatile than those of larger vessels (Kavussanos, 1996). Such fleet diversification has, however, been criticized by several ship owners, because buying and selling ships to maintain a well-diversified portfolio will be costly due to brokers' commission fees and low liquidity in the S&P market (e.g., 86 Capesize vessels were sold worldwide in 2017[2]). In addition, specialized dry bulk operators may for example not have the experience and knowledge to operate tank ships efficiently (Alizadeh & Nomikos, 2009). However, the latter case can be addressed by outsourcing both the commercial and operational activities to third-party managers.

Attempts have been made to facilitate the management of ship price risk using financial derivatives. The Forward Ship Value Agreement (FoSVA) was introduced as a cash-settled forward contract on the value of the Baltic Sale and Purchase Assessments (BSPA) by Clarkson Securities Limited in 2003 (Adland et al., 2004). Although the FoSVAs seemed appealing for hedging ship price risk, the contracts were not a success. This was partly due to both high bid/ask spreads and the fact there was no clearing mechanism, which resulted in increased credit risk (Adland et al., 2004). Additionally, marine insurers have from time-to-time tried to offer residual value insurance, but this has also been challenging to arrange.

This suggests that it is necessary to consider other financial tools for hedging ship price risk. The freight derivatives market, representing one of few radical innovations in the conservative shipping industry in the past century, started when the first freight index was

[2] Clarkson Shipping Intelligence Network

published by the Baltic Exchange in London in 1985. This market was introduced to facilitate risk management associated with freight rate fluctuations (Stopford, 2009). In the late 1990s the freight futures market became a more bespoke system of principal-to-principal traded Forward Freight Agreements (FFAs). The process of arranging such contracts is similar to the arrangement of traditional time charter contracts. However, no physical trades occur, because the contracts are settled in cash based on the difference between the contract price and the settlement for a specified quantity of cargo or type of vessel on a chosen route (or basket of routes) at a certain date in the future (Alizadeh & Nomikos, 2009). The settlement is typically the month average of the chosen index. Thus, one should enter a long position in FFAs if one believes the freight will increase beyond the contract price and enter a short position in the opposite case.

The FFA market has developed over the last 10-15 years in terms of electronic trading screens, settlement mechanisms and the fact that the percentage of cleared trades rose from 12.5% in 2006 to 99.5% in 2014 (Alizadeh et al., 2015). The practice of passing FFA trades to clearing houses has substantially reduced credit risk (Stopford, 2009). Combined with increased liquidity, the contracts are considered to be suitable tools for both speculation and hedging. A substantial amount of literature has examined the efficiency of hedging spot freight volatility using freight derivatives (e.g. Thoung & Visscher, 1990; Haralambides, 1992; and Kavussanos & Nomikos, 2000). Believing that ship prices share some market properties with expected future freight rates, since the freight rates will affect a ship's profitability, it should be possible to use freight derivatives as a cross-hedge for ship price risk.

The objective of this thesis is to study how a time-weighted portfolio of 4TC average FFAs, whose aim is to reflect the future freight income of a vessel, can be used for hedging price risk for dry bulk vessels of different ages and sizes.

This thesis contributes to extant literature in a number of ways. First, a theoretical link between ship prices and freight derivatives is established through the unbiasedness hypothesis. Second, the efficiency of hedging vessel value risk with constant and time-varying hedge ratios of an FFA portfolio in the dry bulk market is examined for the first time. Third, we compare hedging efficiency between differently aged vessels and across time periods, also for the first time. Our findings can be valuable for several market players in the shipping industry: (i) Ship owners in the dry bulk market can benefit from cost efficient risk management; this will also help them provide leverage and security against loans; (ii) investors can benefit from paper-based asset play opportunities, and non-shipping investors can gain exposure to ship values without having to buy any physical assets; (iii) shipyards can hedge against newbuilding options; (iv) providers of mortgage-backed loans with ships as collateral can benefit from security- and maturity-matching against the ship loan portfolio; and (v) asset underwriters can use our findings to construct residual value insurance products.

The remainder of this thesis is structured as follows: Firstly, we review the relevant literature on financial risk management in shipping. Secondly, we establish a theoretical model which connects ship prices with freight derivatives and test this relationship empirically. Finally, we test the hedging efficiency of freight derivatives on ship prices and present our results and concluding remarks.

2. Literature Review

The literature on second-hand ship price formation can be broadly divided into two groups. The first group uses traditional econometric techniques to explore determinants of ship prices. Strandenes (1984) explains the second-hand ship prices as the weighted average of spot freight rates and long-run expected time charter rates. She later included the newbuilding price as a long-run equilibrium price (Strandenes, 1986). Tslolakis et al. (2003) used a theoretical error-correction model to discover that second-hand ship prices are generally determined by newbuilding and timecharter rates, in most cases, both in the short- and long-run. They have also found that different ship sizes and segments react differently to changes in these variables. Haralambides et al. (2004) have further extended this supply-demand framework by also study newbuilding prices. Beenstock (1985) argues that a supply and demand framework is not sufficient for determining ship prices, as the freight market and ship market are interdependent, which implies that the markets are jointly and dynamically determined. Rather, he claims that ship prices are priced dependent on expectations since they are real capital assets, an idea that Beenstock and Vergottis (1989, 1993) have further developed.

The second group focuses on the time series properties of ship prices. Kavussanos (1996, 1997) examined the fluctuations in second-hand ship prices over time, using Autoregressive conditional heteroskedasticity (ARCH) models. Upon examining the dry bulk sector, he found that the prices of small vessels are relatively less volatile than for larger ones. He argues that this is because larger ships operate in narrower markets, while smaller ships can serve more varied trades.

Similar to other commodities, the literature on freight derivatives has examined the price discovery and the unbiasedness of FFAs in relation to realized spot rates. Kavussanos and Nomikos (1999) have found that futures prices (one and two months before maturity) provide unbiased forecasts of the realized spot rates. Kavussanos et al. (2004) later conclude that the validity of an unbiasedness hypothesis depends on market characteristics, trade routes and the contract's time to maturity.

While much of the literature has examined freight rates as an explanatory variable for ship prices, the development of econometric techniques enables one to study the relationship between the two variables. The Engle-Granger two-step method (Engle & Granger, 1987) and the Johansen test for co-integration (Johansen, 1988, 1991) are both widely used for co-integration analyses in shipping. Alizadeh and Nomikos (2007) have established a theoretical relationship between the prices of 5-year-old ships and time charter rates based on the discounted present value model. They tested this co-integration relationship in the dry bulk sector using the Johansen's (1988) reduced rank co-integration technique, and established a relationship for vessels of all sizes. They later found that this co-integration relationship also applies for second-hand ship prices and freight derivatives rates (Alizadeh & Nomikos, 2012).

Hedging is extensively covered within the literature. At one point, the most common approach was to take a negative position in the futures market[3] equal to the exposure in the spot market, and it is applied and described in many studies, such as Stevens (1976). One substantial weakness associated with this procedure is, however, the implicit assumption that the changes in the spot- and futures position are equal in magnitude, i.e. that the variables are perfectly correlated (Heifner, 1972).

Influenced by the work of Johnson (1960) and Stein (1961), among others, Ederington (1979) presented a framework for finding the minimum variance portfolio and assessing hedging efficiency. He found that by minimizing the variance of a portfolio consisting of spot and futures positions, the variance would be substantially lower than if the traditional approach was implemented. In other words, Ederington solved the problem of not having perfectly correlated spot and futures positions by letting the hedge ratio deviate from one.

The framework proposed by Ederington (1979) later received some criticism. Kroner and Sultan (1993) have argued that the implicit assumption of constant variance in spot and futures prices might be incorrect in many instances, which in turn may lead to problems related to the risk-minimizing properties of a hedge ratio calculated using Ederingtons procedure. They proposed estimating dynamic (or time-varying) hedge ratios; This allows the variance to change over time. While a vast amount of literature examines the different models that can be used for calculating dynamic hedge ratios, generalized autoregressive conditional heteroskedasticity (GARCH) models - introduced by Bollerslev (1986) based on

[3] Often referred to as the naïve or traditional hedging approach.

Engle´s (1982) ARCH-model - appears to be the preferred method, and it has been used by Kavussanos and Visvikis (2008) and Chang et al. (2011), among others.

Using the aforementioned hedging techniques, several studies have examined hedging efficiency in shipping markets. Thuong and Visscher (1990) estimated the hedging efficiency of the BIFFEX freight futures contract using the Minimum Variance Hedge Ratio (MVHR) and found lower efficiency than had previously been found in other commodity markets. However, they examined a short period of time with low fluctuations in the freight rates, which could affect the hedging efficiency. Haralambides (1992) later discovered that the MVHR leads to better hedging efficiency than a naïve hedge. Kavussanos and Nomikos (2000) examined the hedging efficiency of futures in reducing the riskiness of spot positions using time-varying hedge ratios. They found that the risk reduction achieved was lower than for other commodity markets. This may be due to the fact that the freight rate futures contracts they applied, settled against an index of freight routes (Baltic Freight Index), are used as a cross hedge against fluctuations in the individual shipping routes.

The basis risk in freight market hedging has been quantified by Adland and Jia (2017), who illustrated that the physical basis risk never disappears, even for large fleets. Alizadeh et al. (2004) studied the efficiency of hedging marine bunker price fluctuations using different crude oil and petroleum futures contracts; Using both static and dynamic hedge ratios, they found the cross-market hedging efficiency to be low compared to other markets. Research on the financial management of vessel value risk is lacking within the extant literature. Alizadeh and Nomikos (2012) studied the efficiency of hedging ship price risk using FFAs in the dry bulk sector. Their results suggest quite sound hedging performance, thus creating opportunities for further research on the subject.

However, there are some gaps in Alizadeh and Nomikos' (2012) study. Using a single second-calendar FFA contract is not in accordance with the aforementioned literature on ship price formation, which states that ship prices are a time-weighted average of future earnings (e.g., Strandenes, 1984; Kavussanos & Visvikis, 2006a). Furthermore, they only considered the static hedge strategy, which is a limitation compared to other hedging literature. Additionally, since they only examined 5-year-old vessels, their results are not relevant for ship owners with an age-diversified fleet.

The hedging efficiency of freight derivatives portfolios, which aim to match the stream of profits from a vessel's operations, has not yet been investigated for ship price risk management within the maritime literature. Thus, our thesis aims to fill this gap. Furthermore, we examine both the static and dynamic hedging efficiency of ship price risk for the first time. Since we examine vessels with a variety of ages, our thesis contributes to price risk management of age diversified fleets. Firstly, we establish a theoretical relationship between ship prices and FFA prices through the discounted present value model using the unbiasedness hypothesis. Secondly, examining the dry bulk second-hand ship market, we test this relationship empirically using the Engle and Granger (1987) co-integration framework. Thirdly, we compute the hedging efficiency for both static and dynamic adjusted ratios of the FFA portfolio on ship price risk.

3. Theory

3.1 Ship Prices

The second-hand shipping market is a well-functioning market that facilitates easy investments opportunities as well as exit pathways for shipping-investors. In this market, ships worth tens of millions of dollars are traded, according to Stopford (2009, p.198), “like sacks of potatoes at a country market”. It is a market that thrives on volatility, which causes investors to seek profits from asset play. According to Stopford (2009), four factors influence the price of a vessel: freight rates, age, inflation and ship owners’ expectations for the future. In order to value a ship, one must account for all of these four factors. Any vessel can be priced according to the sum of the present value of the expected cash flows from operating the ship and the expected discounted scrap value received when the ship is obsolete (Kavussanos & Visvikis, 2006a). Thus, the freight rate and age are considered in the future cash flows, while inflation and ship owners’ expectations are taken into account in the discount rate. The remainder of this chapter establishes the theoretical valuation model and considers what drives changes in ship prices.

Ship owners measure the rate of return on their investments, and only invest in vessels if they can expect at least as much return from the vessel as from alternative investments. For a ship owner, earnings comprise the capital gain and the return from operation of a ship. Thus, the following equation can determine the expected return:

$$E_t(r_{t+1}) = \left(\frac{E_t(P_{t+1}) - P_t + E_t(\Pi_{t+1})}{P_t}\right) \tag{1}$$

where $E_t(r_{t+1})$ is the expected one period return, $E_t(P_{t+1}) - P_t$ is the expected gain on asset and $E_t(\Pi_{t+1})$ is the expected profits from operations. Used differently, the same variables create the mathematical expression for ship price, P_t:

$$P_t = \left(\frac{E_t(P_{t+1}) + E_t(\Pi_{t+1})}{1 + E_t(r_{t+1})}\right) \tag{2}$$

where the ship price is now explained as the present value of the expected ship price in the next period, plus the operational profits in the next period, all discounted by the expected rate of return. Since this formula holds for every period, the price at t can be written as the sum of all discounted future operational profits and the discounted residual value of the ship:

$$P_t = \sum_{i=1}^{n} \frac{E_t(\Pi_{t+i})}{(1+r_i)^i} + \frac{E_t(P_{t+n}^{RES})}{(1+r_n)^n} \tag{3}$$

where $E_t(P_{t+n}^{RES})$ is the residual value in the last period, which could be the resale price or demolition value, and the discount rate, r_i, is the rate of return demanded by the investor for holding the asset; which should reflect the uncertainty of both the future profits and the residual value generated by the ship. If the discounted cash flows and the residual value are lower than the observed market price, it is more profitable to charter vessels than buy them. However, if the market price is lower than the future cash flows discounted, then an investor should buy the ship.

Having introduced a model for ship price formation, we now examine the components of Equation (3) in greater detail to discover the main factors that result in the high volatility observed in ship prices.

Income is one of the factors that determine the level of the operating profit component from Equation (3). Vessels generate income by transporting cargo and therefore, the level of income depends on the achieved freight rate. Since a ship's price depends on the discounted future expected income, changes to the expected future freight rates lead to changes in ship prices. According to Kavussanos and Visvikis (2006a), freight income is the largest contributor to cash flows from operating vessels.

Freight rates are widely known to be volatile (Alizadeh & Nomikos, 2011). This phenomenon can be explained by the characteristics of the freight market. Freight rates depend on the relationship between supply and demand (Stopford, 2009). Demand in this market is driven by various factors, most importantly the economies of the commodities transported, overall world economic activity, and related macroeconomic variables of major economies (Stopford, 2009). Due to the fact that these aforementioned variables are hard to predict, the demand for shipping services is inherently uncertain and volatile (Kalouptsidi, 2014). Demand is quite inelastic, stemming from a lack of convenient substitutes for ocean freight (Alizadeh & Nomikos, 2011). Furthermore, within this market, supply depends on several factors, such as the number of available vessels, scrapping rates and freight rates

(Stopford, 2009). The supply curve is widely recognized as convex (Alizadeh & Nomikos, 2011), implying that the supply is elastic until the world fleet is fully utilized, at which point it becomes quite inelastic due to the time it takes to order and build a new vessel. An inelastic and volatile demand combined with slow and inaccurate supply adjustment leads to volatile freight rates, as illustrated in Figure 1.

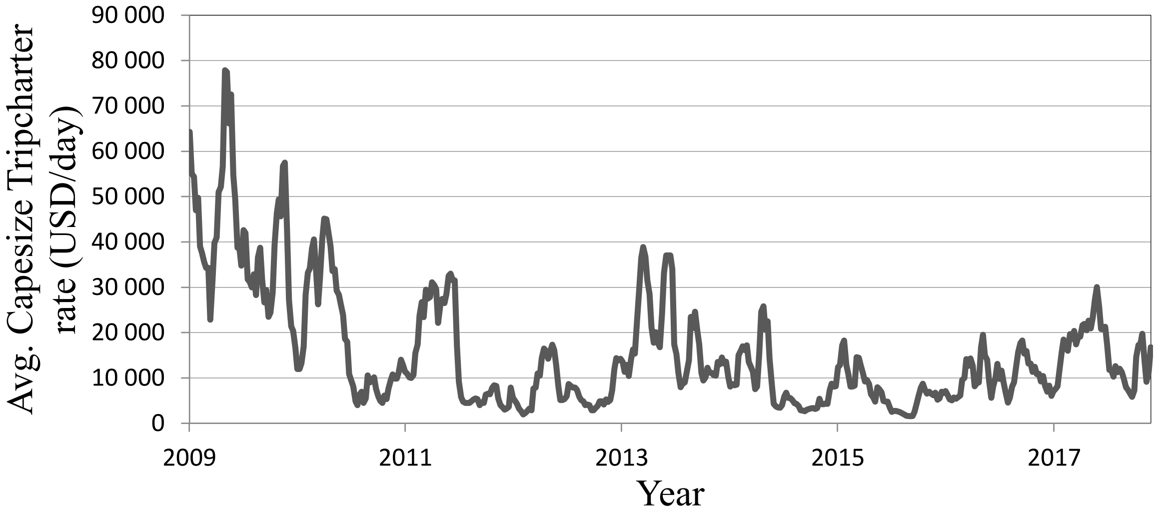

Figure 1*- Average Capesize Tripcharter rate*[4]

Ship prices also depend on the expected level of costs. Costs are incorporated through the operating profits component in Equation (3). Ship owners face different costs associated with owning, maintaining and operating vessels. Alizadeh and Nomikos (2009) have divided cost into four categories: capital costs, operating costs, voyage costs and cargo-handling costs. The following paragraph explores the latter three categories; Capital costs are assessed later in the chapter.

All else equal, we would assume, considering Equation (3), that increased expected costs would result in lower ship prices and vice versa. However, the effect of increased costs depends on the elasticities of supply and demand (Beenstock & Vergottis, 1993). If the demand curve is perfectly inelastic, freight rates will increase at a rate equal to the change in costs. Although the demand curve is not perfectly inelastic in the dry bulk market (Alizadeh & Nomikos, 2011), it is reasonable to assume that changes in costs will be largely offset by changes in freight rates. Hence, changes in costs will have little impact on the ship price.

[4] Average of spot Tripcharter rates for several routes. Source: Clarkson Shipping Intelligence Network

Ship prices are also affected by changes in the scrap value, which in turn depends on the steel price, as well as the supply and demand of scrap (Stopford, 2009). Ship owners want to demolish their vessels when the scrap price is greater than the net present value of expected operational profits, plus the discounted future expected scrap price. Scrap prices fluctuate widely and are almost as volatile as second-hand ship prices (Stopford, 2009). The scrap value's importance for the total ship price depends on the age of the vessel and the state of the freight market. One would assume that scrap price fluctuations would influence the ship prices of older vessels more than newer vessels. The rationale is that the residual value comprises more of the value, for instance, for a 20-year-old vessel than for a 5-year-old vessel, as illustrated in Equation (3). Furthermore, during recessions, scrap value tends to constitute more of the total value of the ships. For example, during the boom that occurred between 2005-2008, the scrap value amounted to 16% of the total value for a 15-year-old Capesize vessel, while, in 2014, during the recession, the scrap value amounted to almost 50% of the total value (Clarkson Research, 2016). It is plausible that freight futures and scrap value are correlated to some extent due to certain similar underlying drivers, such as economic growth. However, it is most likely more efficient to hedge this price component using steel futures.

Ship prices are sensitive to the discount factor (Alizadeh & Nomikos, 2012). Since it depends on such factors as the market premium, the equity beta, the risk-free rate and the cost of debt, it is quite clear that it will vary over time (Miles & Ezzell, 1980). However, it is reasonable to assume that these variables adjust quite slowly (Campbell & Viceira, 2005). Hence, they cannot be the cause of the sudden fluctuations we observe in ship prices. However, over a longer period of time, changes in the discount factor might indeed cause changes to ship prices.

To summarize, we find that ship prices are affected by changes in several variables, such as freight rates, scrap value and the weighted average cost of capital. However, as the freight rates are the main contributor to cash flows and the most volatile variable, we argue that changes in ship prices are primarily caused by changes in the expected freight rates.

3.2 Forward Freight Agreements

To use FFAs to hedge ship price risk, one must first establish a theoretical linkage between FFA prices and ship prices. In the above discussion, we concluded that expected freight rates are the main explanatory variable for ship prices. Therefore, we now discuss whether FFAs can be used as a proxy for a vessel's expected freight income.

While the relationship between the spot and futures prices of continuously storable commodities is based on a no-arbitrage argument, this cost-of-carry relationship does not hold for the non-storable freight service (Kavussanos & Visvikis, 2006a). As a result, the interdependence between spot freight rates and FFA rates may not be as strong as for storable commodities (Kavussanos & Visvikis, 2006b). However, Kavussanos and Visvikis (2006b) have noted that the relationship between spot freight rates and FFA rates is described through the following relationship:

$$F_{t,t+i} = E_t(S_{t+i}) \tag{4}$$

where $F_{t,t+i}$ is the current price of an FFA with expiration t+i and $E_t(S_{t+i})$ is the expectation formed at t of the future spot rates at expiration of the forward contract. Kavussanos and Visvikis (2006b) further argue that this relationship's validity depends on how precisely expectations are formed in the market. Assuming rational expectations, i.e. that it is not possible to forecast the expectation error with the information given when the expectation is formed, they state the relationship as follows:

$$F_{t,t+i} = E_t(S_{t+i}) + u_t; \quad u_t \sim iid(0, \sigma^2) \tag{5}$$

where u_t is an independent and identically distributed stochastic term with a zero-mean and variance σ^2. According to this unbiasedness hypothesis, futures prices must be unbiased estimators of the future spot freight rates (Kavussanos & Visvikis, 2006b). As follows, futures prices help discover future spot prices if the relationship in Equation (5) is verified with actual data (Kavussanos & Visvikis, 2006b).

A large quantity of research has examined whether FFAs are unbiased predictors of future spot rates or not. Kavussanos et al. (2004) studied whether the unbiasedness hypothesis persists. They have found that the co-integrating relationship between spot freight rates and FFA prices reveals that the unbiasedness hypothesis holds for FFA prices one and two months prior to maturity for all routes investigated. For longer contracts, however, the results were dependent on the routes. Alizadeh and Nomikos (2009) have determined that the directional accuracy of forward rates is at reasonably sound levels.

The difference between the physical and the "paper" traded FFA freight market is also of interest for the discussion of whether FFA can be used as a proxy for freight rates. Alizadeh and Adland (2018) have determined that while time charter rates and FFA prices are co-integrated, time charters are generally priced higher than FFAs. They have also noted that this difference may be caused by compensating for credit risk in the time charter market and convenience yield; due to the fact that the physical contract provides access to transportation. However, in this thesis we assume that the FFA rates are unbiased predictors of future expected spot freight rates, allowing us to replace the freight rates in Equation (3) with the FFA prices as follows:

$$P_t = \sum_{i=1}^{n} \frac{F_{t,t+i}}{(1+r_i)^i} + \frac{E_t(P_{t+n}^{RES})}{(1+r_n)^n} \tag{6}$$

From Equation (6) one can observe that forward rates should have significant impact on ship prices, since the ship price are discounted prices of FFAs with consecutive maturities, a correlation which has been confirmed by Alizadeh and Nomikos (2009). This relationship confirms the hypothesis that FFA contracts appear to be an appropriate tool for hedging vessel value risk.

From a hedger's point of view, according to Equation (6), the ideal strategy for a ship owner would be to short sell an FFA portfolio with duration equal to the remaining lifetime of the vessel. Optimally, the loss following reduced ship prices will be neutralized by the gain from the FFA portfolio, and vice versa. However, a practical constraint is that FFAs are only available with relatively short maturities. Thus, any time frame longer than two years is not feasible or is associated with high transaction costs (Alizadeh & Nomikos, 2012). This thesis applies a fixed maturity portfolio with duration equal to two years. Despite two years being a relatively short time horizon with respect to a vessel's lifetime, it may be a good approximation due to the characteristics of the freight market.

Freight rates are widely considered to exhibit mean reverting properties; unlike other financial assets that follow a random walk (Adland & Cullinane, 2005). The dry bulk market is among the most competitive markets (Stopford, 2009). As a consequence, due to supply-side adjustments, very low and very high freight rates will not persist in the long-run (Koekebakker et al., 2006). Long-run equilibrium freight rates will be linked to the marginal cost faced by shipowners. The mean reverting freight rates ensure that the long end of the forward curve will be quite stable, leading the nearest contracts to be more volatile than those further away (Alizadeh & Nomikos, 2009). In other words, there is more uncertainty associated with the near contracts than the far contracts, as the latter are more tightly linked to the stable long-run expected freight rate.

However, the speed at which the freight rates are mean reverting is also relevant for assessing the theoretical appeal of the two-year fixed maturity portfolio. Faster mean reverting properties should yield higher hedging efficiency, as the two-year portfolio would capture more of the volatile portion of the forward curve. High freight rates trigger orders for new vessels, and the speed of the mean reverting process is consequently linked to the delivery lag, which is usually between 18 and 36 months (van Dellen, 2011). On the other hand, low freight rates lead to scrapping of existing tonnage. However, due to the long potential technical life of a vessel, it might take some time before freight rates return to the long-run average (Tvedt, 2003).

Based on the previous discussion, one can argue that, due to the volatility characteristics of the forward curve and the speed of the mean reversion process, the next two years of the forward curve will capture most of the volatility. Hence, we argue that the two-year fixed-maturity portfolio is a good approximation.

3.3 Hedging

This thesis aims to find static and dynamic hedge ratios, and in the following section we will lay the theoretical groundwork for calculating the optimal ratios and their performance in variance reduction. Hedging is commonly understood as an approach toward minimizing or removing the risk of price fluctuations. We adapt this definition, and the objective of the hedging conducted in this thesis will be to minimize variance.

Ederington (1979) proposes a framework for finding the optimal static hedge ratio. By using this theory, we consider a portfolio of ship holdings with value X_P and FFA portfolio holdings of X_F, where $b = -X_F / X_P$ is the proportion of the ship position that is hedged with futures contracts. The hedge ratio that minimize the variance of the returns of the total portfolio is:

$$b^* = \frac{\sigma_{PF}}{\sigma_F^2} \tag{7}$$

where b* is the portfolio variance minimizing ratio, σ_{PF} is the covariance of ship prices return and FFA portfolio returns and σ_F^2 is the subjective variance of the FFA portfolio returns. Additionally, Ederington (1979) has shown that the hedging efficiency, i.e. the reduction in variance achieved by holding the hedged portfolio rather than the unhedged, is found by:

$$e = \frac{\sigma_{PF}^2}{\sigma_P^2 \sigma_F^2} = \rho^2 \tag{8}$$

where e is the reduction in variance, σ_P^2 is the subjective variance of the spot returns and ρ^2 is the population coefficient of determination. Ederington (1979) used the sample variances and sample covariances to examine the efficiency of hedging with futures contracts, which we in this thesis will determine using the Classic Linear Regression Model. While the optimal hedge ratio is set ex post, the hedging efficiency is a measure of the futures potential for reducing risk. This variance reduction is only achieved if the hedge ratio used equals the optimal hedge ratio ex post. This proposes a problem for hedgers who need to decide their hedge ratios ex ante. We test the robustness of the estimates by conducting an out-of-sample test, i.e. to test whether the optimal hedge ratio from one period performs well in the subsequent.

From Equation (7) one can see that the optimal static hedge ratio requires both the variance and the covariances to be constant over the examined time period. However, time-varying volatility is a common phenomenon in financial time series (Bollerslev et al., 1992). Kavussanos (1996) has found both freight rate volatilities and ship price volatilities to be time-varying. The optimal hedge ratio will also fluctuate if the volatility is time-varying.

Dynamic hedge ratios represent an approach for addressing the problem of time-varying volatility. Baillie and Myers (1991) note that the optimal dynamic hedge ratio, the ratio of spot to futures that minimizes the conditional variance of the hedged portfolio returns, is as follows:

$$b_{t-1} = \frac{Cov(\Delta P_t, \Delta F_t | \Omega_{t-1})}{Var(\Delta F_t | \Omega_{t-1})} \tag{9}$$

where b_{t-1} is the optimal hedge ratio conditional on the information available at time t – 1, $Cov(\Delta P_t, \Delta F_t | \Omega_{t-1})$ is the conditional covariance of ship prices returns and futures returns and $Var(\Delta F_t | \Omega_{t-1})$ is the conditional variance of futures returns. Compared to the optimal static hedge ratio in Equation (7), the only difference is that the covariance and variance are conditional on information available at t – 1, thus the hedge ratio is set every period and is dynamic. We use the time-varying hedge ratio to construct a hedged portfolio. For comparison with the static strategy, we use the following measure of hedging efficiency, E, derived by Ederington (1979):

$$E = \frac{\sigma_u^2 - \sigma_h^2}{\sigma_u^2} \tag{10}$$

where σ_u^2 is the variance of the unhedged portfolio returns, i.e. the return of the ship price index, and σ_h^2 is the variance of the returns of the hedged portfolio.

4. Data & Methodology

4.1 Data

The data set consists of weekly ship prices and FFA prices between January 7th, 2005 and December 30th, 2016, all of which were collected from the Clarkson Shipping Intelligence Network and the Baltic Exchange, respectively. This time frame has, to the best of our knowledge, not previously been used for this purpose. We study Capesize (180,000 dwt), Panamax (75,000 dwt) and Handymax (55,000 dwt) vessels.

The ship price index is based on Clarkson's best estimate of the price that a standard[5] generic ship would have obtained in the market. Hence, the procedure relies heavily on Clarkson's subjective assessment and may, therefore, be subject to measurement errors. Adland and Koekebakker (2007) argue that the index does not always react to changes in market fundamentals. They suggest that this may be due to a combination of low transaction volume during certain periods and the brokers' reliance on the last deal done. The stickiness may lead to a lower correlation between the variables, which in turn will lead to lower hedging efficiency.

Despite the limitations related to this assessment technique, it appears to be the best attainable method. In other markets, the indexes are usually derived directly from the most recent transactions. However, there are several reasons why this method is suboptimal for use in the second-hand ship market. First, a transaction can take months to complete (Stopford, 2009). Hence, the agreed terms of the most recently announced transactions may be based on old information and, consequently, not reflect the state of the current market. Secondly, as a consequence of the relatively modest amount of transactions and the heterogeneous characteristics of the vessels, there may be long periods in which there are no relevant transactions at all.

[5] Standard ship in average condition, built at "first class competetive" Far East or European shipyard.

Table 1 *- Components of the Baltic average 4TC contracts for Capesize and Panamax vessels.*

Route	Size (dwt)	Description	Weights
4TC Capesize			
C8 03	172,000	Delivery Gibraltar to Hamburg range for transatlantic round voyage.	25%
C9 03	172,000	Delivery Continent Europa to Mediterranean for a trip to the Far East.	25%
C10 03	172,000	Delivery China to Japan range for a transpacific round voyage.	25%
C11 03	172,000	Delivery China to Japan range for a trip to European continent and the Mediterranean.	25%
4TC Panamax			
P1A 03	74,000	For a transatlantic round delivery and redelivery Skaw-Gibraltar range.	25%
P2A 03	74,000	Delivery Skaw-Gibraltar range, for a trip to the Far East, redelivery Taiwan-Japan range.	25%
P3A 03	74,000	Transpacific round either via Australia or the Pacific, delivery and redelivery Japan/South Korea range.	25%
P4A 03	74,000	Delivery Japan-South Korea range for a trip via US West Coast-British Columbia range or Australia, redelivery Skaw-Passero range.	25%

Source: The Baltic Exchange (2011)

The FFA portfolio price series is constructed using the 4TC average contracts. We use the Friday closing prices. If a Friday closing price is for some reason not reported, we apply the Thursday closing price. The 4TC contracts are based on an average of four key routes in the relevant sub-market (Table 1). These contracts are chosen for two reasons. Firstly, these are the most traded FFA contracts and are therefore the most liquid (Alizadeh et al., 2015). Liquidity is an important consideration in hedging, and necessary to trade large quantities quickly, at low cost and with little price impact (Alizadeh et al., 2015). Secondly, it seems plausible that the average of several routes has higher correlation with the vessel price than would one specific route, as the rate for one route can be affected by local conditions. The Capesize contracts are used as a hedging tool for the Capesize vessels, while the Panamax contracts are used for both Panamax and Handymax vessels, as the two latter sub-markets are more similar in terms of size and market characteristics (Stopford, 2009). Handymax FFAs are not considered in this thesis due to low liquidity (Kavussanos & Visvikis, 2006a).

We construct the two-year fixed maturity FFA portfolio by weighting each contract in accordance to number of days in the delivery period of the contract, in line with the method used by Alizadeh and Adland (2018). We adjust the weight of the nearest contract to be the days left of the current quarter[6]. Likewise, the farthest contract is weighted such that the total hedging period at any time equals two years. For instance, on the 3rd of February 2012 the

[6] We acknowledge that it may not be easy to exactly replicate this day-weighted portfolio, since FFAs in practice are traded in multiples of 5 days (Alizadeh and Adland, 2018). However, we believe that this will have minor implications for our analysis.

FFA portfolio is constructed as [(Q1x58 + Q2x90 + Q3*90 + Q4*90 + CAL13*365 + CAL14x33)/730][7]. The portfolio composition and weights are attached in Appendix 1.

Holding this fixed maturity portfolio, the freight income of a ship is fixed for exactly the next two years at any point in time. Previous literature (e.g. Alizadeh & Nomikos, 2009) has examined seasonal effects within the freight market, which would impact the portfolio. However, since yearly returns are used in this thesis, the same time of the year is always compared. Consequently, seasonal effects are not considered to be a problem.

Observations of the data indicate that the price of the FFA contracts often fluctuates significantly when the delivery period of the contract changes. This is also observed in other studies such as that by Kavussanos and Nomikos (2000). However, as we are holding a dynamically updated portfolio, the majority of the contracts will be rolled over far ahead of maturity (as illustrated in Appendix 1). The exception is the current quarter contract, which will be held until maturity. Nevertheless, we argue that the total effect on the FFA portfolio is negligible, due to the slight importance of this contract for the overall performance of the portfolio. Consequently, we decide not to make any adjustments.

One should consider the basis risk, which is defined to be the risk of deviation between the revenue stream being hedged (i.e., the return on the actual ship) and the revenue stream from the hedging instrument (i.e., the return on the FFA portfolio) (Adland and Jia, 2017). When hedging ship prices using freight derivatives, the cross-hedge risk will be the most important basis risk. Cross-hedge implies that the hedge instrument and the hedge object do not have the same underlying asset, which is the case when hedging ship price risk using freight derivatives. There is also risk of deviation between the actual ship hedged and the ship price index used in our model; when hedging a ship with different technical specifications than the standard vessels in the ship price index, the hedging efficiency might vary from the efficiency achieved by our model[8]. This basis risk could however be reduced when hedging

[7] Where Q1 is the FFA price for the first quarter of 2012, Q2 is the FFA price for the second quarter of 2012, Q3 is the FFA price for the third quarter of 2012, Q4 is the FFA price for the fourth quarter of 2012, CAL13 is the FFA price for 2013 and CAL14 is the FFA price for 2014.

[8] Adland and Jia (2017) argue that the technical specifications of the vessel is one of the most important sources of physical basis risk in freight market hedging.

a larger fleet of ships, since the average vessel of the fleet will likely move towards the standard vessel specified in the index[9].

Additionally, Alizadeh et al. (2015) have suggested that the performance measurements of FFA portfolios should also consider the transaction cost, especially if the portfolio specifications require frequent trading. Thus, bid-ask spread level should be incorporated. However, this would only marginally affect the static hedging strategy, since it requires less frequent portfolio adjustments; The effect would be greater for the dynamic adjusted portfolio.

4.2 Descriptive Statistics

Table 2 summarizes statistics for the 4TC average contracts used in the Capesize FFA portfolio, as well as the total portfolio. The tendencies are similar for the Panamax contracts, which can be found in Appendix 2. The nearest contracts are more volatile than contracts for away, a pattern known as "volatility term structure" (Alizadeh & Nomikos, 2009). This finding is in accordance with extant literature[10], and can be explained by the expected mean reverting properties of the spot freight rates. In other words, there is more uncertainty associated with the near contracts than the far contracts, as the latter is tighter linked to the stable long-run expected freight rate. The forward curve is on average backwardated, meaning that the mean charter price seems to decline with increased time distance to contract. This indicates that, over the examined time period, the market tends to anticipate lower future spot rates (Alizadeh & Nomikos, 2009).

[9] A result found in freight market hedging by Adland and Jia (2017).

[10] Adland and Cullinane (2005), Alizadeh and Nomikos (2011) among others.

Table 2 *-Descriptive statistics of the 4TC average Capesize contracts*

	Current quarter	First quarter	Second quarter	Third quarter	First calendar	Second calendar	FFA portfolio
Mean ($)	38580	36870	34567	32653	31168	26183	31190
St.dev levels	43075	40229	36840	32692	29706	18660	28847
Min	760	2975	3810	3710	6266	7900	5983
Max	213375	175938	166281	147524	143750	96961	132240

Table 3 summarizes the descriptive statistics for ship prices. As expected, younger vessels are more expensive than older vessels, with mean prices varying between USD 18.67 million for a 20-year-old vessel and USD 57.94 million for a 5-year-old vessel. The price reduction from the newest to the oldest ships seems to follow a linear depreciation. Interestingly, there is a small difference between the minimum price of the 15- and 20-year-old vessels. This may be the result of the least efficient vessels, often the oldest ones, being sent to scrap when freight rates are low, due to negative cash flow from operations (Stopford, 2009). The ship value, for older vessels, may then primarily be determined by the scrap value, which is less dependent on a ship's age.

Table 3 *- Descriptive statistics of ship prices and annual returns*

	Capesize				Panamax	Handymax
	5-year	*10-year*	*15-year*	*20-year*	*5-year*	*5-year*
Mean ($m)	57.94	41.74	29.37	18.67	34.68	30.40
Return	-0.064	-0.068	-0.075	0.023	-0.055	-0.052
Min	23	12	7	6	13	12
Max	156	116	92.5	70	92	75
St.dev return	0.376	0.446	0.482	0.547	0.396	0.364
Corr. FFA						
Level	0.964	0.956	0.967	0.942	0.971	0.970
Returns	0.909	0.919	0.918	0.812	0.942	0.928

Corr.FFA denotes the correlation between the ship prices and the FFA portfolio.

Table 3 shows that the weekly return of younger vessels is less volatile than that of older vessels. Thus, it appears that volatility is positively correlated with the age of the vessel. Equation 3 shows that the prices of older vessels will, by definition, be more influenced by the current freight market conditions than the prices of younger vessels. Having previously established that the prices of near contracts are more volatile than the prices of far contracts, due to the mean reverting characteristics of the freight market, this finding was expected.

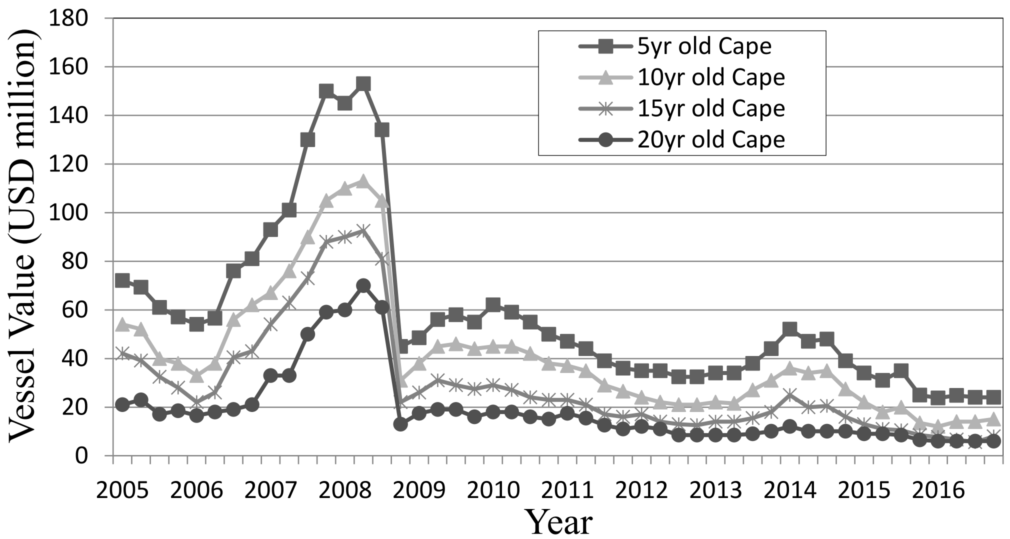

Figure 2 *- Ship prices for Capesize vessels*

Figure 2 depicts the movements in ship prices of differently aged Capesize vessels between 2010-2016. All of the vessels were most expensive in late 2008, followed by a collapse during the financial crisis. Subsequently, the ship prices continued to decrease until 2016, interrupted by some increases, where they reached the lowest prices in the examined time period.

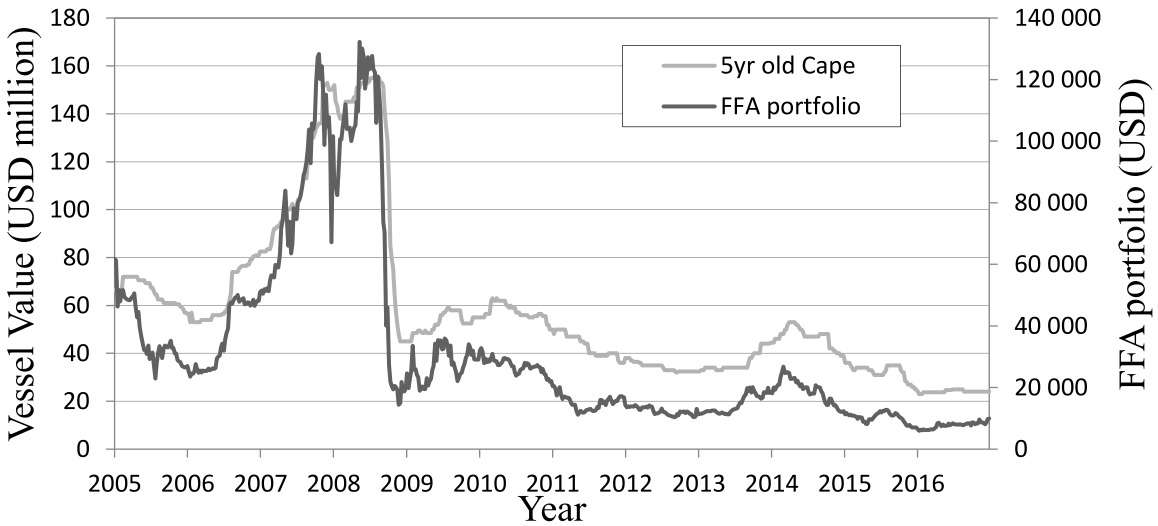

Figure 3 *- Comparison between movements in 5-year-old Capesize vessel and FFA portfolio*

From Figure 3 it can be observed that the correlation between ship prices and the FFA portfolio seems to be high in levels. Nevertheless, the portfolio appears to fluctuate more than the ship price index. There are two reasons for this. Firstly, the mean reverting property of spot freight rates indicates that long-term freight rates will vary less. Equation (3) states that ship prices are determined by all future cash flows over the ship's economic life discounted, which indicates that long-term equilibrium freight rates should be able to explain a large portion of the ship prices (Strandenes, 1984). Thus, the price of the 2-year FFA portfolio should be more volatile. Secondly, it may be due to low transaction activity in the S&P market, which may cause the index to not capture every price movement. This is in accordance with the discussion of the ship price index construction discussed in section 4.1.

4.3 The Estimation Models

The regression model used for estimating the static hedge ratios is as follows:

$$\Delta P_t = \alpha + \beta \Delta F_t + \varepsilon_t \tag{11}$$

where ΔP_t is the percentage return of vessels between t-52 and t, α is the constant term, β is the slope coefficient and ΔF_t is the percentage return on the FFA portfolio between t-52 and t. Yearly returns are used for two reasons: First, because the weekly and monthly FFA returns have a low correlation with the corresponding returns for ship prices. As previously noted, this can to some extent be explained by the stickiness observed in the ship price index, as well as other factors. Secondly, this is in accordance with the method applied by Alizadeh and Nomikos (2012).

Considering the ship price time series, one must be cautious when calculating yearly returns. When brokers value ships, they typically write down the ship price to scrap value linearly over 25 years (Adland et al., 2004). A ship owner who wants to hedge a 5-year-old vessel does not hold a dynamic updated portfolio of 5-year-old ships, but a physical asset that ages every year. Thus, we write off the vessel with an appropriate one-year amount over each return period.[11]

Another problem with using yearly returns for weekly observations is that it creates a moving average of the error term. This implies that the models may not be suitable for determining hedging efficiency, as the standard errors and R^2 can be biased. A simple solution to this problem is to use yearly non-overlapping observations for both ship prices and portfolio prices. This would however, lead to very few observations over the selected

[11] The 1-year depreciation is calculated by dividing the price difference between a 5- and a 10-year-old vessel by five at each point in time. For the 10-year-old ships, the price difference between 10- and 15-year-old ships is used and so on.

period. To overcome the problem of overlapping observations, the stationary bootstrap technique of Politis and Romano (1994) is used. This is in accordance with Alizadeh and Nomikos (2012). This technique involves resampling blocks of the original observations with replacement to regenerate new series of random paths that ship prices and FFAs could have followed during the last year, while still maintaining the serial dependence property of the original series (Politis & Romano, 1994). Then, we use these series to calculate yearly percentage returns for ship prices and FFAs. By doing this 10,000 times we are able to generate 10,000 non-overlapping returns for both series. Finally, we use the regression model (Equation 11) to estimate the hedging efficiency and hedge ratio. The algorithm used to generate the series can be found in Appendix 3, as well as the results. The results indicates that the problem of overlapping returns is not too comprehensive, as the hedge ratio and hedging efficiency does not deviate too much from the regressions with the original data. This is in accordance with the findings of Alizadeh and Nomikos (2012). Hence, our results appears to be robust to model misspecifications.

We estimate the model using OLS. The slope coefficient obtained by the OLS regression is the variance minimizing hedge ratio from Equation (7). The hedging efficiency is found by the regression's R^2. Because these are trending markets, we expect the serial correlation assumption to be violated. This might lead to biased standard errors. In addition, due to the fact that financial time series often exhibit time-varying volatility, there may also be a problem with heteroskedasticity (Engle, 2001). To correct for this, we apply a Newey-West (1987) correction for serial correlation and heteroskedasticity to the standard errors from the regression.

To test the robustness of the static hedge ratios, we conduct an out-of-sample test. We use the period from 2005-2009 to set the static hedge ratios, before we assess their performance in the period 2009-2016.

The dynamic hedge ratios are estimated using Engle's (2002) dynamic conditional correlation GARCH (1,1) model. This model estimates the conditional covariances of ship price returns and futures returns and the variance of futures returns. The GARCH (1,1) specification is the most commonly used GARCH model for financial time series, based on its ability to adequately capture the dynamic of the variance (Alizadeh & Nomikos, 2009). This has also been shown by Kavussanos and Nomikos (2000), who estimated dynamic hedge ratios in the freight derivatives market. We define the model, in accordance with Chang et al. (2011), as follows:

$$y_t|F_{t-1} \sim N(0, Q_t), t = 1, 2, \ldots, n \tag{12}$$

$$Q_t = D_t \Gamma_t D_t \tag{13}$$

where $y_t = (y_{1t}, \ldots, y_{mt})'$ is a sequence of independently and identically distributed random vectors, F_{t-1} is the information available at t-1, m is the number of returns, $D_t = diag(h_1^{1/2}, \ldots, h_m^{1/2})$ is a diagonal matrix of conditional variances and Γ_t is the correlation matrix containing the conditional correlations. The conditional variance is defined as a univariate GARCH(p,q) model as follows:

$$h_{it} = \omega_i + \sum_{k=1}^{p} \alpha_{ik} \varepsilon_{i,t-k}^2 + \sum_{l=1}^{q} \beta_{il} h_{i,t-l} \tag{14}$$

where α_{ik} is the parameter of lagged squared error terms (the ARCH effect) and β_{il} is the lagged variance parameters (the GARCH effect). In line with Alizadeh and Nomikos (2009) we use the Maximum Likelihood method for estimating the parameters of interest, in the statistical software Stata. Measures of the time-varying variances and covariances are extracted from the estimation and used to calculate the optimal time-varying hedge ratio from Equation (9). To compare the hedging efficiency with the static hedge, we construct portfolios where the hedge ratio is dynamically adjusted every week. Then, we calculate the hedging efficiency of this portfolio using Equation (10).

4.4 Stationarity

Wooldridge (2016) states that a stationary time series has a constant mean, a constant variance and constant autocovariances for each lag. In order to use the time series for evaluating hedging efficiency, the time series must be stationary. Otherwise, shocks in the series will not fade away and may lead to spurious regression, i.e. the test statistic depicts a relationship between the two series that should not be present.

The FFAs are expected to move around a constant mean due to the characteristics of the market, as explained in section 3.2. Consequently, the freight rates cannot exhibit asymptotically explosive behaviour, as implied by non-stationarity (Koekebakker et al., 2006). As previously established, ship prices are dependent on the expectation for future freight rates. Therefore, we would expect the mean reversion properties of the FFAs to also apply for the second-hand ship prices. In addition, the ship prices also depend on the long-run interest rates. Wu and Chen (2001) have found that the interest rates in the Eurocurrency market display mean reverting properties and are stationary.

In addition to a constant mean, a stationary series has a constant variance and constant autocovariance. We do not expect the autocovariance structure of any of the series studied to change over the relevant period. Furthermore, we also assume constant variance. This assumption is somewhat controversial, as a number of studies have found that many financial series exhibit time-varying variance, e.g. Kroner and Sultan (1993), Engle (2001) and Myers (1991).

The time series are tested for stationarity using the Augmented Dickey-Fuller (ADF) test, which has a null hypothesis of non-stationarity and alternative hypothesis of stationarity (Dickey & Fuller, 1979). The ADF test is applied to the following model:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{P} \delta_i \Delta y_{t-i} + \varepsilon_t \tag{15}$$

where the change of the time series y_t is regressed on lagged observations of itself, y_{t-1}, α is the drift component and δ_i are parameters on the lags of y that is intended to clean up any serial correlation in Δy_t. The null hypothesis is $y = 0$, which indicates non-stationarity.

Determining the number of lags is not an exact science (Wooldridge, 2016), however, we find the number of lags by minimizing the Schwarz criterion (SBIC). The level series are specified without a trend, but with an intercept, as the series does not exhibit any clear trends, but fluctuates around a non-zero value. The return series (both weekly and monthly) fluctuate around zero and have no clear trend. Hence, we specify the ADF regression without trend and intercept.

Table 5 *- Augmented Dickey Fuller (ADF) test results*

		Level	Weekly	Monthly
Capesize	*5-year*	-2.01	-7.27	-4.84
	10-year	-1.97	-8.46	-5.08
	15-year	-1.87	-8.31	-5.13
	20-year	-2.15	-8.65	-5.78
FFA Portfolio	*Capesize FFAs*	-2.06	-8.79	-5.93

The table shows the ADF test statistic for the series in level, weekly returns and monthly returns. The weekly returns are the first difference of the level series. The 5% critical value for the ADF is -2.860 for the level series and -1.950 for the return series.

The results in Table 5 indicates that we cannot reject the null hypothesis regarding the existence of unit root in any of the level time series, which means that these series should not be used for hedging purposes in OLS (Granger & Newbold, 1974). The series of weekly and monthly[12] returns are clearly stationary for both ship prices and FFAs. This is in accordance with the results of both Adland et al. (2004) and Alizadeh and Nomikos (2012). Table 5 only includes the results for the Capesize vessels and the Capesize FFA portfolio, as the results for the smaller vessels are similar; however, these results can be found in Appendix 4.

We have not tested the yearly returns, in which we are most interested, for stationarity, as we do not have an adequate amount of non-overlapping observations to draw any clear conclusions from the test. However, both the weekly and monthly returns are stationary. Since we expect the yearly returns to share similar statistical properties, we find it reasonable to argue that the yearly returns also are stationary. This is also in accordance with the findings of Alizadeh and Nomikos (2012).

4.5 Co-integration

Having established a theoretical relationship between ship prices and FFA prices in section 3.2, we investigate this relationship empirically using the co-integration framework proposed by Engle and Granger (1987). Two variables are co-integrated if a linear combination between them is stationary. Two non-stationary variables that are co-integrated are believed to have a long-run equilibrium. The relationship between the variables is of great importance to assess the appropriateness of the hedge instrument. We observe the time series in levels, and the variables have to be I(1) in order to use the Engle-Granger test. We previously found

[12] The monthly returns are non-overlapping.

that this assumption is satisfied, as the weekly returns, which are the first difference of the level series, were clearly stationary.

If we have:

$$P_t - \beta F_t \tag{16}$$

where P_t equals ship prices at t and F_t equals FFA prices at t, this process will generally be I(1) for any value of β. However, if there exist some $\beta \neq 0$ which makes $P_t - \beta F_t$ an I(0) process, the two time series are co-integrated with β as the co-integration parameter (Engle & Granger, 1987).

While Wooldridge (2016) expects spot and futures prices of storable commodities to be co-integrated, this is not necessarily true for spot and futures prices of two different commodities. Nevertheless, ships are believed to be priced in accordance to their future operational earnings discounted and freight forward prices are assumed to be unbiased predictors of the future spot freight rates, as stated by Equation (5) (Alizadeh & Nomikos, 2009). Therefore, we imagine that market agents' expectations will bind the two series together in the long-run and therefore, make them co-integrated. We test the co-integration relationship with the Engle-Granger procedure, which first estimates:

$$P_t = \hat{\alpha} + \hat{\beta} F_t \tag{17}$$

where $\hat{\beta}$ is consistent for β. We then apply the Dickey-Fuller test to the test residuals, $\hat{u} = P_t - \hat{\alpha} - \hat{\beta} F_t$ from Equation (17). If the null hypothesis of unit root is rejected, then the residuals are stationary and $P_t - \beta F_t$ is I(0) for some β. As previously stated, this result implies that the two series are assumed to be co-integrated. On the contrary, if we fail to reject the null hypothesis then we do not believe the series to be co-integrated.

The test results indicate a strong long-run relationship between ship prices and FFA portfolio prices for all sizes and vintages of vessels[13]. The long-run relationship with FFA prices is strongest for the youngest vessels. The economic interpretation of the co-integration relationship is that the difference between ship prices and FFAs will not drift apart over time, and there will be a tendency for them to come back together. Thus, as has already been

[13] Test results are included in Appendix 5.

theoretically established, there is a relationship between these variables. This further strengthens our belief that FFA is an appropriate hedging instrument.

Engle and Granger (1987) have suggested that ignoring the co-integration relationship between the variables may lead to model misspecification, which in turn may lead to an underestimation of the hedge ratio (Ghosh, 1993). Including an error-correction term can capture this effect (Engle & Granger, 1987). However, Tong (1996) have argued that when the variables are linked through a no-arbitrage relationship, the effect of the error-correction term should be minimal due to the fact that the variables will not deviate much from each other. Even though the relationship between freight rates and ship prices is not a no-arbitrage relationship, the freight rates and ship prices are tightly related. Thus, we will not specify a model with an error-correction term, as we expect the effect to be minimal.

5. Empirical Results

In this section, we will present and discuss the results from the estimation models described in section 4.3. The discussion is split into two sub sections: static and dynamic hedging efficiency. First, we investigate the static hedging efficiency across different vintages of vessels. Thereafter, we examine the differences in static hedging efficiency among the three sizes of vessels previously introduced in this thesis: Capesize, Panamax and Handymax. Furthermore, we calculate the static out-of-sample hedging efficiency for all sizes and vintages of vessels to confirm the robustness of the aforementioned results. Finally, we investigate the dynamic hedging efficiency for all sizes and vintages of vessels.

5.1 Static Hedging Efficiency

5.1.1 Comparison Across Age

The focus of this section will be on the results from the Capesize vessels, because the tendencies are similar for the smaller vessels. The results from the Panamax and Handymax vessels can be found in Appendix 6.

Table 6 *- Hedge ratio and efficiency for Capesize vessels*

	Capesize			
	5-year	*10-year*	*15-year*	*20-year*
FFA portfolio return	0.557^{***}	0.667^{***}	0.721^{***}	0.594^{***}
	(0.011)	(0.012)	(0.015)	(0.023)
Constant	-0.090^{***}	-0.099^{***}	-0.110^{***}	-0.085^{***}
	(0.006)	(0.007)	(0.008)	(0.010)
Number of Observ.	574	574	574	574
R^2	0.824	0.842	0.841	0.658
F	2682.8	3049.0	3022.7	1099.8
Breusch-Godfrey	466.42	451.36	449.60	521.75
	[0.00]	[0.00]	[0.00]	[0.00]
White test	26.21	21.99	71.51	141.95
	[0.00]	[0.00]	[0.00]	[0.00]

P-values in [] and standard errors in (). ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. Standard errors are corrected for serial correlation and heteroskedasticity using the Newey-West (1987) method.

The hedge ratios are 0.557, 0.667, 0.721 and 0.594 for the 5-, 10-, 15- and 20-year-old Capesize vessels, respectively - as seen from the slope coefficients in Table 6. The regression's R^2 are 82.4%, 84.2%, 84.1% and 65.8%, respectively. This means that hedging 55.7% of a 5-year-old vessel's value with the FFA portfolio leads to an 82.4% hedging efficiency in the examined time period. The FFA portfolio return is significant in explaining ship price return for all ship ages at a 1% significance level.

Table 6 depicts an increasing hedge ratio from the 5-year-old Capesize to the 15-year-old Capesize. We argue that this is connected to the difference in volatility between the aforementioned vessel ages. As presented in the descriptive statistics, ship price volatility also increases with age. Furthermore, the volatility of the FFAs is larger than the volatility in ship prices for all ages. Therefore, to hedge a more volatile ship price, one needs to hold more of the FFA portfolio in order to "match" the price fluctuations. Admittedly, the hedge ratio for the 20-year-old Capesize is lower than for the 15-year-old Capesize, although the former has higher variance. However, we argue that these are not comparable due to the significantly lower hedging efficiency achieved by hedging the 20-year-old Capesize.

The relatively low hedging efficiency for the 20-year-old vessels can be explained by Equation (3), as a vessel's value is considered the sum of all future earnings discounted and the residual value discounted. At the end of a ship's economic lifetime, the future profits are a smaller fraction of the value than that of a younger ship. This implies that the residual value becomes more important; however, it is not efficient to hedge this aspect with freight futures. The reason that the hedging efficiency is nevertheless quite high could be that the FFA portfolio is correlated with some variable that explains the residual value. This variable could, for example, be scrap prices, which are shown to have a high correlation with freight rates (Alizadeh & Nomikos, 2009). For example, when freight rates are low, owners of relatively inefficient vessels may be forced to sell them for scrap. This increases the supply of scrap vessels, which reduces the market value.

5.1.2 Comparison Across Size

Table 7 summarizes the results from the hedging efficiency comparison across 5-year-old vessels of a variety of sizes. The optimal hedge ratio is 0.557 for Capesize vessels, 0.659 for Panamax vessels and 0.596 for Handymax vessels, which leads to a hedging efficiency of 82.4%, 88.8% and 86.2%, respectively. The FFA portfolio returns explain the ship price return at a 1% significance level for vessels of all sizes.

***Table** 7 - Hedging efficiency comparison between different sized 5-year-old vessels*

	Capesize	**Panamax**	**Handymax**
FFA portfolio return	0.557^{***}	0.659^{***}	0.596^{***}
	(0.012)	(0.014)	(0.013)
Constant	-0.089^{***}	-0.085^{***}	-0.080^{***}
	(0.006)	(0.007)	(0.008)
Number of observ.	575	575	575
R^2	0.824	0.888	0.862
F	2679	4515	3567
Breusch-Godfrey	466.4	409.8	430.7
	[0.00]	[0.00]	[0.00]
White test	26.21	106.68	37.42
	[0.00]	[0.00]	[0.00]

P-values in [] and standard errors in (). ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. Standard errors are corrected for serial correlation and heteroskedasticity using the Newey-West (1987) method.

Although all vessels achieve respectable hedging efficiency, the results indicate that the smaller vessels (Panamax and Handymax) outperform the larger Capesize vessels. This may be due to differences in volatility and the fact that the 4TC Panamax contracts, for some reason, are a better indicator of the overall market performance in the Panamax and Handymax markets than the 4TC Capesize contracts are for the Capesize market. Interestingly, the results in Table 7 suggest that sound hedging efficiency can be achieved using Panamax derivatives to hedge Handymax vessels. This yields opportunities for Handymax price risk management as an alternative to the low liquid derivatives market in this sector.

5.1.3 Out-of-sample

The last 417 observations of the sample (that is, after 2 January 2009) are kept to evaluate the static hedging performance. The general out-of-sample hedging performance, shown in Table 8, is respectable. However, as expected, the hedging efficiency is lower for all types of vessels compared to the in-sample results. The general tendencies are the same: hedging efficiency is negatively correlated with vessel age, and the smaller vessels outperform the Capesize vessels with variance reduction ranging from 85.2% to 61.5%.

Table 8 *- Out-of-sample hedging performance*

		Hedge ratio	Out-of-sample
Capesize	*5-year*	0.531	72.4 %
	10-year	0.645	73.1 %
	15-year	0.771	66.6 %
	20-year	0.639	40.3 %
Panamax	*5-year*	0.624	85.2 %
	10-year	0.674	83.3 %
	15-year	0.752	79.3 %
	20-year	0.769	61.5 %
Handymax	*5-year*	0.549	77.6 %
	10-year	0.611	77.4 %
	15-year	0.629	78.4 %
	20-year	0.675	67.0 %

These results indicate that the optimal hedging efficiency and ratio are relatively stable between the two periods, at least for the youngest vessels. This is of great importance for hedgers, as they need to choose their hedge ratio ex ante. Hence, an out-of-sample test is a more realistic way to evaluate the performance of this hedging strategy. In addition, the period in which the hedge ratio was calculated is regarded as being quite different to the out-of-sample period. The variance is assumed to be higher in the first period (2005-2009), as this was the period leading up to and during the financial crisis, while the out-of-sample period (2009-2016) coincides with the less volatile post-financial crisis period. This shows that the hedging strategy is also quite stable in different business climates.

5.2 Dynamic Hedging Efficiency

The dynamic hedging efficiencies calculated using the dynamic conditional correlation model are summarized in Table 9. We use the full sample to improve the numerical performance of the estimation (Power et al., 2013). Interestingly, the dynamic hedge ratio underperforms the static hedge in reducing variability in returns for the hedged portfolio despite the superior statistical property of the GARCH model compared to the simple OLS model. This result was also found for other commodities. Myers (1991), who examined hedging efficiency in the wheat futures market, and Garcia et al. (1995), who examined hedging efficiency in the soybean futures market, found the static hedge ratio to be more adequate than the time-varying hedge ratio in variance reduction. However, it might be that other dynamic model specifications would be more appropriate for our data. Hence, we cannot conclude that dynamic hedge ratios in general underperform the static hedge ratio in hedging vessel value.

Table 9 *- Hedging efficiency with the dynamic and a static approach*

		Dynamic	Static
Capesize	*5-year*	77.4 %	82.4 %
	10-year	61.5 %	84.2 %
	15-year	79.9 %	84.1 %
	20-year	68.5 %	65.8 %
Panamax	*5-year*	71.8 %	88.8 %
	10-year	68.8 %	88.3 %
	15-year	81.8 %	84.2 %
	20-year	25.9 %	77.7 %
Handymax	*5-year*	59.1 %	86.2 %
	10-year	48.4 %	86.4 %
	15-year	43.8 %	82.3 %
	20-year	65.5 %	78.7 %

The optimal dynamic hedge ratio for a 5-year-old Capesize vessel is presented as an example in Figure 4, together with the optimal static hedge ratio for comparison. The conditional hedge ratio is clearly changing as new information arrives in the market. There are brief periods during which the dynamic hedge ratio implies substantial over-hedging (hedge ratio > 1) or speculation (hedge ratio < 1).

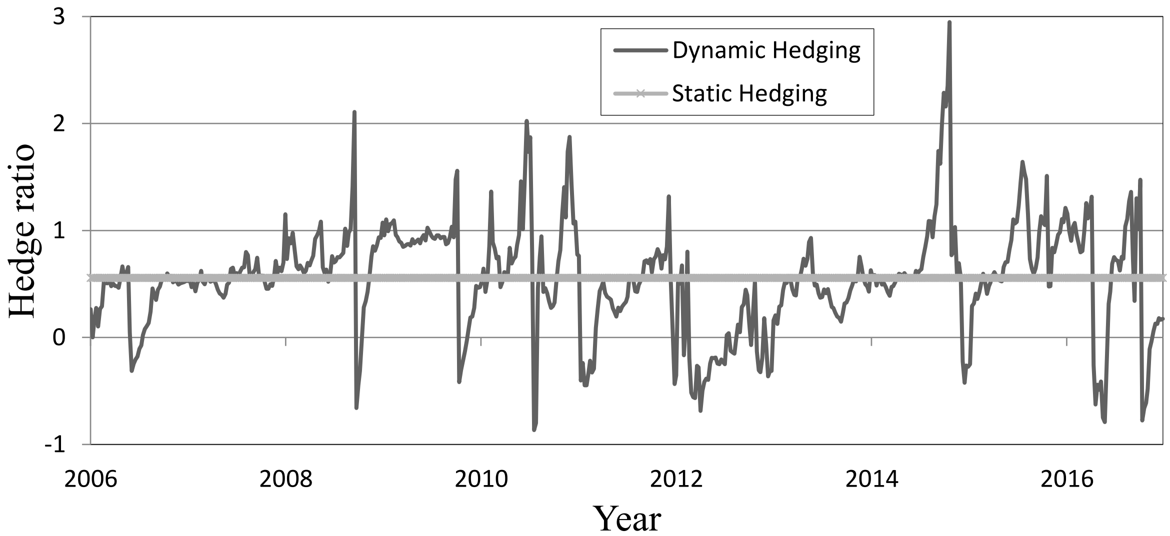

Figure 4 *- Dynamic hedge ratio for Capesize vessels*

6. Concluding Remarks

In this thesis, we have argued that ship price risk in the dry bulk sector can efficiently be managed using an FFA portfolio. First, using the unbiasedness hypothesis, we theoretically established a relationship between the ship price and the freight derivatives portfolio through the discounted cash flow model. Second, we empirically proved this relationship through the co-integration framework, which confirmed that freight derivatives are a suitable tool for ship price risk management. Third, we calculated static and dynamic hedge ratios and tested hedging efficiency in- and out-of-sample.

The variance reductions in the ship price risk for the dry bulk carriers are considered to be respectable within the cross-hedge literature. However, there are some differences across age and size of the vessels. The hedging efficiency is lower for older ships, and the hedger needs a larger short position in the FFA portfolio compared to the younger vessels. This is in accordance with the theoretical framework presented; one should expect that the future freight earnings constitute a smaller fraction of an old vessel's value compared to a newer one.

Furthermore, the hedging efficiency for smaller vessels is greater than the one for larger vessels. However, the hedge ratio does not differ substantially across sizes. Interestingly, we found that a portfolio of Panamax freight derivatives can be used for hedging ship price risk of Handymax vessels with a hedging efficiency of approximately 86%. This is a practical alternative to the illiquid derivatives market in the Handymax sector.

Comparing the static hedging efficiency from the OLS model with the dynamic hedging efficiency of a GARCH(1,1) model, we found that the static hedge ratio is superior in variance reduction for all ages and sizes. This implies that the hedger should not dynamically adjust the ratio of the FFA portfolio short position to the ship position.

Our findings have practical implications for risk management in the dry bulk sector, thus making our work the most comprehensive contribution to the limited ship price risk management literature. Since ship values constitute much of a shipping company's balance sheet, this thesis can contribute to an overall reduction of risk in the shipping sector.

Our results can primarily help ship owners reduce ship price risk efficiently and without the substantial transaction cost related to traditional asset diversification, as well as providing leverage against loans. In addition, other market players somehow exposed to ship price risk, such as ship yards, lending banks and asset underwriters, may use our findings to optimize their exposure. Additionally, our results can be useful for non-shipping investors seeking exposure to shipping markets without having to buy the steel, such as private investors, hedge funds and financial institutions.

Our analysis relies on a single data source, which is considered to be a limitation of our thesis. Due to basis risk, the hedging efficiencies attained in this thesis may not be achievable for shipowners; a certain ship's price movements may deviate from the price movements of the index used in this thesis. Furthermore, in this thesis, we are only hedging ship price returns and not a ship owner's overall returns, which could lead to "underhedging". Additionally, assumptions made in our estimation models may be a limitation of the results presented.

We believe our thesis can serve as a basis for further research of both ship price risk management and other risk management purposes within shipping markets using FFAs. Regarding ship price risk management, it would be interesting to investigate how different dynamic model specifications will compete against the static hedging efficiency. Additionally, our analysis could be supplemented by investigating whether ship price risk management is a common practice by different market participants, and which tools they use. Regarding risk management using FFAs, further research could investigate whether shipping company value risk can be hedged using FFAs.

7. References

Adland, R., & Cullinane, K. (2005). A Time-Varying Risk Premium in the Term Structure of Bulk Shipping Freight Rates. *Journal of Transport Economics and Policy* 39(2): 191-208.

Adland, R., & Jia, H. (2017). Simulating physical basis risks in the Capesize freight market. *Maritime Economics & Logistics* 19(2): 196–210.

Adland, R., & Koekebakker, S. (2007). Ship Valuation Using Cross-Sectional Sales Data: A Multivariate Non-Parametric Approach. *Maritime Economics & Logistics* 9(2): 105-118.

Adland, R., Jia, H., & Koekebakker, S. (2004). The Pricing of Forward Ship Value Agreements and the Unbiasedness of Implied Forward Prices in the Second-Hand Market for Ships. *Maritime Economics & Logistics* 6(2): 109-121.

Alizadeh, A. H., & Adland, R. (2018). Explaining price differences between physical and derivative freight contracts. *Working paper*.

Alizadeh, A. H., & Nomikos, N. K. (2007). Investment timing and trading strategies in the sale and purchase market for ships. *Transportation Research Part B* 41(1): 126-143.

Alizadeh, A. H., & Nomikos, N. K. (2009). *Shipping derivatives and risk management (1st ed.)* Palgrave Macmillian, London.

Alizadeh, A. H., & Nomikos, N. K. (2011). Dynamics of the Term Structure and Volatility of Shipping Freight Rates. *Journal of Transport Economics and Policy* 45(1): 105-129.

Alizadeh, A. H., & Nomikos, N. K. (2012). Ship Finance: Hedging Ship Price Risk Using Freight Derivatives. In: Talley, W.K., *Blackwell Companion to Maritime Economics*. Wiley Blackwell: 433-451.

Alizadeh, A. H., Kappou, K., Tsouknidis, D., & Visvikis, I. D. (2015). Liquidity effects and FFA returns in the international shipping derivatives market. *Transportation Research Part E: Logistics and Transportation Review* (76): 58-75.

Alizadeh, A. H., Kavussanos, M. G., & Menachof, D. A. (2004). Hedging against bunker price fluctuations using petroleum futures contracts: constant versus time-varying hedge ratios. *Applied Economics* 36(12): 1337-1353.

Baillie, R. T., & Myers, R. J. (1991). Bivariate Garch Estimation of the Optimal Commodity Futures Hedge. *Journal of Applied Econometrics* 6(2): 109-124.

Beenstock, M. (1985). A Theory of ship prices. *Maritime Policy and Management* 12(3): 215–225.

Beenstock, M., & Vergottis, A. (1989). An econometric model of the world market for dry cargo freight and shipping. *Applied Economics* 21(3): 339-356.

Beenstock, M., & Vergottis, A. (1993). *Econometric Modelling of World Shipping.* Chapman and Hall, London.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics* 31(3): 307-327.

Bollerslev, T., Chou, R., & Kroner, K. (1992). ARCH Modeling in finance: A review of the theory and empirical evidence. *Journal of Econometrics* 52(1): 5-59.

Campbell, J., & Viceira, L. (2005). The Term Structure of the Risk-Return Trade-Off. *Financial Analysts Journal* 61(1): 34-45.

Chang, C.-L., McAleer, M., & Tansuchat, R. (2011). Crude oil hedging strategies using dynamic multivariate GARCH. *Energy Economics* 33(5): 912-923.

Clarkson Research. (2016, 09 02). *Clarksons Research*. Retrieved from Clarkson Research: https://clarksonsresearch.wordpress.com/tag/scrap-value/

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series With a Unit Root. *Journal of the American Statistical Association* 74(366): 427-431.

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

Engle, R. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica* 50(4): 987-1007.

Engle, R. (2001). GARCH 101: The Use of ARCH/GARCH Models in Applied Econometrics. *Journal of Economic Perspectives* 15(4): 157-168.

Engle, R. (2002). Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. *Journal of Business & Economic Statistics* 20(3): 339-350.

Engle, R., & Granger, C. (1987). Co-Integration and Error Correction: Representation, Estimation, and Testing. *Econometrica* 55(2): 251-276.

Garcia, P., Roh, J., & Leuthold, R. M. (1995). Simultaneously determined, time-varying hedge ratios in the soybean complex. *Applied Economics* 27(12): 1127-1134.

Ghosh, A. (1993). Hedging with Stock Index Futures: Estimation and Forecasting with Error Correction Model: Introduction. *The Journal of Futures Markets* 13(7): 743-752.

Granger, C., & Newbold, P. (1974). Spurious Regressions In Econometrics. *Journal of Econometrics* 2(2): 111-120.

Haralambides, H. E. (1992). Freight futures trading and shipowners' expectations. In Conference Proceedings. *6th World Conference on Transportation Research*. Lyon, France, 1411-1422.

Haralambides, H. E., Tsolakis, S., & Cridland, C. (2004). Econometric Modelling of Newbuilding and Secondhand Ship Prices. *Research in Transportation Economics* (12): 65-106.

Heifner, R. (1972). Optimal Hedging Levels and Hedging Effectiveness in Cattle Feeding. *Agricultural Economics Research* 24(2): 25-36.

Johansen, S. (1988). Statistical Analysis of Cointegration Vectors. *Journal of Economic Dynamics and Control* 12(2): 231-254.

Johansen, S. (1991). Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models. *Econometrica* 59(6): 1551-1580.

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

Kalouptsidi, M. (2014). Time to Build and Fluctuations in Bulk shipping. *American Economic Review* 104(2): 564-608.

Kavussanos, M. G. (1996). Comparisons of Volatility in the Dry-Cargo Ship Sector: Spot versus Time Charters, and Smaller versus Larger Vessels. *Journal of Transport Economics and Policy* 30(1): 67-82.

Kavussanos, M. G. (1997). The Dynamics of Time-Varying Volatilities in Different Size Second-Hand Ship Prices of the Dry-Cargo Sector. *Applied Economics* 29(4): 433-443.

Kavussanos, M. G., & Nomikos, N. K. (1999). The Forward Pricing Function of the Shipping Freight Futures Market. *Journal of Futures Markets* 19(3): 353-376.

Kavussanos, M. G., & Nomikos, N. K. (2000). Constant vs. time-varying hedge ratios and hedging efficiency in the BIFFEX market. *Transportation Research Part E* 36(4): 229-248.

Kavussanos, M. G., & Visvikis, I. D. (2006a). *Derivatives and Risk Management in Shipping.* Witherby Seamanship International, London.

Kavussanos, M. G., & Visvikis, I. D. (2006b). Shipping freight derivatives: a survey of recent evidence. *Maritime Policy & Management* 33(3): 233-255.

Kavussanos, M. G., & Visvikis, I. D. (2008). The Hedging Performance of The Capesize Forward Freight Market. In: Cullinane K., *The International Handbook of Maritime Business.* Edward Elgar Publishing: 331-352.

Kavussanos, M. G., & Visvikis, I. D. (2016). *The International Handbook of Shipping Finance: Theory and Practice.* Palgrave Macmillan, London.

Kavussanos, M. G., Visvikis, I. D., & Menachof, D. (2004). The Unbiasedness Hypothesis in the Freight Forward Market: Evidence from Cointegration Tests. *Review of Derivatives Research* 7(3): 241-266.

Koekebakker, S., Adland, R., & Sodal, S. (2006). Are Spot Freight Rates Stationary? *Journal of Transport Economics and Policy* 40(3): 449-472.

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

Miles, J., & Ezzell, J. (1980). The Weighted Average Cost of Capital, Perfect Capital Markets, and Project Life: A Clarification. *The Journal of Financial and Quantitative Analysis* 15(3): 719-730.

Modigliani, F., & Miller, M. (1958). The Cost of Capital, Corporation Finance and the Theory of Investment. *The American Economic Review* 48(3): 261-297.

Myers, R. (1991). Estimating Time-Varying Optimal Hedge Ratios on Futures Markets. *The Journal of Futures Markets* 11(1): 39-53.

Newey, W. K., & West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica* 55(3): 703-708.

Politis, D. N., & Romano, J. P. (1994). The Stationary Bootstrap. *Journal of the American Statistical Association* 89(428): 1303-1313.

Power, G., Vedenov, D., Anderson, D., & Klose, S. (2013). Market volatility and the dynamic hedging of multi-commodity price risk. *Applied Economics* 45(27): 3891–3903.

Smith, C., & Stulz, R. (1985). The Determinants of Firms' Hedging Policies. *The Journal of Financial and Quantitative Analysis* 20(4): 391-405.

Stein, J. (1961). The Simultaneous Deterimination of Spot and Futures Prices. *The American Economic Review* 51(5): 1012-1025.

Stevens, N. (1976). *A Mortgage Futures Market: Its Development, Uses, Benefits, and Costs.* Review of the Federal Reserve Bank of St. Louis.

Stopford, M. (2009). *Maritime economics (3rd ed.).* Routledge, London.

Strandenes, S. P. (1984). Price determination in the time charter and second hand markets.

Strandenes, S. P. (1986). *NORSHIP – a simulation model for bulk shipping markets.* Bergen, Norway: Center for Applied Research, Norwegian School of Economics and Business Administration.

Sullivan, R., Timmermann, A., & White, H. (1999). Data-Snooping, Technical Trading Rule Performance, and the Bootstrap. *The Journal of Finance* 54(5): 1647-1691.

The Baltic Exchange. (2011). *Manual for Panellists: A Guide to Freight Reporting and Index production.*

Thuong, L., & Visscher, S. (1990). The Hedging Effectiveness of Dry-Bulk Freight Rate Futures. *Transportation Journal* 29(4): 58-65.

Tong, W. (1996). An examination of dynamic hedging. *Journal of International Money and Finance* 15(1): 19-35.

Tsolakis, S., Cridland, C., & Haralambides, H. E. (2003). Econometric Modelling of Second-Hand Ship Prices. *Maritime Economics and Logistics* 5(4): 347-477.

Tvedt, J. (2003). Shipping Markets Model and the Specification of Freight Rate Processes. *Maritime Economics & Logistics* 5(4): 327-346.

van Dellen, S. (2011). An Examination into the Structure of Freight Rates in the Shipping Freight Markets. *Unpublished Doctoral thesis, City University London*.

Wooldridge, J. M. (2016). *Introductory econometrics: a modern approach (6th ed.).* Cengage Learning, Australia.

Wu, J.-L., & Chen, S.-L. (2001). Mean Reversion of Interest Rates in the Eurocurrency Market. *Oxford Bulletin of Economics and Statistics* 63(4): 459-474.

Appendix

Appendix 1

Table A1 *- The FFA portfolio composition and weights*

Contract	Weight in portfolio
Current quarter	Number of days left in the quarter
Nearest quarter	90 days
Second nearest quarter	90 days
Third nearest quarter	90 days
Nearest calendar	365 days
Second nearest calendar	365 minus number of days left in current year

Table A2 *- The FFA portfolio composition*

Month of the year	FFAs shorted in hedgers portfolio
January-March	Q1, Q2, Q3, Q4, CAL1 and CAL2
April-June	Q2, Q3, Q4, CAL1 and CAL2
July-September	Q3, Q4, CAL1 and CAL2
October-December	Q4, CAL1 and CAL2

Appendix 2

Table A3 *-Descriptive statistics of the 4TC average Panamax contracts*

	Current quarter	First quarter	Second quarter	Third quarter	First calendar	Second calendar	FFA portfolio
Mean ($)	21087	20885	19690	18575	17934	15553	17921
St.dev levels	19208	18710	17318	15664	14375	9231	13865
Min	2973	4280	4500	4330	5060	5915	4712
Max	92306	89586	81444	69625	76375	54597	68905

Appendix 3

We calculate the stationary bootstrap time series according to Sullivan, Timmermann and White's (1999) application as follows:

First, we choose a smoothing parameter $q = q_n$, $0 < q_n \leq 1$, $q_n \to \infty$ as $n \to \infty$. A small q is appropriate for data with high serial dependence (Alizadeh & Nomikos, 2012).

1. Set t = 1 and draw X_1* at random, independently and uniformly from {1,…,T}.
2. Increment t by 1. If t > T, stop. Otherwise, draw a standard uniform variable U independently from all other random variables.
    a. If U < q, draw X^*_2 at random, independently and uniformly from {1,…,T}.
    b. If U > q, expand the block by setting $X^*_2 = X(I_1 + 1)$, so X^*_2 is the next observation in the original series following $X(I_1)$.
3. Repeat step 2 until reaching X^*_T.
4. Repeat step 1-3 10,000 times.

Where X^*_i is the resampled data set and X_t is the original sample of data. The varying length of the blocks, with average 1/q, ensures the bootstrapped series to be stationary (Politis & Romano, 1994). In our thesis q is chosen to be 0.01, in accordance to Alizadeh and Nomikos (2012).

Table A4 *- Bootstrap results*

		FFA port.		Constant		R2	F
Capesize	*5-year*	0.544***	(0.003)	-0.088***	(0.002)	0.784	36322
	10-year	0.648***	(0.003)	-0.098***	(0.002)	0.796	38920
	15-year	0.704***	(0.003)	-0.110***	(0.002)	0.799	39729
	20-year	0.583***	(0.005)	-0.085***	(0.003)	0.628	16871
Panamax	*5-year*	0.645***	(0.003)	-0.085***	(0.002)	0.851	56990
	10-year	0.719***	(0.003)	-0.104***	(0.002)	0.856	54886
	15-year	0.795***	(0.004)	-0.110***	(0.002)	0.812	43081
	20-year	0.723***	(0.004)	-0.125***	(0.002)	0.746	29297
Handymax	*5-year*	0.586***	(0.003)	-0.081***	(0.002)	0.834	50100
	10-year	0.656***	(0.003)	-0.094***	(0.002)	0.831	49193
	15-year	0.699***	(0.004)	-0.111***	(0.002)	0.796	38971
	20-year	0.670***	(0.004)	-0.153***	(0.002)	0.760	31723

Figures in () are standard errors. FFA port. denotes the bootstrapped FFA portfolio. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. The bootstrap series is constructed by 10,000 realizations of non-overlapping 52-week returns based on the stationary bootstrap of Politis and Romano (1994)

Appendix 4

Table A5 *- Augmented Dickey Fuller (ADF) test*

		Level	Weekly	Monthly
FFA portfolio	*Panamax FFAs*	-1.82	-10.43	-6.22
Panamax vessels	*5-year*	-2.06	-7.60	-4.86
	10-year	-2.09	-7.76	-5.73
	15-year	-2.08	-7.60	-5.08
	20-year	-2.12	-9.28	-5.16
Handymax vessels	*5-year*	-1.96	-7.52	-5.83
	10-year	-1.94	-10.16	-5.59
	15-year	-1.99	-8.28	-4.23
	20-year	-1.96	-8.75	-5.16

The table shows the ADF test statistic for the series in level, weekly returns and monthly returns. The weekly returns are the first difference of the level series. The 5% critical value for the ADF is -2.860 for the level series and -1.950 for the return series.

Appendix 5

Table A6 *- Engle-Granger Co-integration test results*

		Level
Capesize	*5-year*	-6.56
	10-year	-4.93
	15-year	-6.59
	20-year	-4.81
Panamax	*5-year*	-5.98
	10-year	-5.89
	15-year	-5.18
	20-year	-4.40
Handymax	*5-year*	-5.68
	10-year	-5.55
	15-year	-4.28
	20-year	-4.32

The table shows the ADF test statistic for the series in levels. Capesize vessels are tested against the Capesize FFA portfolio, while Panamax and Handymax vessels are tested against the Panamax FFA portfolio. The lag length is determined by the SBIC. The 5% critical value for the ADF is -2.860.

Appendix 6

Table A7 *- Hedge ratio and efficiency for Panamax and Handymax vessels*

	Panamax				Handymax			
	5-year	*10-year*	*15-year*	*20-year*	*5-year*	*10-year*	*15-year*	*20-year*
FFA portfolio	0.659***	0.736***	0.809***	0.735***	0.596***	0.671***	0.713***	0.681***
	(0.098)	(0.011)	(0.015)	(0.017)	(0.099)	(0.011)	(0.014)	(0.015)
Constant	-0.085***	-0.103***	-0.110***	-0.125***	-0.080***	-0.093***	-0.111***	-0.153***
	(0.006)	(0.006)	(0.008)	(0.009)	(0.006)	(0.006)	(0.008)	(0.008)
Number of obs.	574	574	574	574	574	574	574	574
R^2	0.888	0.883	0.842	0.777	0.862	0.864	0.823	0.787
F	4515.5	4308.5	3041.1	1994.2	3566.8	3630.4	2725.1	2116.2
Breusch-Godfrey	409.78	413.81	447.40	479.39	430.73	419.05	462.21	481.94
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
White test	106.68	103.52	124.88	82.18	37.40	15.96	117.77	109.51
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]

P-values in [] and standard errors in (). ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. Standard errors are corrected for serial correlation and heteroskedasticity using the Newey-West (1987) method.