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Can You Hedge Dry Bulk Stock Prices Using Forward Freight Agreements?

A Study of Risk Management in the Dry Bulk Shipping Stock Market

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Abstract

This thesis investigates if forward freight agreements (FFA) can be used to hedge stock price risk in the dry bulk shipping sector. We establish a cointegrated relationship between FFAs and dry bulk stock prices based on the link between freight rates and stock price returns of dry bulk companies. Using contracts in the Capesize, Panamax and Supramax segment, we evaluate hedge efficiency and minimum variance hedge ratios derived from the Ederington regression. The hedge efficiency is compared across various hedge intervals, different maturities and selected companies operating in the dry bulk shipping segment.

We discover that the investigated attributes have differing implications for the hedge efficiency. From the comparison across hedge intervals, we find that hedge efficiency both increases and decreases with increasing hedging horizon. Thus, our results are rather unclear, and we cannot draw any conclusions about the implication of hedge horizon. Secondly, we show that forward contracts with a maturity of one calendar year achieve, in general, higher hedging efficiency than forward contracts with a maturity of one quarter. Furthermore, our results indicate that the hedging efficiency of stock prices is partially explained by a company's risk profile in the physical market. Finally, we compare our findings to other studies, and find that the hedging efficiency of FFAs on stock price risk is, in general, mediocre.

We believe that our findings are important for both private investors and investment funds trading in the shipping stock market. Our findings provide useful insight to risk management for equity investors in the dry bulk shipping sector.

Preface

The study is conducted as a concluding part of our Master of Science in Economics and Business Administration at the Norwegian School of Economics and constitutes 30 credits of our major in Financial Economics.

The choice of topic for the thesis is a result of common interests for the shipping industry gained through lectures, seminars and work experience. Pursuing a major in Financial Economics, we aim to get a deeper knowledge of the financial aspects in the industry. Thus, we want to give an empirical contribution to the field of risk management in the dry bulk shipping market.

We would like to thank our supervisor, Roar Ådland, for providing valuable data and guidance to our thesis. His great commitment to the topic has given us important feedback and expertise that have improved our study.

Finally, we would like to express gratitude towards The Norwegian Ship Owners' Association's Fund at the Norwegian School of Economics as we are thankful for receiving grants with reference to our thesis.

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1. Introduction

The companies within the dry bulk shipping segment have experienced large fluctuations in stock prices the past 15 years (see figure 1.1.). The fluctuations in the stock prices create an opportunity for huge profits from speculation on stock prices. However, it can also result in large losses if the investment is made at the wrong stage of the cycle. With the duration and depth of the cycles experienced in the shipping industry, it can take time to profit from an investment made at the wrong stage. Therefore, risk management represents an important role in reducing the volatility associated with an investment in shipping companies.

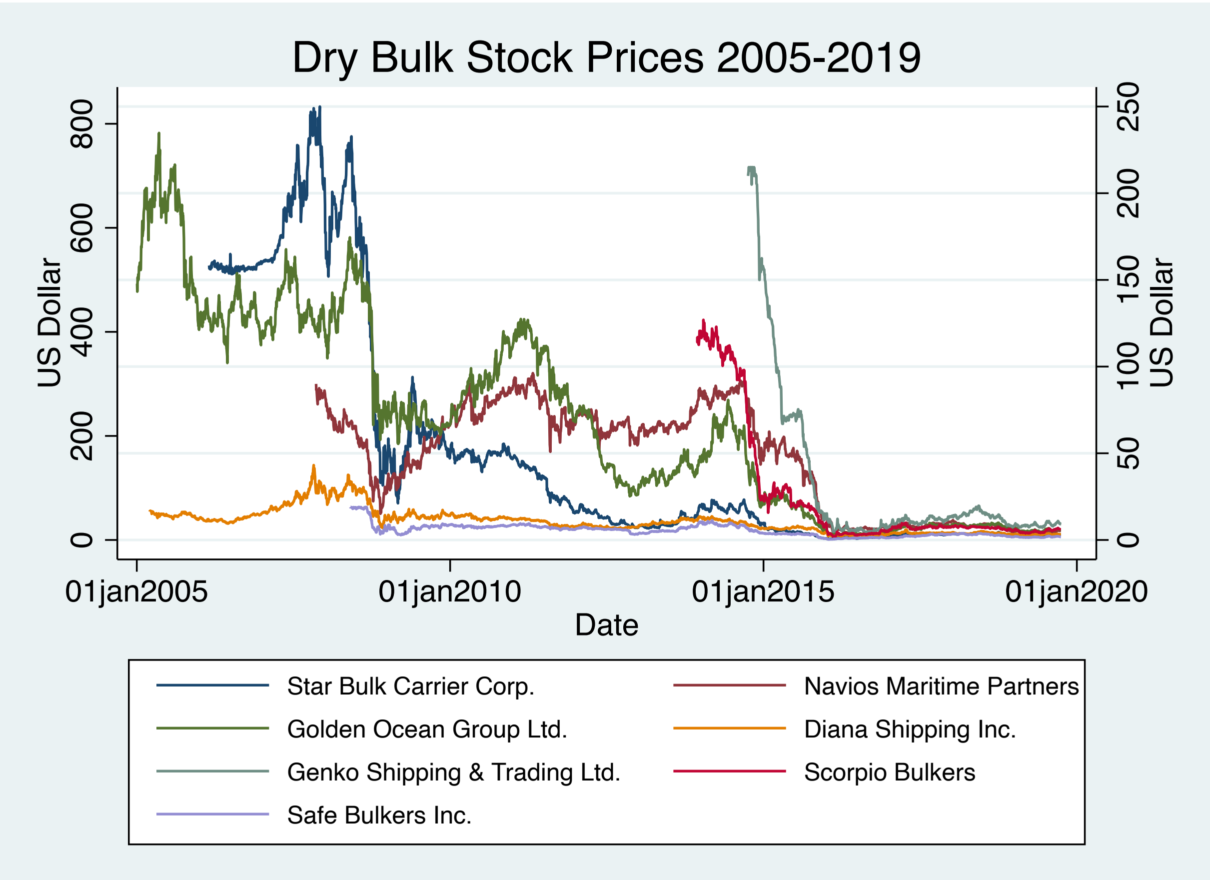

Figure 1.1 - Dry Bulk Stock Prices 2005-2019. Star Bulk Carriers and Navios Maritime Partners are scaled on the left y-axis.
Source: Bloomberg (2019)

The fluctuations in shipping stocks are in line with the volatile earnings in the industry, which come as a consequence of the unique supply and demand characteristics in the shipping market (Syriopoulos & Roumpis, 2009). The demand for seaborne transportation is depending heavily on the development of the world economy and is highly unpredictable with random shocks and quick changes. Further, the supply of sea transport is identified as slow in response to changes in demand. This is because of a building period of several years, and once built, a ship can operate in 15-30 years. Shipowners also tend to overinvest in a market boom, resulting in oversupply and deviation from market equilibrium creating large business cycles. The above-mentioned dynamics result in the characteristic pattern of the shipping industry; irregular peaks and throughs where constant earnings in the long run are quite rare (Stopford, 2003). The volatility in earnings creates high business risk for companies operating in the sector. Main business risks for shipping companies are related to movements in freight rates, bunker prices, exchange rates and interest rates, and these are affecting the interaction between cost and revenue to a great extent. Further, the sector is capital-intensive, resulting in a high debt ratio for many companies, which implies great financial risk (Kavussanos & Visvikis, 2006a). The characteristics of the industry are important for understanding the fluctuations in shipping stocks, as sectoral and company fundamentals may affect the volatility (Syriopoulos & Roumpis, 2009).

Traditionally, stock volatility is solved through diversification, where one spreads the portfolio over many investments to avoid excessive exposure to firm-specific risk. This has been an important strategy for investors (Bodie et al. 2014). Another method of handling the volatility in the shipping stock prices can be found in the derivative market. An investor who is interested in reducing the price risk that she faces in a long position of the stock, can take a short position in a derivative. When entering a hedging position, the investor is looking to reduce her risk by reducing the potential for price movements. If a hedging instrument based on the underlying asset does not exist, the hedger can use an instrument based on a correlated asset, which is called cross-hedging (Chen & Sutcliffe, 2011). An additional advantage of derivatives is that it may allow the investors to perform changes in asset allocations or strategy. For example, an investor can manage short term movements in the market in a more cost-effective and efficient manner by achieving the same effect as buying and selling the underlying asset while not physically buying and selling it. It can be costly to construct a portfolio which contains all the components due to transaction costs and the management time involved in the process, and therefore, a hedging strategy can improve the overall return of a portfolio (Pagdin & Hardy, 2018).

The derivatives market in shipping started with trading of dry cargo freight futures in 1985 when the Baltic International Freight Futures Exchange (BIFFEX) was established in

London. The underlying asset was The Baltic Freight Index (BFI), which was a weighted average of freight rates within 13 major routes that dry bulk vessels traded on. BIFFEX included Capesize, Panamax and Handysize[1] freight rates with different weights to the index set according to the importance of the route (Kavussanos & Visvikis, 2006a). The BIFFEX started out as a success. However, the trading volume decreased, and in 2002, The London International Financial Futures and Options Exchange (LIFFE), ended the listing of BIFFEX. The decreasing trading volume can be explained among the underlying asset's insufficient capability to track developments in each sub-market, which consequently resulted in a low hedging efficiency (Kavussanos & Visvikis, 2006b).

In 1992, the Forward Freight Agreement (FFA) was introduced to the market as an over-the-counter (OTC) derivative and as an alternative to the BIFFEX to settle better hedges. The FFA is an agreement between a seller and a buyer to settle a freight rate for a stated volume of cargo or type of vessel, for one or several of the major trading routes in the tanker, dry bulk or LPG market at a specific date in the future. The FFA contracts are OTC private contracts, and therefore involve holding counterparty risk. To eliminate this risk, the FFAs can be market-to-market cleared in a clearing house. This will secure the flexible OTC nature of FFAs (Kavussanos & Visvikis, 2016).

As the underlying asset of FFAs is freight rate assessments for one or several routes produced by the Baltic Exchange, the FFA became a more accurate alternative for physical hedging compared to the BIFFEX. Even though trades are feasible on all routes published in the market and with different maturities, the individual routes were the most attractive and used to hedge the exposure to the spot market in the first decades. However, in recent years, the trading has shifted towards FFAs based on global weighted average spot rate per vessel size settling on longer time horizons, where quarter and calendar years are the most liquid contracts (Adland & Alizadeh, 2018). The shift can partly be explained through the development in the physical spot freight market, as charterers increase their flexibility in terms of routing, cargo size and issues regarding demurrage (Adland & Jia, 2017). Furthermore, according to Alizadeh (2013), the forward freight market is following a "volatility term structure", which states that volatility in FFA prices decreases as the maturity of the contract increases. This is because when the spot freight rates experience shocks, either positive or negative, they will deviate from a long-run mean. This will affect the contracts with shorter time to maturity to a larger extent. However, in the long run, one expects the freight rates to revert back to their long-run

[1] Description of Baltic Sale and Purchase Assessment for the vessels is given in Table A.4.3

mean, and therefore, the contracts with longer time to maturity are less exposed to these types of fluctuations (Alizadeh & Nomikos, 2009).

In this paper, we examine if there exists a long-run relationship between shipping stock prices and FFAs to theoretically justify the use of FFA as a hedging instrument. We expect that the two financial instruments are highly correlated as FFA contracts aim to reflect the future freight income of a vessel, and therefore, it could be argued that they also reflect the future expected earnings of a shipping company. We have selected seven companies, which all are operating within the dry bulk segment of shipping. These companies differ in terms of exposure to the spot market, fleet composition and fleet size. As there are several factors influencing the stock price of the companies, other than the future expected earnings, we therefore want to test how efficient this cross-hedging strategy is.

The objective of this thesis is to study how 5TC, 4TC and 5TC FFA contracts in the Capesize, Panamax and Supramax segment, respectively, can be used for hedging the price risk of shipping stocks. The hedging efficiency is compared across different hedging intervals, across different maturities and across different companies operating in the dry bulk shipping segment.

This thesis contributes to existing literature in numerous ways. Firstly, a theoretical link between dry bulk shipping stocks and forward freight agreement is established. Secondly, the efficiency of using FFA contracts to hedge dry bulk shipping stocks is explored for the first time. Thirdly, we examine, for the first time, the differences in hedging efficiency between several hedging horizons, across different term structures and between companies operating in the dry bulk shipping market. We believe the thesis is relevant for both private investors and investment funds trading in this fluctuating market. Considering the limited literature on this topic, our findings provide useful insight to risk management for equity investors in the dry bulk shipping sector.

The remainder of this thesis is structured as follows; Section 2 presents a literature review where we examine relevant literature on the topics of risk management and shipping stock characteristics. In section 3 we find a cointegrated relationship between the two variables, and further establish a theoretical link between dry bulk stock prices and FFAs. Finally, in section 4 we present our results and discuss the performance of the cross-hedging strategy.

2. Literature Review

To answer the thesis question, we need to establish the theoretical foundation of key concepts and current knowledge. We categorize four main areas relevant for our study; hedging with different time horizons (1), cross-hedging (2), hedging with FFA (3), and recent studies on the close relationship between freight rates and shipping stocks (4).

Firstly, the majority of studies on hedging concentrate on hedging with shorter time horizons, such as daily intervals, neglecting that investors have different holding periods for their investments and that the hedging strategy may depend on the time horizon (Cotter & Hanly, 2009). In their study, Cotter and Hanly (2009) investigate hedge strategies for a cash position in an equity index (FTSE100), a commodity (Crude Oil) and foreign exchange (USD vs. GBP) using associated futures contracts across daily, weekly and monthly time horizons. They find that the optimal hedge ratios and hedging effectiveness tend to increase with hedging horizon. This is consistent with the findings of Chen et al. (2004) from their study on the relationship between hedge ratio and hedging horizon. The article analyzes hedging strategies using 25 different commodity futures to hedge the associated spot prices over 9 different hedge horizons, where the shortest horizon is daily and the longest is 8 weeks.

Secondly, there is a growing range of research within cross-hedging with commodities and financial assets in various markets. Olson, et al. (2017) exploit the evidence of increasing correlation between commodity and equity markets and investigate if this can result in more effective cross-hedges. They study the performance of a cross-hedge between monthly returns of S&P 500 and commodity futures. Using futures from energy, industrial metals, precious metals, agriculture and livestock markets, they find that increased correlation has not been sufficient to make the commodity futures an effective hedge for the equity index. To illustrate, the highest hedging efficiency is achieved using industrial metals and resulted in a 10% variance reduction. In contrast to their study, we will assess if the risk of equity in dry bulk shipping companies can be effectively hedged using derivatives from the shipping market. Thus, we will look into a specific market and use derivatives with underlying asset from the same market, potentially causing lower basis risk compared to Olson et. al (2017). Therefore, it could be interesting to investigate if this strategy provides a better hedging efficiency.

The basis risk associated with cross-hedging must be taken into account. It should be noted that FFA contracts are not perfect hedging instruments for the stock price of shipping companies, as the shipping stock prices depend on various factors. Grammenos and Marcoulis (1996) argue that the average age of the fleet plus financial leverage are important factors for explaining shipping stock returns. Moreover, Drobetz, et al. (2016) examine the factors affecting stock betas of shipping companies. Stock market beta is a main determinant of expected stock returns in both the Capital Asset Pricing Model (Lintner, 1965; Mossin, 1966; Sharpe, 1964) and multifactor beta pricing models (Fama & French, 1995, 1993; Ross, 1976). Drobetz et al. (2016) find that industry-specific risk characteristics, such as freight rate volatility and credit spread, have a significant impact on the beta of shipping companies. In addition, operating and financial leverage are found as important factors in determining stock betas. Further, they discover greater levels of beta in years experiencing high freight rate volatility and during cyclical downturns. They argue that the strong time variation in shipping stock market betas is mainly affected by the cyclical nature of the shipping industry. Depending on the stage of the cycle, shipping companies are either more or less risky than the average firm in the S&P 500 index. Therefore, their study concludes that systematic risk levels in shipping stock seem to have specific determinants compared to the average firm in the S&P 500 index and that market risk alone is not sufficient in explaining shipping stock returns. Freight rate volatility is also highlighted by Syriopoulos and Roumpis (2009) as the most important factor affecting the volatility of shipping stock returns. They find that earnings and shipping stock returns are highly correlated and thus, shipping earnings feature a critical determinant in analyzing shipping stock returns. These previous findings show that earnings is an important, but not the only variable, affecting stock returns of shipping companies. Therefore, this could increase the basis risk, which can influence the performance of the hedging instrument used.

Furthermore, there are deviations between freight revenue and the FFA rates. Adland and Jia (2017) elaborate on physical basis risk in the freight market, defined as the deviation between the earnings of a vessel fleet and realized Baltic 4TC Capesize average, and argue that it will never disappear. The authors present five main factors for basis risk between FFA rates and the physical freight market; technical specifications, actual operating speed and fuel consumption, geographical trading pattern, timing mismatch and vessel unemployment (Adland & Jia, 2017). These findings are important when cross-hedging strategies are applied as they indicate that FFA rates is not a perfect substitute to earnings, which further increase the basis risk. In addition, Adland and Jia (2017) find that physical basis risk is greater for short forward contracts. This is because physical trading patterns, generating earnings for a shipowner, will achieve higher geographical diversification over longer periods compared to shorter periods. Further, they show that an increase in fleet size reduces basis risk. However, this effect is small when exceeding a fleet of approximately 10 vessels.

Nevertheless, studies have shown that forward freight agreements have achieved satisfactory hedging efficiencies despite the presence of basis risk. Alizadeh and Nomikos (2012) investigate the link between the price of a vessel and its associated future earnings and resale value. In their study, they use FFA rates as a proxy for the vessels' future earnings, and thus, find a theoretical link between ship prices and forward freight agreements. They use this link to investigate the hedging efficiency using FFAs to hedge ship prices. They find that in the Capesize market, if one hedges 85% of the ship value, variability is reduced by 86.5%, using a yearly hedging horizon. They find similar results for Supramax and Panamax, indicating that FFAs are good hedging instruments for ship prices. Based on their success, we will assess if the relationship between earnings and FFA could be used to investigate if there exists a theoretical link between shipping stocks and forward freight agreements. However, it should be noted that our paper differs notably from the study of Alizadeh and Nomikos. While the authors focus on risk management from the perspective of a shipowner, we are looking to find a hedging strategy for an equity investor in the shipping markets.

Further, Alizadeh and Nomikos (2012) use the Ederington regression (1979) to determine optimal hedge ratios and hedge effectiveness. This technique accounts for imperfect correlation and difference in standard deviations between the variables and derives minimum variance hedge ratios that minimizes the variance of returns (MVHR) on the hedged portfolio. In support of our decision to use MVHR, Haralambides (1993) argues that MVHR can increase the hedging efficiency compared to a naïve one-to-one hedge ratio. He investigates which technique achieves superior variance reduction when shipowners hedge freight rates using Baltic International Freight Futures Exchange (BIFFEX) contracts. The author states that MVHR does not outperform the naïve hedge ratio at all times. Nevertheless, in the long run, the MVHR will give far better results for the hedger than the naïve hedge ratio (Haralambides, 1993).

Lastly, there is limited literature on the relationship between shipping derivatives and shipping stocks. Michail and Melas (2019) propose a trading strategy for a portfolio of listed tanker companies in the US market. The authors investigate if there exists a cointegrated relationship between weekly returns from the stock market and the Baltic Tanker Index. Further, they test how to exploit the close relationship between stock market performance and freight rates to create a trading strategy, where crossovers are considered to determine the strategy. When the lag of the cointegrated relationship exceeds a six-week moving average of the relationship, it is a buy signal. Moreover, when the short-run moving average moves below the six-week moving average, this is considered a sell signal. Michail and Melas (2019) find that a trading strategy on the basis of the cointegrating relationship outperforms a standard buy-and-hold strategy by approximately 50%, dependent on the investment horizon. The strategy works well also in downturns, and they state that the relationship can be exploited as a hedging strategy as well as a trading strategy. However, such a hedging strategy is based on trading signals from crossovers and does not represent actual earnings from a vessel or a fleet. Still, we want to study a hedging strategy based on the cointegrated relationship Michail and Melas (2019) utilize, but with a cross-hedge strategy taking a short position in FFAs. To our knowledge, this has not yet been investigated, creating a gap in the literature we intend to fill with our thesis. Therefore, we aim to investigate if the relationship is applicable for hedging dry bulk shipping stock prices using derivatives with freight rates as the underlying asset.

3. Data and Methodology

In this section we provide a description of the data we use in this thesis, test for a long-run cointegrated relationship between the variables, and present the methodology we apply in our study.

3.1 Description of Data

This thesis applies data collected from the Baltic Exchange and Bloomberg. The FFA rates, published on the Baltic Exchange, contain daily forward prices from January 4, 2016 to September 30, 2019. We study time charter rates for the weighted average of five routes for Capesize and Supramax Tess52 vessels, 5TC, as well as the weighted average of four routes for Panamax vessels, 4TC. Compared to route-specific contracts also available for these vessels, time charter contracts by ship size attract a larger part of FFA traders due to greater flexibility (Adland & Jia, 2017). Thus, due to higher market liquidity, we choose to focus on these contracts in our research.

As quarter and calendar year FFA contracts are the most liquid (Adland & Alizadeh, 2018), we use contracts with maturity of one quarter and one calendar year to examine the hedging efficiency of FFA. It is assumed that the hedger purchases a contract with maturity the next quarter (calendar year) and holds this contract until the last trading day of that following quarter (calendar year). For instance, a quarterly contract purchased on the final trading day of 2015, expires in the second quarter of 2016. A hedger would hold this contract until the last trading day of the first quarter of 2016, before selling it, and would then purchase a new FFA contract which expires in the third quarter the same year – and further on. When the holding period of the underlying asset exceeds the time to maturity of the hedging instrument, this could create roll-over risk if the contracts are not traded at their theoretical fair value (Chen & Sutcliffe, 2011; Chrisholm, 2002). For example, if the hedger rolls from a contract traded at a discount to a contract trading at a premium, this could create a loss for the hedger, and vice versa.

We see in Table A.2.1 that quarterly and calendar year contracts are in general highly correlated with the stock prices studied in this thesis, which is the most important element in risk management and hedging (Alizadeh & Nomikos, 2012). However, to fully understand if FFA prices and the dry bulk stocks are connected by a long-run relationship, it is not accurate to only view the presented level correlations. It is shown by Johansen (2012) how one can obtain spurious correlations using non-stationary time series, in which one cannot draw conclusions about the relationship between the variables. Therefore, we test for stationarity and cointegrated relationships later in this section.

The stock prices, collected from Bloomberg, are time series of daily prices for seven companies. Reported observations of forward prices and stocks prices exclude weekends, as well as UK and US public holidays. This is because the stock prices are obtained from American stock exchanges, New York Stock Exchange and Nasdaq, and the Baltic Exchange does not publish FFA prices on UK public holidays. The stocks we examine are Golden Ocean Group (GOGL), Star Bulk Carriers Corporation (SBLK), Diana Shipping Inc (DSX), Genco Shipping & Trading Limited (GNK), Navios Maritime Partners (NMM), Scorpio Bulkers (SALT) and Safe Bulkers (SB). These companies own dry bulk vessels similar or equal to the vessels associated with the chosen FFA contracts and their market capitalization is above $150 million. A further description of the FFAs and the stocks can be found in table A.4.1 and A.4.2.

3.2 Descriptive Statistics

Summaries of descriptive statistics for the daily, weekly, monthly, quarterly and yearly log returns of FFA contracts and stock prices are reported in tables A.1.1 through A.1.5. Consulting the summaries, we see that the standard deviations of the stock price returns are, in general, larger than the standard deviations of the FFA returns, indicating that the returns of the stock prices are more volatile. The hedge ratio will be affected due to this asymmetry, which will be illustrated later in the thesis. Test for autocorrelation and Breusch Pagan test for heteroskedasticity reveal that autocorrelation and heteroskedasticity are present in the data (see tables A.1.6 and A.1.7). This causes the standard errors to be incorrect, and thus the estimators to be inefficient. To correct for this, Newey-West regression is applied to the standard errors of the data (Newey & West, 1987).

Stationarity is tested on the logarithmic forward and stock prices, as well as their first differences, using Augmented Dickey Fuller (Dickey & Fuller, 1979) (table A.1.8). The number of lags used in the test is determined by minimizing the Schwarz Bayesian information criterion (Schwarz, 1978). The Augmented Dickey Fuller results reveal that while the variables are non-stationary, their first differences are stationary. This indicates that the variables are integrated of order one, I(1), which makes regressing them potentially valid. Thus, we want to test for cointegration to examine if there exists a long-run equilibrium between the stock prices and the FFA rates. The cointegrated relationship is tested using the augmented Engle-Granger test (Engle & Granger, 1987), including lags determined by Schwarz Bayesian information criterion. Trends in the variables are tested for in table A.1.9, and as all series exhibit a quadratic trend, we also specify this in the Engle-Granger test. The results, presented in table A.1.10, indicate that we can reject the null hypothesis of no cointegration for most relationships between the companies and FFAs. The exceptions are the relationships between Safe Bulkers and all calendar year FFAs, as well as Navios Maritime Partners and the FFA contract 5TC_S+1CAL. Thus, we can explain the regressions of stock prices on FFA prices in a meaningful manner for the cointegrated time series. However, for those who are not cointegrated we should be careful regarding interpretation of further regressions, and because of this, we choose to exclude these regressions from the analysis.

3.3 Minimum Variance Hedge Ratio

As running Engle-Granger cointegration tests indicate long-run cointegrated relationships between the stock prices and forward freight rates, we want to find a theoretical explanation for these relationships. Syriopoulos and Roumpis (2009) argue that freight rates, affecting a shipping company's income, is a critical factor for analysis of the volatility of shipping stocks. Consulting the Dividend Growth Formula (Gordon, 1959) this can be shown as:

$$P_t = \frac{Div_{t+1}}{r_E - g} \tag{1}$$

This equation is used for predicting the price of a stock. The theory says that the price of the stock at present time is the sum of all its future dividend payments when discounted back to their present value. This can also be written as:

$$P_t = \frac{E_{t+1} \, * \, d}{r_E - g} \tag{2}$$

The dividend factor has been substituted by earnings and a dividend payout ratio. Thus, the price of a stock is equal to all future earnings multiplied by the company's dividend payout ratio when discounted back to present value.

As forward freight contracts are used to manage volatility in freight rates, and thus the freight revenue of a shipping company, we want to substitute earnings with FFA in the equation. Whether forward freight contracts are unbiased predictors of future earnings or not have been investigated in multiple studies. Kavussanos et al. (2004) states that FFAs one or two months prior maturity are unbiased predictors of freight rates for all routes because of the cointegrated relationship. However, in other cases the unbiasedness is dependent on the route. Adland and Alizadeh (2018) find that time charter rates and FFA prices are cointegrated and move together in the long run, while on a general basis time charter rates are priced higher than FFA contracts. They find that this premium is related to the fact that time charter contracts provide access to transportation service, while derivatives do not, in addition to default risk being priced in as a risk premium in the time charter price. In our thesis we consider the forward freight rates as unbiased predictors of future expected freight rates, and from this we can write:

$$P_t = \frac{FFA_{t+1} * d}{r_E - g} \tag{3}$$

This equation illustrates the theoretical relationship between shipping stock prices and forward freight prices. Thus, if an investor is long in a stock of a dry-bulk shipping company, she would take a short position in FFA in the holding period. The stockholder then secures her earnings by offsetting a loss in the stock price with a gain in the FFA, and the other way around, referred to as cross-hedging. When an investor cross-hedges she needs to take the hedge ratio into account. If the hedger chooses the same exposure to stock prices and FFA contracts, she chooses a naïve hedge ratio. However, when the two investments have imperfect correlation and different volatility, choosing the ratio that minimizes variance could be more preferable.

To determine a hedge ratio that minimizes variance, Ederington (1979) employed portfolio theory. We consider a portfolio of stock prices p and forward prices f, where Δp_t and Δf_t is the change in stock and FFA prices between time t and t-1. We then have the equation:

$$\Delta p_t = \alpha + \beta \Delta f_t + \varepsilon_t; \;\; \varepsilon_t \sim iid(0, \sigma^2) \tag{4}$$

In this regression the variance minimizing hedge ratio is determined by the slope coefficient beta. Beta determines the percentage of the value of a stock that should be hedged using forward freight rates. Hedging efficiency is measured by R^2, thus the percentage of volatility reduced by using FFAs in hedging.

This thesis uses multiple hedging intervals, reflecting the distance between t and t-1; daily, weekly, monthly, quarterly and yearly. As investors have different holding periods for their investments, we want to investigate which holding period gives the greatest hedging efficiency for the dry-bulk stocks. It should be noted that the use of a forward contract with a maturity of one quarter for a yearly hedge horizon, requires rollovers to new contracts prior to maturity, thus creating roll-over risk for this hedge.

A problem with the Ederington regression is that overlapping observations cause the R^2 and standard errors to be inefficient and incorrect. This is due to the error term N_t following a moving average process (Alizadeh & Nomikos, 2012). To correct for this issue, non-overlapping observations can be used. As we have daily data, we will not have the problem of overlapping observations regarding calculation of the daily returns. However, with non-overlapping observations for the weekly, monthly, quarterly and yearly returns we will have 196, 45, 15 and 3 observations. We want to correct for the small samples to obtain solid hedge ratios, and to achieve this we employ the wild clustered bootstrap by Roodman et al. (2019). Bootstrapping is a procedure that is used to achieve an estimation of the distribution of an estimator or test statistic, which can be advantageous when this is difficult to calculate (Horowitz, 2001). We use the post-estimation command boottest in Stata to obtain the t-statistics and the associated bootstrapped p-values for the hedge ratio coefficient (Roodman et al., 2019). By using the boottest command we generate 10000 wild cluster bootstrap samples, and we can reliably interpret the hedge ratio coefficient from the Ederington regressions.

4. Results and Analysis

To investigate whether one can use FFAs to hedge fluctuations in shipping stock prices, we have estimated the minimum variance hedge ratios and their associated hedge efficiency. The following sections present the estimated results, where we will discuss our findings. First, we compare hedging efficiency across all hedging intervals included in the study: daily, weekly, monthly, quarterly and yearly. Moreover, we investigate the difference in hedging efficiency for the quarterly and calendar year forward freight contracts. Furthermore, we examine the contrast in achieved hedging efficiency for the dry bulk stocks included in this thesis. Finally, we compare our findings to other studies, and elaborate on the performance of the conducted cross-hedge strategy. All tables in the result section display non-overlapping, bootstrapped results. From Tables A.3.1-A.3.9 in Appendix, we see that the hedge ratios differ between actual and bootstrapped values in several cases. This can reflect inconsistent and biased estimators, and hence, that overlapping observations affect the magnitude of the coefficient estimate. In addition, the R^2 of the regression differs notably in certain estimations. Overall, these results question the robustness of our findings with overlapping observations.

4.1 Comparison across hedging intervals

As all forward contracts, whether it is for Capesize, Panamax or Supramax, reveal the same trend, we will in this section focus on a comparison of the results of the 4TC_P+1CAL contract for all hedging intervals. The results for the other types of forwards can be found in Table 4.3.1 and Appendix A.3.1 through A.3.9.

Table 4.1.1 presents the non-overlapping, bootstrapped results from the Ederington regression for all hedging intervals. For weekly, quarterly and yearly returns, the minimum variance hedge ratio is not significant for several companies. In these cases, the use of FFA as a hedging instrument does not reduce the variance of the dry bulk stocks, and thus we cannot utilize these results in our analysis. However, for the estimated hedge ratios proven significant, we find that the minimum variance hedge ratio and the hedging efficiency increase with the hedging horizons. For example, if one hedges 146.15% of the GOGL stock, one can reduce the variance with 56.87% with a hedging horizon of one quarter.

Cotter and Hanly (2009), as well as Chen et al. (2004), find in their studies that the optimal hedge ratios and hedging efficiency increase with the hedging horizon. Thus, unlike previous literature on the relationship between hedging efficiency and hedging interval, we find rather unclear results. The hedging efficiency and hedge ratio tend to rise with increasing hedging horizons for the significant results, indicating that longer hedging intervals give superior hedge effectiveness. At the same time, multiple hedge ratios are not significant for longer hedging horizons, especially yearly, and do not reduce the variance of the stock prices. This suggests that longer hedging intervals achieve lower hedge efficiency compared to shorter. Thus, our results are conflicting.

Adland and Jia (2017) find that physical basis risk is greater for short forward contracts than for longer forward contracts. This is because physical trading patterns, generating earnings for a shipowner, will achieve higher geographical diversification over longer periods compared to shorter periods. Applying this line of reasoning to hedging intervals, we see that longer hedging horizons will be less exposed to physical basis risk than shorter horizons. Considering our results in the light of Adland and Jia's findings (2017), it could be expected that longer hedging horizons would achieve higher hedge ratios and hedge efficiency due to lower physical basis risk.

Moreover, consulting the correlation matrices in A.2.2 through A.2.6 we see increasing correlation from a daily hedge horizon to a yearly hedge horizon. An explanation for increased correlation could be noise and temporary events affecting the short-term returns of the stock prices, which make them deviate more from the FFA returns. In the long run, stock prices and FFA prices follow a common trend, reflected by the cointegrated relationship found using Engle-Granger test. This is supported by the findings of Drobetz et al. (2016). They argue that the strong time variation in shipping stock market betas is mainly affected by the cyclical nature of the shipping industry, indicating that the shipping industry fundamentals determine the risk of shipping stocks to a greater extent compared to the general stock market. Thus, we could expect higher correlation between shipping stocks and FFA over time. As correlation is an important factor in hedging, we would expect that the higher correlation for longer hedging horizons against the correlation for shorter hedging horizons would contribute to an improved hedging efficiency. However, we do not observe this due to contradictory results. Thus, our results are unexpected seeing the finding of Cotter and Hanly (2009), Chen et al. (2004), Adland and Jia (2017), and Drobetz et al. (2016).

TABLE 4.1.1

Estimates of OLS hedge ratios and hedge effectiveness for returns of stock prices using 4TC_P+1CAL

		Daily	*Weekly*	*Monthly*	*Quarterly*	*Yearly*
GOGL						
	β	0.7235	0.6642	1.2033	1.4615	3.3308
		(0.1022)	(0.2840)	(0.2725)	(0.4251)	(1.1403)
		[7.08***]	[3.80***]	[4.00***]	[3.63**]	[2.07]
	R^2	7.73%	8.47%	31.96%	56.87%	81.01%
SBLK						
	β	0.5782	0.4556	1.0229	1.1155	4.4120
		(0.1108)	(0.3228)	(0.5185)	(0.8303)	(0.2190)
		[5.22***]	[2.02]	[2.17*]	[1.58]	[14.25***]
	R^2	3.54%	2.55%	12.16%	20.03%	99.51%
DSX						
	β	0.4369	0.5670	1.0537	1.3017	1.9719
		(0.1027)	(0.3084)	(0.4489)	(0.3922)	(1.6371)
		[4.26***]	[2.87*]	[3.22**]	[3.11*]	[0.85]
	R^2	2.37%	5.03%	23.36%	49.12%	42.04%
GNK						
	β	0.6569	0.4397	1.3964	2.7290	4.0839
		(0.1413)	(0.3285)	(0.3850)	(0.3856)	(3.1296)
		[4.65***]	[1.58]	[2.89***]	[6.92***]	[0.92]
	R^2	3.14%	1.58%	19.72%	82.72%	45.99%
NMM						
	β	0.3904	0.3363	0.9884	2.0919	6.0550
		(0.1035)	(0.2710)	(0.3621)	(0.6536)	(2.6217)
		[3.77***]	[1.39]	[2.30**]	[3.34*]	[1.63]
	R^2	1.70%	1.23%	13.51%	52.80%	72.73%
SALT						
	β	0.5508	0.5949	1.5930	2.0428	2.3804
		(0.1175)	(0.4237)	(0.7436)	(0.7035)	(2.2449)
		[4.69***]	[2.42]	[3.57*]	[3.22*]	[0.75]
	R^2	3.15%	3.61%	27.32%	50.97%	35.99%
SB						
	β	-	-	-	-	-
	R^2	-	-	-	-	-

Standard errors are illustrated in (), while t-statistics are in [].

$^{*, **, ***}$ Denotes significance level at 10%, 5%, and 1% level.

4.2 Comparison across term structure

In this section, we compare the hedging efficiency using quarterly and calendar year FFAs from the Capesize segment for daily and monthly returns of stocks. As in the previous section, we choose to focus on one of the forward types considering the similar trend for the other types.

The results from hedging shipping stock prices with 5TC_C+1Q and 5TC_C+1CAL contracts with daily and monthly hedging horizon are presented in Table 4.2.1. Again, insignificant hedge ratios do not reduce variance, and therefore cannot be analyzed in this thesis. We find that, in general, forward contracts with a maturity of one calendar year achieve higher hedge ratios and hedge efficiency than forward contracts with a maturity of one quarter. For instance, if you hedge 90.49% of the GOGL stock with 5TC_C+1CAL and a hedging horizon of one month, you achieve a hedge efficiency of 28.71%. On the contrary, the MVHR for hedging the GOGL stock for the same hedging horizon with 5TC_C+1Q is 22.34%, and its associated hedging efficiency is 13.65%.

With reference to the presented literature, Adland and Jia (2017) investigate the difference in physical basis risk for short and long forward contracts. They find that longer contracts will have less physical basis risk due to geographical diversification in trading patterns over longer periods. Thus, if we expect less time varying differences between longer contracts and FFA prices than for shorter contracts, we could expect higher correlation between the variables. Examining the correlation matrices in A.2.2. through A.2.6 we see that, in most instances, the correlation between longer forwards and stock prices, is higher than the respective correlation for shorter forwards. Due to this, we might expect more successful hedges with longer contracts. Our results support this reasoning, as we observe superior hedging efficiency using contracts with a maturity of one calendar year compared to contracts with a maturity of one quarter.

Further, volatility in FFA prices decreases as the maturity of the contract increases, known as “volatility term structure” in the forward freight market (Alizadeh, 2013). This is because spot freight rates are expected to revert back to their long-run mean, thus making longer contracts less exposed to fluctuations (Alizadeh & Nomikos, 2009). As presented in the descriptive statistics, FFA price volatility decreases with incresed time to maturity, which is consistent

TABLE 4.2.1

Estimates of OLS hedge ratios and hedge effectiveness for daily and monthly returns of stock prices using 5TC_C+1Q and 5TC_C+1CAL

	Daily		*Monthly*	
	5TC_C+1Q	5TC_C+1CAL	5TC_C+1Q	5TC_C+1CAL
GOGL				
β	0.1310	0.6445	0.2234	0.9049
	(0.0349)	(0.0705)	(0.0871)	(0.2356)
	[3.76***]	[9.14***]	[2.55***]	[4.06***]
R^2	3.97%	9.46%	13.65%	28.71%
SBLK				
β	0.1158	0.5470	0.1488	0.8924
	(0.0328)	(0.0874)	(0.1026)	(0.2477)
	[3.53***]	[6.26***]	[1.24]	[2.86**]
R^2	2.22%	4.88%	3.62%	16.68%
DSX				
β	0.0768	0.3321	0.1564	0.6296
	(0.0263)	(0.0831)	(0.0715)	(0.2500)
	[2.92***]	[4.00***]	[1.90**]	[2.88***]
R^2	1.15%	2.11%	8.11%	16.85%
GNK				
β	0.1471	0.5977	0.2140	1.0006
	(0.0438)	(0.1407)	(0.0927)	(0.3269)
	[3.36***]	[4.25***]	[1.68***]	[3.01***]
R^2	2.46%	4.01%	6.44%	18.06%
NMM				
β	0.0693	0.4443	0.1620	0.4035
	(0.0292)	(0.0790)	(0.0964)	(0.3316)
	[2.37***]	[5.63***]	[1.50*]	[1.33]
R^2	0.83%	3.38%	5.22%	4.15%
SALT				
β	0.0853	0.4532	0.1908	0.9035
	(0.0279)	(0.0889)	(0.0983)	(0.4113)
	[3.05***]	[5.10***]	[1.50**]	[2.69**]
R^2	1.18%	3.29%	5.23%	15.03%
SB				
β	0.1225	-	0.2284	-
	(0.0321)		(0.1048)	
	[3.82***]		[1.97**]	
R^2	2.15%	-	8.67%	-

Standard errors are illustrated in (), while t-statistics are in [].

*, **, *** Denotes significance level at 10%, 5%, and 1% level.

with the “volatility term structure" in the forward freight market. This difference in volatility implies that, in general, one will hedge a larger part of the stock prices using a calendar year FFA contract than a quarterly FFA contract. The increased hedge ratio leads to a higher variance reduction.

These findings could indicate that investors price the dry bulk stocks based on expected earnings the following year rather than the following quarter. Therefore, a one calendar year contract could be seen as a better proxy for shipping stock earnings. Thus, our results suggest that longer forward contracts are better hedging instruments than shorter contracts due to better correlation with the stock prices and lower volatility.

4.3 Comparison across companies

In this section, we will investigate differences in company specific characteristics and whether these can have an impact on hedging efficiency. Three main areas are of interest; exposure to volatility in freight rates, vessel size, and fleet size.

4.3.1 Exposure to volatility in freight rates

From our results presented, we find that GOGL stock return, in general, has the highest correlation with the return of selected FFA contracts, which derives the highest hedge ratio, resulting in the highest hedging efficiency. This line of reasoning is valid for both selected term structures and for most hedging intervals. For instance, from Table 4.3.1, we see that if one hedges 30.34% of the GOGL stock price using a Panamax FFA with maturity of one quarter, the variance is reduced by 5.01% for daily returns. Furthermore, we see from Table A.2.2-A.2.6 in Appendix that the correlations between the return of NMM stock and the return on FFAs, are generally lower compared to other stocks, especially in shorter hedging intervals. This also applies to the hedging efficiencies of the NMM stock, as the variance reduction is, in general, lower compared to other stock prices.

To explain these differences, we want to investigate if the companies’ operating leverage, which refers to exposure to future freight rates, can affect the hedging efficiency. Shipping companies can implement different strategies regarding risk management, where the weight between long-term contracts and exposure to the spot market differ with reference to the company’s desired risk control. According to Drobetz et al. (2016), operating leverage is an important determinant of a shipping company’s level of risk. This could affect the volatility in earnings and hence, also the volatility in a company's stock price. Another important aspect is that a company exposed primarily to the spot market, could possibly have a higher correlation with FFAs compared to a company primarily operating with long-term time charters. This is because long-term contracts at a fixed price will not be affected by changes in the freight rates within the contract period (Grammenos, 2010).

Among the companies in this analysis, we find that GOGL is the company most exposed to fluctuations in freight rates, where 67.1% and 16.45% of the company's fleet is operating in the spot market and on index-based time charter, respectively (Golden Ocean Group Limited, n.d.). This could explain the higher correlation with FFA resulting in higher hedging efficiency. Moreover, NMM is not exposed to the spot market, while the company has almost equal weight between fixed time charter contracts and index-based time charter contracts (Navios Maritime Partners L.P., n.d.). Therefore, NMM has already hedged parts of the company's earnings through fixed contracts. We further find that NMM's fleet consists of 13.5% container vessels, which cannot be hedged using FFAs (Navios Maritime Partners L.P., n.d.). Consequently, this could affect the hedging performance of the forward contracts negatively.

Our results are consistent with the statements of Grammenos (2010) and Drobetz et al. (2016), and could indicate a close relationship between risk management in a shipping company and the hedging efficiency. It should be noted that in a market boom, a company wants to capture the upside and operate more in the spot market or on indexed based time charter contracts. Meanwhile, in a weak market, a company wants to secure its income with longer time charter contracts and a fixed freight rate. Therefore, the exposure to fluctuations in freight rates can differ from where the companies are in the business cycle, hence, a company's risk management strategy is not necessarily constant over time. Thus, this could be relevant for an investor to elaborate on when she is entering a hedging position for a shipping stock.

4.3.2 Vessel size

We want to examine if fleet composition, in terms of vessel size, can have an impact on the hedging efficiency as larger vessels are on average generating higher returns compared to smaller vessels. Earnings of larger vessels are also expected to be more volatile and can consequently result in more fluctuation in stock returns (Syriopoulos & Roumpis, 2009). Hence, there could be more volatility to offset in companies with a fleet mainly consisting of the largest vessels.

As shown in Table 4.3.1, GOGL achieves a daily hedge ratio of 13.10% and hedge efficiency of 3.97% using a Capesize contract with a maturity of one quarter. In our sample, GOGL has the fleet with the highest portion of Capesize, the largest vessel class, and is also performing better in terms of higher hedging efficiency compared to the other companies. This indicates that there is more risk to offset in the company's stock price. On the other hand, SALT has no vessels in the largest vessel segment. However, we do not find consistent results that indicate lower volatility in the stock return of SALT nor lower hedging efficiency for the company. We therefore cannot conclude that a company's fleet composition affects the hedging performance

4.3.3 Fleet size

Lastly, we look at differences in the hedging performance related to the size of the fleet. According to Adland and Jia (2017), a larger fleet results in less volatile earnings and lower basis risk. However, their findings state that the effect is small when exceeding a fleet of approximately 10 vessels.

In comparison of the companies, we see that SBLK has the largest fleet of 118 vessels. However, the company does not obtain the highest nor the lowest variance reduction. Furthermore, NMM has the smallest fleet of 37 vessels. According to the presented literature, it should thus obtain a higher hedging efficiency as there is more risk to offset with a smaller fleet. As discussed in section 4.3.1, NMM achieves, in general, lower hedging efficiency compared to other companies. Thus, we do not find distinct results confirming that a larger fleet size results in lower hedging efficiency for the stock prices.

All the selected companies have a fleet greater than 10 vessels, and therefore, the diversification effect of a larger fleet is low. It is important to notice that, for example, SBLK, in addition to having a large fleet size, is exposed to the spot market to a great extent. The different combination of fleet size and risk profile for all the selected companies are causing difficulties in isolating the effects. This could be an explanation of the inconsistent results regarding fleet size.

TABLE 4.3.1

Estimates of OLS hedge ratios and hedge effectiveness for daily returns of stock prices and quarterly FFAs

	5TC_C+1Q	4TC_P+1Q	5TC_S+1Q
GOGL			
β	0.1310	0.3034	0.2779
	(0.0349)	(0.0618)	(0.1006)
	[3.76***]	[4.91***]	[2.76***]
R^2	3.97%	5.01%	3.00%
SBLK			
β	0.1158	0.2225	0.2228
R^2	(0.0328)	(0.0636)	(0.0941)
	[3.53***]	[3.50***]	[2.37**]
	2.22%	1.93%	1.38%
DSX			
β	0.0768	0.1967	0.1998
R^2	(0.0263)	(0.0536)	(0.0796)
	[2.92***]	[3.67***]	[2.51**]
	1.15%	1.77%	1.30%
GNK			
β	0.1471	0.2991	0.2850
R^2	(0.0438)	(0.0809)	(0.1089)
	[3.36***]	[3.70***]	[2.62***]
	2.46%	2.40%	1.55%
NMM			
β	0.0693	0.1325	0.1659
R^2	(0.0292)	(0.0538)	(0.0631)
	[2.37**]	[2.46**]	[2.63***]
	0.83%	0.72%	0.80%
SALT			
β	0.0853	0.2324	0.2497
R^2	(0.0279)	(0.0625)	(0.1007)
	[3.05***]	[3.72***]	[2.48**]
	1.18%	2.07%	1.70%
SB			
β	0.1225	0.3641	0.3483
R^2	(0.0321)	(0.0704)	(0.0992)
	[3.82***]	[5.17***]	[3.51***]
	2.15%	4.46%	2.91%

Standard errors are illustrated in (), while t-statistics are in [].

*, **, *** Denotes significance level at 10%, 5%, and 1% level.

4.4 Evaluation of the cross-hedge strategy

In this section, we will evaluate the performance of FFA as a hedging instrument for stock prices. We will compare our results to findings from other cross-hedging studies and elaborate on aspects that can explain possible differences in achieved hedging efficiency.

Comparing our findings to the results of Olson et al. (2017), we observe that for monthly returns, our study achieves superior hedging efficiency. An example can be seen in Table 4.1.1, where the hedge efficiencies for monthly returns of all companies, using 4TC_P+1CAL, are higher than the best result of 10% variance reduction found by Olson et al. (2017). In their study, they investigate the hedging efficiency using commodities for hedging the S&P 500. On the contrary, we look into a specific market and use derivatives with an underlying asset from the same market, potentially causing lower basis risk. This could explain why we achieve a superior hedging efficiency compared to the results of Olson et al. (2017).

We will also examine our results in the light of the findings of Alizadeh and Nomikos (2012) and their study on the performance of FFA as a hedging instrument used to hedge vessel prices. They find that in the Capesize market, if one hedges 85% of the ship value, variability is reduced by 86.5%, using a yearly hedging horizon. Further, they find similar results for Supramax and Panamax, indicating that FFAs are good hedging instruments for ship prices. Consulting Table 4.1.1, we see that the achieved hedging efficiency for SBLK, considering a yearly hedging horizon, is 99.51%, using 4TC_P+1CAL. Thus, a comparison of this result to the findings of Alizadeh and Nomikos, signals that FFA contracts perform well as a hedging instrument for stock prices, as well as ship prices. In longer hedge horizons where hedge ratios are proven significant, we in general see increasing hedge efficiency compared to shorter hedge horizons. However, the hedge ratio and hedge efficiency for SBLK is the only significant result using 4TC_P+1CAL, suggesting that the contract is not able to reduce variance for the stock price of other companies. Examining the longer hedge horizons, these are prevailing results for all forward contracts utilized in the study. Whereas the results presented by Alizadeh and Nomikos are consistent, we have conflicting findings, implying an inferior performance of our cross-hedge strategy.

Thus, we find that the hedging efficiency of forward freight agreements on stock price risk is, in general, mediocre. Though superior to the findings of Olsen et. al (2017), our findings are inferior compared to the results of Alizadeh and Nomikos (2012). In addition, the results, especially for longer hedging intervals, are inconsistent, as they are either reducing variance to a large degree or not at all.

The mediocre results could possibly be explained by a mismatch between the FFA contracts and the company's exposure to the physical market. We see that all companies have a fleet consisting of at least two different vessel classes. In this case, ship owners diversify business risk through a portfolio of ships from different sub-markets. As a result, the companies obtain a more diverse income stream from transporting different commodities with different patterns in demand and price. For example, if the demand for iron ore is decreasing and a Capesize vessel is generating lower profits, there could at the same time be a high season for grain in the U.S. resulting in high demand and high profits in the Panamax and Supramax segment. Following, if a company’s fleet does not solely consist of one vessel size, the basis risk between the stock performance and a specific FFA contract could be higher as the company generates income from different vessel sizes. This line of reasoning could be used to understand the differing results in hedging efficiency for the stock prices examined in this thesis and ship prices investigated by Alizadeh and Nomikos (2012). Whereas Alizadeh and Nomikos used FFAs based on the vessel they hedged, we use only one type of FFA for a company with two or more vessel types.

The findings have similarities with the reasons for closing down the BIFFEX in 2002. The decrease in trading volume of BIFFEX contracts can be explained by the underlying asset’s insufficient capability to track developments in each sub-market, which consequently resulted in low hedging efficiency (Kavussanos & Visvikis, 2006b). Thus, with the use of only one type of forward contract in the hedging strategy at a time, it can be difficult to follow the development in each sub-markets of a company’s fleet, and consequently a company’s earnings, creating increased basis risk. A possible solution to this could be to use a portfolio of FFA contracts from the different sub-markets to reduce the basis risk. It would be interesting to examine if this solution could potentially achieve improved hedging efficiency for shipping stock prices, thus this creates opportunities for further research on the subject.

5. Concluding Remarks

In this thesis, we have studied the performance of forward freight agreements as a hedging instrument for the volatility in dry bulk stock prices. Having found a long-run cointegrated relationship between the selected stock prices and the FFAs, we established a theoretical link between the variables using the Dividend Growth Formula. Through the Ederington regression we computed the minimum variance hedge ratios and their associated hedge efficiencies.

We compare the difference in hedge efficiency across hedge intervals, term structure and companies, where we find that these attributes have differing implications for the variance reduction of stock prices. The comparison of hedge efficiency across hedge intervals gives inconsistent results. We find that for significant hedge ratios the variance reduction increases with increased hedge horizon. However, multiple hedge ratios for longer hedge horizons are insignificant, indicating decreased hedge efficiency with increasing time horizon. Furthermore, forward contracts with maturity of one calendar year achieve, in general, higher hedging efficiency than forward contracts with maturity of one quarter, in accordance with the volatility term structure in the shipping market. Moreover, we show that a company's operating leverage can partially explain the hedging efficiency of stock prices, where companies more exposed to fluctuations in freight rates achieve higher variance reduction. Finally, we evaluate our cross-hedging strategy and compare it to the findings of other studies. Compared to Olson et al. (2017), we find superior hedging efficiency, while in comparison to Alizadeh and Nomikos (2012), we achieve inferior hedging efficiency. Thus, we find that the hedging efficiency of FFAs on stock price risk is, in general, mediocre.

Our study has several weaknesses. Firstly, our dataset only contains observations from January 2016 to September 2019, while our original dataset included time series from January 2005 until September 2019. However, the variables where not cointegrated in the original dataset and we therefore changed the time period of the model. This indicates that the model does not perform well in the long run. If we had exploited the original time series, only data on the stock price of Golden Ocean Group Limited and Diana Shipping Inc. would be available from the start date among the selected companies. An additional weakness is the assumptions we have made in the thesis, which are not necessarily equivalent with reality.

Managing the risk of dry bulk stock prices is important for private investors and investment funds in this highly volatile sector. Our thesis provides a way to partially offset this risk, and thus could be of great importance for such investors. To our knowledge, there are no studies investigating the hedging efficiency of forward freight agreements for dry bulk stock prices. Thus, our findings provide useful insight for equity investors in the dry bulk shipping sector.

Our thesis opens for further possible studies of risk management in the shipping market. As we have utilized the static minimum variance hedge ratio in this thesis, it would be interesting to investigate if various types of dynamic hedge ratios would provide a higher variance reduction. It would also be interesting to examine if hedging dry bulk stocks with a portfolio of FFAs from different sub-markets can achieve improved hedging efficiency compared to our findings. Furthermore, an analysis of the hedge efficiency using FFAs to hedge stock prices in other shipping markets, such as LPG and tankers, could enrich our study on risk management of shipping stock prices.

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Appendix

A.1 Descriptive Statistics

TABLE A.1.1

Descriptive statistics of daily returns of stock prices and nearest quarter and calendar FFA

Stock/FFA	Observations	Mean	St.Dev	Min	Max
GOGL	906	0.004%	0.0364	-18.23%	25.62%
SBLK	906	0.132%	0.0430	-30.77%	24.44%
DSX	906	-0.045%	0.0397	-32.90%	20.61%
GNK	906	-0.042%	0.0519	-28.45%	42,20%
NMM	906	-0.131%	0.0420	-33.65%	18.88%
SALT	906	-0.057%	0.0434	-24.77%	28.87%
SB	906	0.052%	0.0463	-32.58%	19.78%
5TC_C+1Q	946	0.107%	0.0545	-61.81%	55.49%
4TC_P+1Q	946	0.076%	0.0265	-26.45%	11.08%
5TC_S+1Q	946	0.045%	0.0224	-33.28%	9.796%
5TC_C+1CAL	946	0.066%	0.0173	-11.92%	7.64%
4TC_P+1CAL	946	0.061%	0.0139	-10.05%	8.96%
5TC_S+1CAL	946	0.051%	0.0108	-7.51%	10.37%

TABLE A.1.2

Descriptive statistics of weekly returns of stock prices and nearest quarter and calendar FFA

Stock/FFA	Observations	Mean	St.Dev	Min	Max
GOGL	902	0.069%	0.0807	-45.62%	35.67%
SBLK	902	0.653%	0.0930	-53.70%	45.02%
DSX	902	-0.130%	0.0896	-67.67%	45.79%
GNK	902	-0.304%	0.1189	-64.51%	68.71%
NMM	902	-0.467%	0.1028	-72.59%	47.19%
SALT	902	-0.018%	0.1008	-58.45%	68.25%
SB	902	0.466%	0.1061	-73.72%	57.49%
5TC_C+1Q	942	0.704%	0.1238	-70.22%	72.55%
4TC_P+1Q	942	0.486%	0.0659	-35.80%	19.37%
5TC_S+1Q	942	0.378%	0.0541	-37.47%	15.57%
5TC_C+1CAL	942	0.338%	0.0409	-24.74%	13.06%
4TC_P+1CAL	942	0.325%	0.0350	-13.16%	12.34%
5TC_S+1CAL	942	0.269%	0.0287	-11.37%	11.30

TABLE A.1.3

Descriptive statistics of monthly returns of stock prices and nearest quarter and calendar FFA

Stock/FFA	Observations	Mean	St.Dev	Min	Max
GOGL	888	1.135%	0.1414	-47.65%	38.68%
SBLK	888	3.693%	0.1823	-45.73%	84.90%
DSX	888	0.426%	0.1413	-61.58%	48.92%
GNK	888	-0.252%	0.2147	-88.18%	74.92%
NMM	888	-1.321%	0.1787	-88.16%	59.47%
SALT	888	1.049%	0.1840	-103.93%	75.63%
SB	888	3.466%	0.1863	-65.73%	78.09%
5TC_C+1Q	926	3.393%	0.2595	-73.88%	104.46%
4TC_P+1Q	926	2.459%	0.1199	-32.87%	44.01%
5TC_S+1Q	926	1.938%	0.1018	-36.40%	30.57%
5TC_C+1CAL	926	1.579%	0.0810	-33.02%	23.64%
4TC_P+1CAL	926	1.540%	0.0655	-19.91%	22.06%
5TC_S+1CAL	926	1.291%	0.0584	-17.65%	18.49%

TABLE A.1.4

Descriptive statistics of quarterly returns of stock prices and nearest quarter and calendar FFA

Stock/FFA	Observations	Mean	St.Dev	Min	Max
GOGL	848	4.148%	0.2178	-49.12%	69.94%
SBLK	848	9.567%	0.2834	-50.27%	102.00%
DSX	848	1.918%	0.1850	-68.65%	57.62%
GNK	848	1.174%	0.2908	-104.18%	104.80%
NMM	848	-2.022%	0.2294	-91.47%	53.06%
SALT	848	4.524%	0.2482	-96.10%	79.49%
SB	848	9.034%	0.2964	-53.52%	145.54%
5TC_C+1Q	884	11.019%	0.4108	-95.02%	91.66%
4TC_P+1Q	884	7.350%	0.1889	-32.23%	59.51%
5TC_S+1Q	884	5.735%	0.1623	-32.52%	41.77%
5TC_C+1CAL	884	4.854%	0.1510	-49.47%	45.10%
4TC_P+1CAL	884	4.623%	0.1244	-35.06%	38.77%
5TC_S+1CAL	884	4.086%	0.1103	-30.81%	36.71%

TABLE A.1.5

Descriptive statistics of yearly returns of stock prices and nearest quarter and calendar FFA					
Stock/FFA	Observations	Mean	St.Dev	Min	Max
GOGL	675	17.27%	0.4707	-69.43%	103.27%
SBLK	675	31.367%	0.5505	-66.91%	153.38%
DSX	675	7.091%	0.3063	-53.83%	72.75%
GNK	675	12.331%	0.5306	-96.44%	120.47%
NMM	675	-11.174%	0.4376	-102.61%	74.48%
SALT	675	13.865%	0.4964	-72.14%	136.74%
SB	675	21.509%	0.6779	-101.90%	153.66%
5TC_C+1Q	695	25.896%	0.4196	-90.30%	144.16%
4TC_P+1Q	695	25.483%	0.3163	-46.22%	88.13%
5TC_S+1Q	695	20.610%	0.2632	-34.40%	71.43%
5TC_C+1CAL	695	20.686%	0.2932	-42.04%	61.95%
4TC_P+1CAL	695	20.545%	0.2868	-35.73%	61.41%
5TC_S+1CAL	695	18.770%	0.2612	-34.78%	59.25%

TABLE A.1.6

Test statistics from test for autocorrelation *H_0: No autocorrelation in the data*						
Stock/ FFA	5TC_C+1Q	4TC_P+1Q	5TC_S+1Q	5TC_C+1CAL	4TC_P+1CAL	5TC_S+1CAL
GOGL	126.99***	112.59***	110.29***	108.85***	104.62***	106.15***
SBLK	117.49***	86.86***	91.05***	102.02***	96.61***	99.30***
DSX	99.68**	97.97***	100.01***	92.53***	93.31***	95.20***
GNK	140.33***	130.10***	129.45***	117.17***	119.64***	121.26***
NMM	178.16***	179.78***	179.88***	179.15***	177.96***	178.35***
SALT	133.16***	121.88***	128.73***	129.51***	124.05***	127.52***
SB	137.55***	142.20***	137.80***	156.65***	154.35***	156.57***

*, **, *** Denotes significance level at 10%, 5%, and 1% level.
The test is conducted by regressing the residuals of the regressions on the lagged residuals.

TABLE A.1.7

Chi2(1) test statistics from Breusch-Pagan test for heteroscedasticity
H_0: No heteroscedasticity in the data

Stock/ FFA	5TC_C+1Q	4TC_P+1Q	5TC_S+1Q	5TC_C+1CAL	4TC_P+1CAL	5TC_S+1CAL
GOGL	11.47***	32.68***	3.08*	15.62***	5.84**	7.83***
SBLK	111.67***	132.66***	183.48***	200.98***	220.87***	146.22***
DSX	4.47**	0.08	2.95*	3.56*	0.93	0.28
GNK	19.49***	51.14***	69.72***	52.35***	75.13***	75.36***
NMM	13.91***	30.71***	21.89***	13.75***	11.18***	12.45***
SALT	32.67***	21.33***	27.13***	16.41***	10.61***	7.53***
SB	10.79***	19.04***	37.07***	57.98***	70.26***	46.10***

*, **, *** Denotes significance level at 10%, 5%, and 1% level.

TABLE A.1.8

Test statistics from Augmented Dickey Fuller (ADF)
H_0: Variable contains a unit root

	Level		First-Difference	
Stock/FFA	ADF	Lags	ADF	Lags
GOGL	-1.706	1	-13.757	1
SBLK	-1.005	1	-13.344	1
DSX	-3.126	1	-13.598	1
GNK	-2.978	1	-12.647	1
NMM	-2.054	1	-15.776	1
SALT	-1.380	1	-13.763	1
SB	-1.632	1	-12.929	1
5TC_C+1Q	-2.552	1	-7.559	1
4TC_P+1Q	-1.954	2	-3.542	2
5TC_S+1Q	-1.385	1	-6.159	1
5TC_C+1CAL	-0.990	2	-9.216	2
4TC_P+1CAL	-0.144	1	-12.783	1
5TC_S+1CAL	-0.603	2	-7.078	2

The 5% critical value is -3.410 for the ADF test on the level variables, and -3.427 for the ADF test on the first-difference variables. The number of lags used in the test is determined by minimizing the Schwarz criterion (SBIC) and the ADF regressions include a correction for trend.

TABLE A.1.9

Test statistics from control for linear and quadratic trends in the variables *H_0: There is no trend in the variable*		
	Trend	
Stock/FFA	Linear - Date	Quadratic – Date_sq
GOGL	19.69	-43.99
SBLK	29.57	-48.71
DSX	11.03	-29.68
GNK	13.06	-22.64
NMM	-12.09	-30.16
SALT	13.49	-35.97
SB	18.86	-56.58
5TC_C+1Q	29.51	-15.33
4TC_P+1Q	43.23	-36.5
5TC_S+1Q	42.29	-52.27
5TC_C+1CAL	39.62	-33.21
4TC_P+1CAL	39.12	-48.55
5TC_S+1CAL	39.24	-52.27

TABLE A.1.10

Test statistics from Engle-Granger test for cointegration between FFAs and stocks
H_0: The series are not cointegrated

Stock/ FFA	5TC_C+1Q	4TC_P+1Q	5TC_S+1Q	5TC_C+1CAL	4TC_P+1CAL	5TC_S+1CAL
GOGL	-5.458	-5.399	-5.250	-6.220	-5.821	-5.374
SBLK	-4.998	-5.333	-4.830	-4.554	-4.432	-4.075
DSX	-6.331	-5.749	-5.304	-6.301	-5.436	-5.278
GNK	-5.415	-4.519	-4.898	-5.031	-4.275	-4.221
NMM	-5.288	-4.755	-5.006	-4.405	-3.982	-3.852
SALT	-5.957	-5.637	-5.121	-4.762	-4.242	-4.147
SB	-4.898	-4.560	-4.369	-3.590	-3.535	-3.387

The 5% critical value for the Engle-Granger test is -4.168, while the 10% critical value is -3.885. The test is conducted with corrections for quarterly trends in the data.

A.2 Correlation Matrices

TABLE A.2.1

Correlation matrix for log levels of FFA and stocks						
Stock/ FFA	5TC_C+1Q	4TC_P+1Q	5TC_S+1Q	5TC_C+1CAL	4TC_P+1CAL	5TC_S+1CAL
GOGL	0.7792	0.8763	0.8747	0.9037	0.9138	0.9093
SBLK	0.8197	0.9319	0.9250	0.9270	0.9402	0.9375
DSX	0.6567	0.7081	0.6892	0.7436	0.7456	0.7355
GNK	0.6113	0.7151	0.7129	0.7830	0.7815	0.7750
NMM	0.1724	0.1432	0.1498	0.1925	0.2038	0.1936
SALT	0.6730	0.7842	0.7576	0.7746	0.8024	0.7888
SB	0.7620	0.8388	0.8434	0.8248	0.8469	0.8458

TABLE A.2.2

Correlation matrix for daily log returns of FFA and stocks						
Stock/ FFA	5TC_C+1Q	4TC_P+1Q	5TC_S+1Q	5TC_C+1CAL	4TC_P+1CAL	5TC_S+1CAL
GOGL	0.1992	0.2237	0.1731	0.3076	0.2781	0.2496
SBLK	0.1490	0.1389	0.1174	0.2209	0.1880	0.1651
DSX	0.1070	0.1330	0.1140	0.1453	0.1539	0.1811
GNK	0.1569	0.1548	0.1246	0.2002	0.1772	0.1768
NMM	0.0913	0.0848	0.0897	0.1840	0.1302	0.1352
SALT	0.1087	0.1437	0.1304	0.1813	0.1774	0.1619
SB	0.1465	0.2113	0.1707	0.2047	0.2189	0.2292

TABLE A.2.3

Correlation matrix for weekly log returns of FFA and stocks						
Stock/ FFA	5TC_C+1Q	4TC_P+1Q	5TC_S+1Q	5TC_C+1CAL	4TC_P+1CAL	5TC_S+1CAL
GOGL	0.3002	0.3858	0.3549	0.4572	0.4528	0.4652
SBLK	0.2236	0.3122	0.2483	0.3484	0.3592	0.3315
DSX	0.2329	0.3083	0.2652	0.3331	0.3500	0.3523
GNK	0.1698	0.2466	0.2689	0.2649	0.2856	0.3262
NMM	0.1593	0.1890	0.2163	0.2342	0.2275	0.2282
SALT	0.2425	0.3618	0.3340	0.3268	0.3844	0.3693
SB	0.2308	0.3498	0.3178	0.3505	0.3768	0.3764

TABLE A.2.4

Correlation matrix for monthly log returns of FFA and stocks						
Stock/ FFA	5TC_C+1Q	4TC_P+1Q	5TC_S+1Q	5TC_C+1CAL	4TC_P+1CAL	5TC_S+1CAL
GOGL	0.5279	0.5475	0.5257	0.6333	0.5964	0.5987
SBLK	0.2997	0.4523	0.4131	0.4744	0.4769	0.4621
DSX	0.3393	0.4109	0.3252	0.4389	0.4280	0.3855
GNK	0.1718	0.3308	0.3286	0.4216	0.4351	0.4678
NMM	0.3274	0.3521	0.3840	0.3653	0.3322	0.3620
SALT	0.2814	0.4387	0.4371	0.4182	0.4824	0.4646
SB	0.3269	0.3909	0.3640	0.4288	0.3775	0.3552

TABLE A.2.5

Correlation matrix for quarterly log returns of FFA and stocks

Stock/ FFA	5TC_C+1Q	4TC_P+1Q	5TC_S+1Q	5TC_C+1CAL	4TC_P+1CAL	5TC_S+1CAL
GOGL	0.5478	0.6949	0.6640	0.7861	0.7886	0.7828
SBLK	0.4831	0.6263	0.5906	0.6640	0.6767	0.6718
DSX	0.4119	0.4737	0.4048	0.6100	0.6045	0.5508
GNK	0.2010	0.4362	0.3969	0.5743	0.6345	0.6152
NMM	0.4464	0.5687	0.5431	0.6399	0.6621	0.6186
SALT	0.3446	0.6118	0.5119	0.6243	0.7418	0.6750
SB	0.4890	0.4175	0.4302	0.4403	0.3863	0.3931

TABLE A.2.6

Correlation matrix for yearly log returns of FFA and stocks

Stock/ FFA	5TC_C+1Q	4TC_P+1Q	5TC_S+1Q	5TC_C+1CAL	4TC_P+1CAL	5TC_S+1CAL
GOGL	0.8734	0.9360	0.9322	0.9252	0.9499	0.9367
SBLK	0.8065	0.9145	0.8973	0.8569	0.9148	0.9009
DSX	0.7587	0.8495	0.8267	0.8076	0.8566	0.8394
GNK	0.7584	0.8476	0.8647	0.8639	0.8889	0.8764
NMM	0.8576	0.8850	0.9077	0.8892	0.9017	0.8877
SALT	0.7895	0.9090	0.8558	0.7839	0.8499	0.8264
SB	0.8300	0.9227	0.9154	0.8605	0.9032	0.8836

A.3 Results

TABLE A.3.1

Estimates of OLS hedge ratios and hedge effectiveness for weekly returns of stock prices and quarterly FFAs

	5TC_C+1Q		4TC_P+1Q		5TC_S+1Q	
	Actual	*Bootstrap*	*Actual*	*Bootstrap*	*Actual*	*Bootstrap*
GOGL						
β	0.1937	0.2053	0.4701	0.4812	0.5257	0.5117
	(0.0344)	(0.0475)	(0.0624)	(0.1056)	(0.0987)	(0.1571)
	[5.63***]	[4.88***]	[7.53***]	[5.87***]	[5.32***]	[4.69***]
R^2	9.01%	11.04%	14.88%	18.33%	12.60%	12.41%
SBLK						
β	0.1664	0.1844	0.4387	0.3875	0.4240	0.4448
	(0.0329)	(0.0478)	(0.0722)	(0.1280)	(0.0978)	(0.1716)
	[5.05***]	[3.44***]	[6.08***]	[3.56***]	[4.34***]	[3.13**]
R^2	5.00%	5.79%	9.75%	7.51%	6.16%	5.94%
DSX						
β	0.1670	0.2312	0.4175	0.4502	0.4363	0.3583
	(0.0325)	(0.0461)	(0.0759)	(0.1185)	(0.1064)	(0.1441)
	[5.14***]	[5.45***]	[5.50***]	[4.81***]	[4.10***]	[2.84**]
R^2	5.43%	13.42%	9.51%	12.93%	7.03%	4.94%
GNK						
β	0.1615	0.1461	0.4430	0.3034	0.5870	0.5978
	(0.0448)	(0.0608)	(0.0989)	(0.1472)	(0.1343)	(0.2037)
	[3.61***]	[2.23***]	[4.48***]	[2.23*]	[4.37***]	[3.46***]
R^2	2.89%	2.52%	6.08%	3.08%	7.23%	7.16%
NMM						
β	0.1311	0.1416	0.2935	0.2263	0.4084	0.5015
	(0.0331)	(0.0541)	(0.0714)	(0.1128)	(0.0993)	(0.1866)
	[3.96***]	[2.49***]	[4.11***]	[1.90*]	[4.11***]	[3.32***]
R^2	2.54%	3.14%	3.57%	2.26%	4.68%	6.65%
SALT						
β	0.1956	0.1972	0.5510	0.5803	0.6183	0.7878
	(0.0339)	(0.0556)	(0.0829)	(0.1572)	(0.1269)	(0.2318)
	[5.76***]	[3.39***]	[6.65***]	[5.04***]	[4.87***]	[5.32***]
R^2	5.88%	5.64%	13.09%	14.02%	11.16%	15.46%
SB						
β	0.1958	0.2026	0.5605	0.5326	0.6189	0.6488
	(0.0363)	(0.0480)	(0.0787)	(0.1443)	(0.1229)	(0.2302)
	[5.40***]	[3.62***]	[7.12***]	[4.79***]	[5.04***]	[4.48***]
R^2	5.33%	6.38%	12.24%	12.84%	10.10%	11.47%

Standard errors are illustrated in (), while t-statistics are in [].

*, **, *** Denotes significance level at 10%, 5%, and 1% level.

TABLE A.3.2

Estimates of OLS hedge ratios and hedge effectiveness for monthly returns of stock prices and quarterly FFAs

	5TC_C+1Q		4TC_P+1Q		5TC_S+1Q	
	Actual	*Bootstrap*	*Actual*	*Bootstrap*	*Actual*	*Bootstrap*
GOGL						
β	0.2874	0.2234	0.6478	0.4602	0.7319	0.4784
	(0.0186)	(0.0871)	(0.0469)	(0.2225)	(0.0584)	(0.2876)
	[15.46***]	[2.55***]	[13.81***]	[2.57**]	[12.53***]	[2.41*]
R^2	27.87%	13.65%	29.97%	16.31%	27.64%	14.59%
SBLK						
β	0.2105	0.1488	0.6903	0.4083	0.7418	0.4566
	(0.0260)	(0.1026)	(0.0633)	(0.2848)	(0.0805)	(0.3140)
	[8.11***]	[1.24]	[10.90***]	[1.57]	[9.21***]	[1.60]
R^2	8.98%	3.62%	20.46%	6.76%	17.06%	7.00%
DSX						
β	0.1847	0.1564	0.4861	0.3608	0.4527	0.3483
	(0.0191)	(0.0715)	(0.0513)	(0.2458)	(0.0652)	(0.3465)
	[9.66***]	[1.90**]	[9.48***]	[1.90]	[6.95***]	[1.65]
R^2	11.51%	8.11%	16.88%	9.56%	10.58%	7.37%
GNK						
β	0.1420	0.2140	0.5944	0.6621	0.6949	0.6301
	(0.0358)	(0.0927)	(0.0765)	(0.1999)	(0.1116)	(0.2800)
	[3.97***]	[1.68***]	[7.77***]	[2.49***]	[6.23***]	[2.11**]
R^2	2.95%	6.44%	10.94%	15.47%	10.80%	11.60%
NMM						
β	0.2254	0.1620	0.5268	0.3693	0.6761	0.3401
	(0.0242)	(0.0964)	(0.0561)	(0.1929)	(0.0822)	(0.2216)
	[9.33***]	[1.50*]	[9.38***]	[1.55*]	[8.23***]	[1.28]
R^2	10.72%	5.22%	12.40%	6.58%	14.75%	4.62%
SALT						
β	0.1994	0.1908	0.6757	0.6512	0.7921	0.7836
	(0.0269)	(0.0983)	(0.0694)	(0.3884)	(0.1001)	(0.5000)
	[7.41***]	[1.50**]	[9.73***]	[2.54]	[7.91***]	[2.83*]
R^2	7.92%	5.23%	19.24%	15.93%	19.10%	19.10%
SB						
β	0.2346	0.2284	0.6097	0.5012	0.6681	0.5092
	(0.0277)	(0.1048)	(0.0568)	(0.2606)	(0.0753)	(0.3561)
	[8.47***]	[1.97**]	[10.74***]	[1.98**]	[8.87***]	[1.82*]
R^2	10.69%	8.67%	15.28%	10.37%	13.25%	8.86%

Standard errors are illustrated in (), while t-statistics are in [].

*, **, *** Denotes significance level at 10%, 5%, and 1% level.

TABLE A.3.3

Estimates of OLS hedge ratios and hedge effectiveness for quarterly returns of stock prices and quarterly FFAs

	5TC_C+1Q		4TC_P+1Q		5TC_S+1Q	
	Actual	*Bootstrap*	*Actual*	*Bootstrap*	*Actual*	*Bootstrap*
GOGL						
β	0.2918	0.0764	0.8058	0.3190	0.8966	0.4014
	(0.0217)	(0.1809)	(0.0416)	(0.4076)	(0.0563)	(0.5090)
	[13.47***]	[0.43]	[19.35***]	[0.84]	[15.91***]	[0.92]
R^2	30.01%	1.38%	48.28%	5.56%	44.09%	7.74%
SBLK						
β	0.3348	0.1729	0.9450	0.2082	1.0377	0.2294
	(0.0278)	(0.2864)	(0.0548)	(0.6359)	(0.0736)	(0.7676)
	[12.04***]	[0.74]	[17.25***]	[0.41]	[14.10***]	[0.39]
R^2	23.34%	4.03%	39.23%	1.69%	34.89%	1.53%
DSX						
β	0.1864	0.2239	0.4666	0.5572	0.4642	0.6439
	(0.0168)	(0.1540)	(0.0402)	(0.3741)	(0.0515)	(0.4774)
	[11.08***]	[1.45]	[11.60***]	[1.67*]	[9.01***]	[1.66*]
R^2	16.97%	13.89%	22.44%	21.79%	16.38%	21.67%
GNK						
β	0.1430	0.2939	0.6754	1.1463	0.7156	1.4202
	(0.0322)	(0.198)	(0.0539)	(0.4176)	(0.0746)	(0.5350)
	[4.44***]	[1.17]	[12.53***]	[2.34**]	[9.59***]	[2.60**]
R^2	4.04%	9.55%	19.03%	35.33%	15.75%	40.39%
NMM						
β	0.2505	0.0023	0.6945	0.5872	0.7724	0.6912
	(0.0235)	(0.1925)	(0.0385)	(0.4968)	(0.0522)	(0.6274)
	[10.68***]	[0.01]	[18.04***]	[1.06]	[14.81***]	[1.08]
R^2	19.93%	0.01%	32.34%	10.07%	29.50%	10.39%
SALT						
β	0.2092	0.0962	0.8086	0.6885	0.7879	0.8313
	(0.0259)	(0.2313)	(0.0514)	(0.6277)	(0.0733)	(0.800)
	[8.09***]	[0.36]	[15.74***]	[1.28]	[10.74***]	[1.34]
R^2	11.87%	1.00%	37.42%	14.02%	26.20%	15.22%
SB						
β	0.3546	0.1396	0.6590	0.2570	0.7908	0.2512
	(0.0275)	(0.2273)	(0.0631)	(0.5342)	(0.0796)	(0.6318)
	[12.88***]	[0.74]	[10.44***]	[0.60]	[9.94***]	[0.50]
R^2	23.91%	3.99%	17.43%	3.47%	18.51%	2.47%

Standard errors are illustrated in (), while t-statistics are in [].

*,**,*** Denotes significance level at 10%, 5%, and 1% level.

TABLE A.3.4

Estimates of OLS hedge ratios and hedge effectiveness for yearly returns of stock prices and quarterly FFAs

	5TC_C+1Q		4TC_P+1Q		5TC_S+1Q	
	Actual	*Bootstrap*	*Actual*	*Bootstrap*	*Actual*	*Bootstrap*
GOGL						
β	0.9767	1.3152	1.3923	1.6802	1.6652	2.6638
	(0.0310)	(0.3818)	(0.0246)	(0.4087)	(0.0244)	(0.1872)
	[31.53***]	[2.44]	[56.63***]	[2.91]	[68.32***]	[10.06***]
R^2	76.29%	85.57%	87.62%	89.42%	86.90%	99.02%
SBLK						
β	1.0547	1.6846	1.5907	2.0855	1.8744	2.6038
	(0.0368)	(0.1574)	(0.0350)	(0.2831)	(0.0356)	(1.315)
	[28.66***]	[7.57***]	[45.43***]	[5.21]	[52.66***]	[1.40]
R^2	65.05%	98.28%	83.64%	96.45%	80.52%	66.24%
DSX						
β	0.5521	0.8107	0.8223	1.0726	0.9610	2.0914
	(0.0237)	(0.5950)	(0.0241)	(0.7006)	(0.0243)	(0.4825)
	[23.30***]	[0.96]	[34.13***]	[1.08]	[39.63***]	[3.07***]
R^2	57.56%	48.14%	72.17%	53.96%	68.35%	90.38%
GNK						
β	0.9561	1.6702	1.4212	2.2003	1.7411	4.1918
	(0.0468)	(1.1322)	(0.0448)	(1.3266)	(0.0446)	(0.8383)
	[20.43***]	[1.04]	[31.76***]	[1.17]	[39.01***]	[3.53]
R^2	57.52%	52.11%	71.85%	57.90%	74.76%	92.59%
NMM						
β	0.8915	2.4092	1.2237	3.0988	1.5072	5.1358
	(0.0324)	(0.9046)	(0.0287)	(1.0045)	(0.0272)	(0.0019)
	[27.48***]	[1.88]	[42.63***]	[2.18]	[55.41***]	[1925.43***]
R^2	73.54%	78.00%	78.33%	82.63%	82.39%	99.99%
SALT						
β	0.9311	0.9875	1.4258	1.3166	1.6122	2.6682
	(0.0307)	(0.8213)	(0.0296)	(0.9738)	(0.0378)	(0.7481)
	[30.38***]	[0.85]	[48.18***]	[0.96]	[42.70***]	[2.52***]
R^2	62.33%	41.96%	82.62%	47.75%	73.24%	86.42%
SB						
β	1.3366	2.7159	1.9765	3.3821	2.3550	4.4391
	(0.0501)	(0.0607)	(0.0419)	(0.2155)	(0.0441)	(1.7983)
	[26.70***]	[31.64]	[47.17***]	[11.10***]	[53.37***]	[1.75]
R^2	68.88%	99.90%	85.13%	99.19%	83.80%	75.29%

Standard errors are illustrated in (), while t-statistics are in [].

*, **, *** Denotes significance level at 10%, 5%, and 1% level.

TABLE A.3.5

Estimates of OLS hedge ratios and hedge effectiveness for daily returns of stock prices and calendar year FFAs

	5TC_C+1CAL	4TC_P+1CAL	5TC_S+1CAL
GOGL			
β	0.6445	0.7235	0.8418
	(0.0705)	(0.1022)	(0.1317)
	[9.14***]	[7.08***]	[6.39***]
R^2	9.46%	7.73%	6.23%
SBLK			
β	0.5470	0.5782	0.6579
	(0.0874)	(0.1108)	(0.1481)
	[6.26***]	[5.22***]	[4.44***]
R^2	4.88%	3.54%	2.73%
DSX			
β	0.3321	0.4369	0.6663
	(0.0831)	(0.1027)	(0.1657)
	[4.00***]	[4.26***]	[4.02***]
R^2	2.11%	2.37%	3.28%
GNK			
β	0.5977	0.6569	0.8495
	(0.1407)	(0.1413)	(0.2011)
	[4.25***]	[4.65***]	[4.23***]
R^2	4.01%	3.14%	3.12%
NMM			
β	0.4443	0.3904	-
	(0.0790)	(0.1035)	
	[5.63***]	[3.77***]	
R^2	3.38%	1.70%	-
SALT			
β	0.4532	0.5508	0.6513
	(0.0889)	(0.1175)	(0.1601)
	[5.10***]	[4.69***]	[4.07***]
R^2	3.29%	3.15%	2.62%
SB			
β	-	-	-
R^2	-	-	-

Standard errors are illustrated in (), while t-statistics are in [].

*, **, *** Denotes significance level at 10%, 5%, and 1% level.

TABLE A.3.6

Estimates of OLS hedge ratios and hedge effectiveness for weekly returns of stock prices and calendar year FFAs

	5TC_C+1CAL		4TC_P+1CAL		5TC_S+1CAL	
	Actual	*Bootstrap*	*Actual*	*Bootstrap*	*Actual*	*Bootstrap*
GOGL						
β	0.8973	0.7659	1.0448	0.6642	1.310	1.2569
	(0.0765)	(0.1401)	(0.1018)	(0.2840)	(0.1196)	(0.2403)
	[11.73***]	[6.34***]	[10.26***]	[3.80***]	[10.96***]	[6.11***]
R^2	20.90%	17.31%	20.50%	8.47%	21.64%	19.39%
SBLK						
β	0.7884	0.6853	0.9558	0.4556	1.0767	0.9795
	(0.0884)	(0.1438)	(0.1273)	(0.3228)	(0.1574)	(0.3455)
	[8.91***]	[4.36***]	[7.51***]	[2.02]	[6.84***]	[3.54***]
R^2	12.14%	9.01%	12.90%	2.55%	10.99%	7.46%
DSX						
β	0.7264	0.6665	0.8973	0.5670	1.1025	1.1246
	(0.1184)	(0.1589)	(0.1698)	(0.3084)	(0.1960)	(0.2977)
	[6.14***]	[5.25***]	[5.28***]	[2.87*]	[5.63***]	[4.73***]
R^2	11.10%	12.56%	12.25%	5.03%	12.41%	12.61%
GNK						
β	0.7663	0.5553	0.9716	0.4397	1.3542	1.1100
	(0.1203)	(0.2276)	(0.1525)	(0.3285)	(0.1811)	(0.4187)
	[6.37***]	[2.87**]	[6.37***]	[1.58]	[7.48***]	[3.25***]
R^2	7.02%	4.11%	8.16%	1.58%	10.64%	6.39%
NMM						
β	0.5860	0.5236	0.6694	0.3363	-	-
	(0.0881)	(0.1763)	(0.1282)	(0.2710)		
	[6.65***]	[3.12***]	[5.22***]	[1.39]		
R^2	5.48%	4.83%	5.18%	1.23%	-	-
SALT						
β	0.8015	0.7119	1.1087	0.5949	1.3002	1.4989
	(0.1008)	(0.1787)	(0.1533)	(0.4237)	(0.1826)	(0.3824)
	[7.95***]	[4.16***]	[7.23***]	[2.42]	[7.12***]	[5.113***]
R^2	10.68%	8.28%	14.78%	3.61%	13.64%	14.96%
SB						
β	-	-	-	-	-	-
R^2	-	-	-	-	-	-

Standard errors are illustrated in (), while t-statistics are in [].

*, **, *** Denotes significance level at 10%, 5%, and 1% level.

TABLE A.3.7

Estimates of OLS hedge ratios and hedge effectiveness for monthly returns of stock prices and calendar year FFAs

	5TC_C+1CAL		4TC_P+1CAL		5TC_S+1CAL	
	Actual	*Bootstrap*	*Actual*	*Bootstrap*	*Actual*	*Bootstrap*
GOGL						
β	1.1107	0.9049	1.2945	1.2033	1.4539	1.5541
	(0.0610)	(0.2356)	(0.0724)	(0.2725)	(0.0957)	(0.3311)
	[18.20***]	[4.06***]	[17.88***]	[4.00***]	[15.19***]	[4.26***]
R^2	40.11%	28.71%	35.56%	31.96%	35.85%	34.78%
SBLK						
β	1.0729	0.8924	1.3352	1.0229	1.4471	1.4579
	(0.0681)	(0.2477)	(0.1127)	(0.5185)	(0.1363)	(0.5762)
	[15.75***]	[2.86**]	[11.85***]	[2.17*]	[10.62***]	[2.56**]
R^2	22.50%	16.68%	22.75%	12.16%	21.35%	16.11%
DSX						
β	0.7696	0.6296	0.9289	1.0537	0.9360	1.3202
	(0.0623)	(0.2500)	(0.0922)	(0.4489)	(0.1087)	(0.5981)
	[12.35***]	[2.88***]	[10.07***]	[3.22**]	[8.61***]	[3.27**]
R^2	19.27%	16.85%	18.32%	23.36%	14.86%	23.93%
GNK						
β	1.1229	1.0006	1.4343	1.3964	1.7251	1.8740
	(0.0821)	(0.3269)	(0.1161)	(0.3850)	(0.1458)	(0.4880)
	[13.67***]	[3.01***]	[12.36***]	[2.89***]	[11.83***]	[3.20***]
R^2	17.78%	18.06%	18.93%	19.72%	21.89%	23.17%
NMM						
β	0.8100	0.4035	0.9117	0.9884	-	-
	(0.0776)	(0.3316)	(0.1097)	(0.3621)		
	[10.43***]	[1.33]	[8.31***]	[2.30**]		
R^2	13.34%	4.15%	11.03%	13.51%	-	-
SALT						
β	0.9547	0.9035	1.3629	1.5930	1.4684	1.9746
	(0.0822)	(0.4113)	(0.1090)	(0.7436)	(0.1409)	(0.9921)
	[11.61 ***]	[2.69**]	[12.50***]	[3.57*]	[10.42***]	[3.58**]
R^2	17.49%	15.03%	23.27%	27.32%	21.58%	27.39%
SB						
β	-	-	-	-	-	-
R^2	-	-	-	-	-	-

Standard errors are illustrated in (), while t-statistics are in [].

*, **, *** Denotes significance level at 10%, 5%, and 1% level.

TABLE A.3.8

Estimates of OLS hedge ratios and hedge effectiveness for quarterly returns of stock prices and calendar year FFAs

	5TC_C+1CAL		4TC_P+1CAL		5TC_S+1CAL	
	Actual	*Bootstrap*	*Actual*	*Bootstrap*	*Actual*	*Bootstrap*
GOGL						
β	1.1443	1.3491	1.3913	1.4615	1.5563	1.6636
	(0.0346)	(0.2364)	(0.0461)	(0.4251)	(0.0510)	(0.4705)
	[33.08***]	[5.02**]	[30.19***]	[3.63**]	[30.49***]	[3.69*]
R^2	61.80%	66.01%	62.18%	56.87%	61.28%	57.65%
SBLK						
β	1.2575	1.3653	1.5533	1.1155	1.7377	1.4321
	(0.0488)	(0.5013)	(0.0561)	(0.8303)	(0.0667)	(0.8500)
	[25.78***]	[2.85]	[27.70***]	[1.58]	[26.05***]	[1.87]
R^2	44.09%	38.47%	45.79%	20.03%	45.13%	25.83%
DSX						
β	0.7542	1.0778	0.9058	1.3017	0.9301	1.3760
	(0.0386)	(0.3027)	(0.0499)	(0.3922)	(0.0619)	(0.4417)
	[19.52***]	[3.56**]	[18.17***]	[3.11*]	[15.02***]	[2.74*]
R^2	37.21%	49.31%	36.54%	49.12%	30.34%	42.94%
GNK						
β	1.1162	1.9471	1.4948	2.7290	1.6331	2.9954
	(0.0537)	(0.4358)	(0.0788)	(0.3856)	(0.0838)	(0.4939)
	[20.79***]	[4.82***]	[18.97***]	[6.92***]	[19.50***]	[5.95***]
R^2	33.00%	64.14%	40.26%	82.72%	37.85%	77.96%
NMM						
β	0.9810	1.4641	1.2304	2.0919	-	-
	(0.0420)	(0.5628)	(0.0604)	(0.6536)		
	[23.37***]	[2.75]	[20.39***]	[3.34*]		
R^2	40.95%	36.80%	43.84%	52.80%	-	-
SALT						
β	1.0358	1.7049	1.4918	2.0428	1.5298	2.1887
	(0.0541)	(0.5479)	(0.0576)	(0.7035)	(0.0722)	(0.7809)
	[19.15***]	[3.45**]	[25.88***]	[3.22*]	[21.20***]	[2.91*]
R^2	38.98%	47.85%	55.03%	50.97%	45.57%	45.77%
SB						
β	-	-	-	-	-	-
R^2	-	-	-	-	-	-

Standard errors are illustrated in (), while t-statistics are in [].

*, **, *** Denotes significance level at 10%, 5%, and 1% level.

TABLE A.3.9

Estimates of OLS hedge ratios and hedge effectiveness for yearly returns of stock prices and calendar year FFAs

	5TC_C+1CAL		4TC_P+1CAL		5TC_S+1CAL	
	Actual	*Bootstrap*	*Actual*	*Bootstrap*	*Actual*	*Bootstrap*
GOGL						
β	1.4826	3.3326	1.5580	3.3308	1.6861	2.7335
	(0.0249)	(0.4503)	(0.0206)	(1.1403)	(0.0259)	(1.7650)
	[59.52***]	[5.23]	[75.79***]	[2.07]	[65.07***]	[1.10]
R^2	85.59%	96.47%	90.24%	81.01%	87.73%	54.53%
SBLK						
β	1.6058	3.8335	1.7545	4.4120	1.8965	4.3184
	(0.0355)	(0.9350)	(0.0330)	(0.2190)	(0.0408)	(0.6798)
	[45.23***]	[2.90]	[53.19***]	[14.25***]	[46.49***]	[4.49***]
R^2	73.43%	89.37%	83.68%	99.51%	81.16%	95.28%
DSX						
β	0.8422	2.2962	0.9143	1.9719	0.9833	1.2303
	(0.0255)	(1.1185)	(0.0222)	(1.6371)	(0.0258)	(1.9673)
	[33.00***]	[1.45]	[41.22***]	[0.85]	[38.11***]	[0.44]
R^2	65.21%	67.82%	73.37%	42.04%	70.45%	16.35%
GNK						
β	1.5606	4.6678	1.6436	4.0839	1.7784	2.6532
	(0.0416)	(2.0855)	(0.0386)	(3.1296)	(0.0457)	(3.8242)
	[37.50***]	[1.58]	[42.53***]	[0.92]	[38.94***]	[0.49]
R^2	74.63%	74.63%	79.02%	45.99%	76.80%	19.40%
NMM						
β	1.3247	6.2426	1.3748	6.0550	-	-
	(0.0283)	(1.3046)	(0.0249)	(2.6217)		
	[46.83***]	[3.38]	[55.12***]	[1.63]		
R^2	79.07%	91.97%	81.31%	72.73%	-	-
SALT						
β	1.3249	2.8621	1.4700	2.3804	1.5689	1.3768
	(0.0445)	(1.5881)	(0.0425)	(2.2449)	(0.0534)	(2.6324)
	[29.79***]	[1.27]	[34.58***]	[0.75]	[29.36***]	[0.37]
R^2	61.46%	61.89%	72.23%	35.99%	68.30%	12.03%
SB						
β	-	-	-	-	-	-
R^2	-	-	-	-	-	-

Standard errors are illustrated in (), while t-statistics are in [].

*, **, *** Denotes significance level at 10%, 5%, and 1% level.

A.4 Other

TABLE A.4.1

Description of Baltic FFAs		
FFA	*Routes:*	*Weights:*
Capesize 5TC average		
	C8_14	25%
	C9_14	12.5%
	C10_14	25%
	C14	25%
	C16	12.5%
Panamax 4TC average	P1A_03	25%
	P2A_03	25%
	P3A_03	25%
	P4A_03	25%
Supramax 52 5TC average	S1A	12.5%
	S1B	12.5%
	S2	25%
	S3	25%
	S4	25%

Source: Baltic Exchange (2019a, 2019b)

TABLE A.4.2

Stock Description

Stock	*Description*
Golden Ocean Group Limited	▪ Ticker symbol: GOGL ▪ Stock exchange: NASDAQ ▪ Market capitalization: $838.08 m ▪ 79 vessels: 60% Capesize, 36% Panamax, 4% Ultramax
Star Bulk Carriers Corporation	▪ Ticker symbol: SBLK ▪ Stock exchange: NASDAQ ▪ Market capitalization: $926.44 m ▪ 118 vessels: 14% Newcastlemax, 18% Capesize, 6% Post Panamax, 30% Kamsarmax, 2% Panamax, 14% Ultramax, 16% Supramax
Diana Shipping Inc.	▪ Ticker symbol: DSX ▪ Stock exchange: NYSE ▪ Market capitalization: $350.72 m ▪ 42 vessels: 35% Panamax, 12% Kamsarmax, 12% Post Panamax, 32% Capesize, 9% Newcastlemax
Genco Shipping & Trading Limited	▪ Ticker symbol: GNK ▪ Stock exchange: NYSE ▪ Market capitalization: $383.24 m ▪ 42 vessels: 30% Capesize, 3% Panamax, 11% Ultramax, 36% Supramax, 20% Handysize
Navios Maritime Partners L.P.	▪ Ticker symbol: NMM ▪ Stock exchange: NYSE ▪ Market capitalization: $195.03 m ▪ 37 vessels: 13% Container, 8% Ultra-Handymax, 41% Panamax, 38% Capesize
Scorpio Bulkers	▪ Ticker symbol: SALT ▪ Stock exchange: NYSE ▪ Market capitalization: $431.68 m ▪ 52 vessels: 63% Ultramax, 37% Kamsarmax
Safe Bulkers Inc.	▪ Ticker symbol: SB ▪ Stock exchange: NYSE ▪ Market capitalization: $177.22 m ▪ 41 vessels: 34% Panamax, 24% Kamsarmax, 32% Post-Panamax, 10% Capesize

Source: Bloomberg (2019), Golden Ocean Group Ltd. (n.d.), Star Bulk Carriers Corp. (n.d.), Diana Shipping Inc. (n.d.), Genco Shipping & Trading Ltd. (n.d.), Navios Maritime Partners L.P. (n.d.), Scorpio Bulkers (n.d.), Safe Bulkers Inc. (n.d.)

TABLE A.4.3

Baltic Sale and Purchase Assessment		
	Size (Dwt)	*Description*
Baltic BSPA Capesize	180,000	▪ Built in “first class competitive yard” ▪ 199 000 cbm grain ▪ European standard B & W main engine ▪ LOA 290 m and beam 45 m ▪ SSW Draft 18.2 m ▪ Not ice-classed ▪ Five years old ▪ Special survey passed ▪ Delivery 2-3 months, charter free ▪ 2% total commission.
Baltic BSPA Panamax	82,500	▪ Built in “first class competitive yard" ▪ 97,000 cbm grain ▪ European standard B & W main engine ▪ LOA 229 m ▪ Draft 14.43 m ▪ Not ice-classed ▪ Five years old ▪ Special survey passed ▪ Delivery prompt 2-3 months, charter free ▪ 2% total commission.
Baltic BSPA Supramax Tess52	52,454	▪ 67.756 cbm grain ▪ Self-trimming single deck bulk carrier ▪ LOA 189.99 m and beam 32.26 m ▪ Draft 12.02 m ▪ 14.5 knots ballast and 14 knots laden on 30 mt IFO (380CST) ▪ 4 x 30 t cranes ▪ No MDO at sea ▪ Maximum age 10 years

Source: Baltic Exchange (2019a, 2019b)