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Modelling the Return Distribution of Shipping Stocks using Quantile Regression

Risikomodellering av avkastningsfordelingen til shippingaksjer ved bruk av kvantilregresjon

MASTEROPPGAVE - Økonomi og administrasjon/siviløkonom
Trondheim, 26. mai 2016

Hovedprofil: Finansiering og investering

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Preface

This master thesis completes our Master of Science in Business Administration with specialisation in finance, at Trondheim Business School.

The subject of this thesis is to model the risk profile of shipping stocks by the use of quantile regression, and to forecast risk using the Value-at-Risk measure. It has been a challenging, yet captivating, process to immerse ourselves into the world of shipping, learning both about the industry itself and its surrounding risk factors.

We would like to express our gratitude to our supervisor, Professor Sjur Westgaard at Norwegian University of Science and Technology, for valuable guidance and constructive feedback. We also appreciate the input from Associate Professor Stein Frydenberg at Norwegian University of Science and Technology. A special thank you to Aleksander Eilertsen for exceptional help. Finally, we would like to thank Martin Pettersen, Hans Aaknes and Fredrik Sjetne for excellent perseverance and moral support.

The contents of this master thesis reflect our own personal views and are not necessarily endorsed by Trondheim Business School.

Trondheim, 26th May, 2015

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Abstract

This article models the risk profile of shipping stocks using the quantile regression approach. The method enables calculation and stress testing of Value-at-Risk (VaR) directly from the estimated conditional quantiles. Our research serves as an extension to existing research, as we are the first to model the relationship between shipping stock returns and a set of macroeconomic factors across the distribution of conditional returns. We regress the excess return of the portfolios for the container, dry bulk and tanker sectors, on the market portfolio excess return, the volatility index, and changes in the oil price, exchange rate and long-term interest rate. Our results show that factor effects differ across the conditional quantiles, implying that risk exposures vary under different market circumstances. This suggests that the standard regression may be inadequate to uncover the risk-return relation for shipping stocks. This is especially evident for the volatility index, the market portfolio return, and changes in the long-term interest rate. The results have implications for shipping investors who wish to add specific return characteristics to their portfolios, and allows for more informed portfolio adjustments. Moreover, we contribute to the empirical literature investigating tail risk in equity investments, laying the foundation for further research on the area. In the estimation of VaR we discover signs of asymmetric tail risk, with a higher exposure in the lower tail. Scenario analysis of VaR enables risk managers to consider how changes in macroeconomic factors will affect the risk exposure of shipping stocks, and can be helpful in hedging against various global factors.

Sammendrag

Denne artikkelen modellerer risikoprofilen til shippingaksjer ved bruk av kvantilregresjon. Metoden gjør det mulig å både beregne og stressteste Value-at-Risk (VaR) direkte fra de estimerte betingede kvantilene. Vår studie er en forlengelse av eksisterende forskning, da vi er de første til å modellere forholdet mellom avkastningen på shippingaksjer og et sett av makroøkonomiske faktorer over hele den betingede avkastningsfordelingen. Vi foretar en regresjonsanalyse hvor meravkastningen på porteføljer for container, tørrbulk og tank segmentene utgjør våre avhengige variabler. De uavhengige variablene er meravkastningen på markedsporteføljen, volatilitetsindeksen, og endringer i oljepris, valutakurs og den langsiktige renten. Våre resultater viser at faktoreffekter varierer på tvers av de betingende kvantilene, noe som impliserer at risikoeksponering varierer under ulike markedsforhold. Dette tyder videre på at klassisk regresjon ikke alltid er tilstrekkelig for å avdekke forholdet mellom risiko og avkastning for shippingaksjer. Spesielt er dette synlig i forholdet mellom shippingporteføljene og henholdsvis volatilitetsindeksen, avkastning på markedsporteføljen og endringer i den langsiktige renten. Resultatene har implikasjoner for investorer som ønsker å konstruere porteføljer som utnytter de særegne avkastningsegenskapene til shippingaksjer, og gir grunnlag for mer informerte beslutninger ved porteføljeoptimering. I tillegg bidrar vi til forskningsfeltet som fokuser på halerisiko i aksjeinvesteringer, og legger dermed grunnlag for fremtidige studier. VaR-analysen viser tegn til asymmetrisk halerisiko, hvor det er høyere eksponering i nedre hale. Scenarioanalysen av VaR gir grunnlag for bedre risikostyring, da den gjør det mulig å hensynta hvordan endringer i makroøkonomiske faktorer vil påvirke risikoeksponering til shippingaksjer. Videre vil den kunne være nyttig i hedging av risiko mot de ulike globale faktorene.

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1. Introduction

The purpose of this article is to model the risk profile of shipping stocks, examining the three major shipping sectors: container, dry bulk and tanker. By using the quantile regression methodology, this study is the first to identify how a set of pre-specified macroeconomic factors influences the entire return distribution of shipping stocks. Additionally, we show how the model can be applied in Value-at-Risk (VaR) analysis.

Risk factors are generally identified through their ability to negatively affect the expected cash flow of a company, which in turn will reduce the value of the company (Alizadeh and Nomikos, 2009). While the capital asset pricing model (CAPM) postulates that there is only one type of systematic risk influencing the equity of the firm (Sharpe, 1964), several studies present evidence that stock returns are affected by factors beyond the market risk. However, there is no unanimous agreement concerning which risk factors should be included in the multifactor models to explain the additional risk influencing stock returns. Multifactor extensions of the CAPM include microeconomic factors (see Kavussanos and Marcoulis, 1997), portfolio returns (see Fama and French, 1993) and macroeconomic factors (see Chen et al., 1986; Berry et al., 1988; Wasserfallen, 1989; Ferson and Harvey, 1994; Kavussanos et al., 2002). We follow the latter approach to examine the risk influencing shipping stock returns.

Analysing the shipping industry has long been of interest for academics and practitioners alike, due to its rapid growth over the last fifty years caused by: liberalization in international trade; discovery of new raw materials; advances in ship building; and the growth of the world economy. The industry is responsible for transporting more than 75% of the volume of world trade in manufactured goods and commodities, making it impossible to conduct international trade without sea freight. Furthermore, the shipping industry possesses some distinctive characteristics, with its volatile earnings and perfect competition features. The industry is highly capital-intensive, but more importantly very cyclical, where the cycles represent an imbalance between supply and demand (Alizadeh and Nomikos, 2009). Stopford (2009) presents five separate factors that are believed to affect supply and demand. In the demand function he specifies the world economy, seaborne commodity trades, average haul, random shocks and transport costs to be important factors. For supply, the five factors are the world fleet, fleet productivity, shipbuilding deliveries, scrapping and freight revenues. Demand is volatile and quick to respond to shocks while supply is slow to change, making a balance between the two a rare observation (Stopford, 2009). Consequently, as macroeconomic factors reflect the economic climate, they are likely to influence the state of the global shipping market through their strong impact on demand. The identification of these risk factors is crucial, as changes in the supply-demand ratio cause freight rates and stock prices to fluctuate. Previous literature presents empirical evidence that macroeconomic factors significantly influence shipping stock returns (see e.g. Kavussanos and Marcoulis, 2000; Grammenos and Arkoulis, 2002; Westgaard et al., 2007; Drobetz et al., 2010; El-Masry et al., 2010). However, research on the area is limited. Our study is an extension of previous research, and contributes with an increased understanding of the risk profile of shipping stocks.

Existing literature on risk-return modelling in the shipping industry tend to focus on the relation at the conditional mean. However, when using the mean as a measure of location, we lose information about the tails of the distribution. The quantile regression method, developed by Koenker and Bassett (1978), addresses this issue and provides a complete picture of the joint distribution of the data. Recently, quantile regression is seen employed in the finance literature, for instance, to model dependence between financial variables (see e.g., Meligkotsidou et al., 2009; Badshah, 2013; Mensi et al., 2014; Reboredo and Ugolini, 2016) and to investigate value at risk (Engle and Manganelli, 2004). Our study is the first to apply quantile regression to model the risk profile of shipping stocks. Thereby, filling a gap in the shipping literature, we contribute by increasing the understanding of the risk profile and attaining results not uncovered by previous econometric models. Ultimately, we seek to detect dependence structures between shipping stock returns and macroeconomic risk factors across the return distribution, focusing on the three shipping segments separately.

Shipping is a 'low-return, high-risk' business, which distinguishes it from other investments (Stopford, 2009). Given this volatile nature of shipping stock returns, it is of interest for investors to quantify the relevant tail risk. A widely used risk measure to capture tail risk is the VaR analysis, which expresses the loss expected to be exceeded with a given probability, over a certain period of time (Alexander, 2009). The quantile regression method estimates the conditional probability distribution of a return series, and is an ideal candidate for forecasting VaR (Taylor and Timmermann, 2000). The application of quantile regression on historical returns can provide accurate estimation of the tail distribution, and the beta coefficients from the regression may be directly used as input in the VaR estimation. Hence, the need for distributional assumptions is evaded. The use of scenario analysis to stress test VaR uncovers how tail risk responds to changes in the risk factors. With the contribution from our research, investors and portfolio managers are able to take into consideration the state of the shipping market in their evaluations, as our study shows how the impacts of the selected risk factors vary across the distribution of returns. Moreover, the VaR modelling and scenario analysis enables risk forecasting, and will be valuable in asset allocation and risk management.

In our empirical analysis, we use a sample of 34 listed shipping companies based on the sample of Drobetz et al. (2010), for the period 1st August, 2001 to 31st December, 2015. The companies are classified into three market weighted portfolios, representing the major sub-sectors of the shipping industry: container, dry bulk and tanker. The excess returns of the three portfolios are believed to be influenced by the following five macroeconomic factors: excess return on the market portfolio, changes in the oil price, changes in the USD exchange rate, changes in the 10-year Treasury Rate, and the CBOE volatility index (VIX). The first four macroeconomic factors are selected on the basis of previous empirical evidence (see Grammenos and Arkoulis, 2002; Drobetz et al., 2010; El-Masry et al., 2010) and economic intuition. To the best of our knowledge, our paper is the first study to include VIX to explain the risk-return profile of shipping stocks. We expect VIX to drive shipping stock returns, as other studies find market volatility to influence stock returns (see e.g. Fleming et al., 1995; Dennis et al., 2006; Chiang and Li, 2012; Badshah, 2013; Mensi et al., 2014). We use both ordinary least square (OLS) and quantile regression to analyse the contemporaneous relationships between the five macroeconomic factors and shipping stock returns, in the three sectors. The beta estimations of the quantile regression are further used to calculate the VaR for all three sectors.

The analysis generates the following results: We find differences in factor effects across the quantiles of returns, which suggests that the OLS regression method may be inadequate to uncover the risk-return relation for shipping stocks. This is especially evident for VIX, where the OLS estimate is insignificant, while quantile regression captures strong tail dependence. The VIX negatively affects stock returns below the median, while a positive relationship is present above the median. Moreover, the impacts of the market portfolio return and the 10-year rate exhibit varying dependence through the distribution. For the former, the positive impact is stronger in the upper tail of the distribution. The latter exhibits varying influence on the three segments; while the impact is significantly negative in the lower tail for the dry bulk sector, it is positive and significant for tanker and container portfolio, in the intermediate and upper quantiles, respectively. Oil price changes and exchange rate fluctuations are more stable across the quantiles. Changes in the oil price are negatively related to all sectors, where the strongest impact is found on the tanker stock returns. Impact of fluctuations in the U.S. exchange rate is significantly negative for all sectors, and has the strongest impact on the container sector, followed by the dry bulk and tanker sector. The VaR analysis presents evidence of asymmetric tail risk, with a higher exposure in the lower tail. Furthermore, the scenario analysis shows that the factor sensitivities deviate between the three segments; particularly visible for fluctuations in the interest rate. In the events of extreme values in the risk factors, the container and tanker sectors experience higher levels of tail loss than the dry bulk portfolio. The results enable investors to consider the impact of global factors in equity diversification and hedging strategies.

The remainder of this article is organised as follows. In Section 2 we review relevant literature in order to develop a priori hypotheses for the macroeconomic variables. Section 3 describes our empirical methodology and Section 4 presents the data set. Section 5 discusses our empirical findings. Finally, Section 6 provides a conclusion and highlights the weaknesses of our study and outlook for further research.

2. Literature review and hypotheses development

The purpose of this section is to view our contribution in the context of existing relevant research, in order to develop a priori hypotheses on the relations between shipping stock returns and our selected risk factors. We will review some of the key empirical literature examining the effect of the market, oil price, exchange rate, volatility index and interest rate risk on stock returns, where our main focus is on shipping-related studies. Furthermore, we look to empirical literature that utilize quantile regression in the modelling of global stock returns, in order to form an expectation about the dependence structure in the tails of the distribution.

According to Sharpe (1964), who among others introduced the capital asset pricing model (CAPM), there is only one type of systematic risk influencing the equity of a firm; namely the expected return on the market portfolio. Ferson and Harvey (1994) provide evidence that equity return is exposed to factors beyond the market risk, when examining a multifactor asset pricing model for eighteen national equity markets returns. However, they find the world market portfolio to be the most important factor to explain the fluctuation in these stock markets. Kavussanos et al. (2002) find similar results in their empirical investigation of global risk factors on the excess returns of 38 international industries. The return on the world market portfolio significantly affect all industries and is the most important factor explaining variations in international industry returns, compared to other factors such as the Treasury Eurodollar spread, oil price, exchange rate risk, industrial production, and inflation.

Kavussanos and Marcoulis (1997) use the Seemingly Unrelated Regression (SUR) methodology to estimate the relationship between U.S.-listed water transportation and other transport sectors with the stock market and a set of microeconomic factors, over the period 1984 to 1995. Their study reveals that the water transportation industry exhibits lower systemic risk than the market. Drobetz et al. (2010) also find that global shipping stocks exhibit a market beta lower than unity when using a SUR model to investigate dependence between shipping stock returns and a set of global macroeconomic factors over the period from January 1999 to December 2007. However, the results did not support the a priori hypothesis, as they expected the shipping industry to exhibit higher systematic risk than the market – due to the cyclical and capital-intensive nature of the industry.

Barnes and Hughes (2002) examine whether the conditional CAPM holds at other points of the distribution than only at the mean, by using the quantile regression technique. They find that the market beta is significantly negative for underperforming firms and positive in the upper tail of the conditional distribution of returns; but insignificant at the median. Their results introduce a possible explanation for the conflicting and inconclusive results for studies looking at the effect of the market beta on stock returns at the conditional mean. Given the previous discussion, we propose the following testable hypothesis:

Hypothesis 1: There is a positive relation between shipping stock return and the return on the market portfolio, with a market beta higher than unity. Considering the international business of the shipping industry it is clearly influenced by the state of the world economy.

Chen et al. (1986) are the first in a series of studies to examine the undefined factors in the arbitrage pricing theory (APT) of Roll and Ross (1980) using pre-specified macroeconomic variables. They find a set of economic forces that influences the stock market; however, the oil price is not found to have any significant impact on stock returns. Elyasiani et al. (2011) investigate the impact of oil return changes and oil return volatility on excess stock returns, and return volatilities of thirteen U.S. industry sectors, divided into four different industry types. They present evidence that changes in the oil price represent systematic risk in nine out of thirteen industries, most prominently in the oil-user and oil-related sectors.

Focusing solely on shipping stocks, Grammenos and Arkoulis (2002) investigate the impact of global macroeconomic variables between 1989 and 1998. Oil prices are tested alongside industrial production, inflation, changes in exchange rates against the US dollar, and laid up tonnage – using the multivariate least square method. They find the change in oil prices to negatively affect shipping stock returns. In a similar study, Drobetz et al. (2010) hypothesise that oil prices can have both negative and positive influence on shipping stock returns. Oil serves as a proxy for the global economic environment, but also represents an expenditure for shipping companies as it is the main input in the production of shipping services. A significant dependence is found in the container sector only, where the impact is positive.

Poulakidas and Joutz (2009) explain spot tanker rates, and find indications that the demand for tanker services is a derivative of the demand for oil. Moreover, since the demand for oil is inelastic when demand is high, an increase in the oil price causes tanker freight rates to rise. Westgaard et al. (2007) do not find any significant impact of oil price changes, using OLS regression to identify financial risk factors that impact tanker shipping stock returns. An explanation may be that the positive and negative effects cancel each other out.

Reboredo and Ugolini (2016) use quantile regression to test the impact of oil price movements on the return distribution in BRICS countries and three developed economies (U.S., U.K. and European Monetary Union). They find the dependence to be positive and asymmetric. Oil is found to have a stronger impact on stock returns in the lower tail, with mixed evidence of dependence in the upper tail. Mensi et al. (2014) examine the dependence structure between global risk factors and stock returns in BRICS countries between 1997 and 2013, also using the quantile regression approach. They find that the relationship tends to exhibit tail independence. Significant dependence is found around the central and intermediate areas of the distribution, though there are differences between the countries. Further they show that the dependence significantly increases since the onset of the 2008 financial crisis. Based on the presented literature we propose the following testable hypothesis:

Hypothesis 2: There is a relationship between oil price changes and shipping stock returns that is either negative or positive. Oil is a proxy for the world economy, implying a positive relationship. However, since oil represents one of the major costs in producing shipping services, a negative relationship is also probable.

Fleming et al. (1995) investigate the relationship between changes in the CBOE Market Volatility Index (VIX) and S&P 100 index returns, over the period 1986 to 1992. They present evidence of a strong negative contemporaneous correlation, where the volatility-return relation exhibits significant asymmetry: Negative stock market returns are followed by larger absolute changes in VIX than the positive stock market returns. Badshah (2013) empirically tests the leverage hypothesis (see Black, 1976) and the volatility feedback hypothesis (see French et al., 1987), using quantile regression. By studying the daily relation between stock index returns and changes in VIX, the study provides evidence of a strong negative asymmetric return-volatility relationship, where the asymmetry increase from the 0.5 to the 0.95 quantile. Neither the leverage nor the volatility feedback hypothesis explain the asymmetric return-volatility relation. Furthermore, he finds that the OLS regression underestimates the relation between the stock index returns and changes in VIX in the upper quantiles.

Chiang and Li (2012) also use the quantile regression methodology when examining the risk-return relation between daily volatility and stock index returns for four major stock indices in the U.S. market over the period 1997 to 2007. They find the risk-return relationship to evolve from negative to positive as the quantiles increase. For quantiles below the median the excess return is negatively related to risk, and vice versa. Thus, the least square regression provides limited information about the risk-return relation. The finding suggests that during optimistic market conditions, investors anticipate that increased volatility will be compensated by higher return; while for pessimistic markets, stock prices fall when volatility increases, due to increased uncertainty. Similarly, Mensi et al. (2014) find a significantly negative relation between changes in VIX and stock returns in four BRICS markets (Brazil, South Africa, Russia and China) in the lower quantiles when utilizing the quantile regression. However, in contrast to Chiang and Li (2012); for the remaining quantiles they find no significant impact, except for in Brazil. Their findings indicate that the effect of changes in implied volatility is stronger in bearish than in bullish markets, derived from increased levels of fear and anxiety when stock prices fall. From the previous discussion, we present the following testable hypothesis:

Hypothesis 3: There is an asymmetric, negative relation between VIX and shipping stock returns.

Ferson and Harvey (1994) use the trade-weighted U.S. dollar price of the currencies in the G10 countries as they investigate the impact of exchange rate risk, among other factors, on national equity markets. In ten out of the eighteen countries examined, fluctuations in the exchange rate are found to significantly influence stock market returns – where the impact is positive in all except the United States. Jorion (1990) documents that the exposure to exchange rate risk among U.S. multinational corporations have a positive relation in regard to the level of foreign involvement of a company. Similarly, Loudon (1993) finds that exposure to currency risk vary across industries, when investigating Australian stock returns between 1980 and 1991. Specifically, he finds that the value of the Australian dollar has a significant positive impact on 30% of Australian industries. Tsai (2012) use quantile regression to examine the relationship between the exchange rate and stock price indices in six Asian countries. He finds a negative relationship where the dependence is stronger for very high or low exchange rates.

Leggate (1999) measures foreign exchange rate risk in the Norwegian shipping market, but points out that the seriousness of the risk is applicable for the entire industry. She presents evidence that operating profits can be dramatically affected by a rise or fall in the exchange rate. Akatsuka and Leggate (2001) look at the shipping industries in Japan and Norway, and conclude that the exchange rate significantly influences the performance of shipping companies. Further, they document that the level of exposure is of great importance.

Grammenos and Arkoulis (2002) and Drobetz (2010) find that the U.S. dollar (USD) exchange rate is negatively related to shipping stock returns. They explain that USD denominated costs become effectively more expensive as the USD appreciates – and that this effect outweighs the alternative; that a stronger USD increases dollar denominated income for non-U.S. companies. Based on the presented empirical work, we present a testable hypothesis as follows.

Hypothesis 4: The relationship between changes in the U.S. exchange rate and shipping stock returns is either positive or negative. Freight rates are USD denominated, which means that for non-U.S. companies a stronger USD represents higher effective revenues, also called the direct effect. However, shipping companies may also have costs incurring in USD, which counteract this effect. An appreciation of the USD further influences the demand for dollar quoted goods, which also speaks for a negative effect – called the indirect effect (McConville, 1999).

According to Flannery and James (1984) changes in interest rate are correlated with the common stock returns for financial institutions. Prasad and Rajan (1995) examine the effect of exchange and interest rate fluctuations on the equity markets of Germany, Japan, U.K. and U.S. by constructing industry-based portfolios for each market; finding few instances of significant interest rate risk exposure. For the U.S. equity market, only Other Transport industry and the Utilities group display significant relations to changes in interest rate over the period 1981 to 1989. The finding indicates that although banking business exhibits a particular interest rate sensitivity, the effect of interest rate changes is also evident in non-financial sectors.

Joseph (2002) investigates the U.K. stock returns relation to changes in interest and exchange rates for the period 1988 to 2000. He finds the impact of interest rate changes to be significantly related to 34% of all firms in the sample, where the negative effect for both interest rate and exchange rate is more evident in the engineering and electrical sectors. His finding implies that exchange and interest rate changes affect the domestic and international competitiveness of individual firms through their impact on the cash flow, investment, and profitability. Mouna and Anis (2016) examine the influence of the market, the exchange rate, and the interest rate risk effects on two non-financial sectors returns (technology and industry) in eight countries over the period 2006 to 2009 using a AGARCH-M approach. They find that the linkage between interest rate changes and stock returns is primarily negative, where the link is stronger for long-term horizons at low frequencies than for the shortest scales. This finding suggest that investors with long-term perspectives take into account macroeconomic fundamentals in their investment decisions.

El-Masry et al. (2010) examine the effect of exchange rate, interest rate, and oil prices on stock returns of 143 shipping companies from 16 countries, over the period 1997 to 2005. They find that the exposure to fluctuations in both short- and long-term interest rates is evident in 9.79% of all firms in the sample, where the impact is negative for 12 out of 14 firms. They therefore propose a negative relation between shipping stock returns and changes in interest rates. Furthermore, they suggest that an explanation of why so few companies are found to have a significant exposure to both exchange and interest rate, may be the successful hedging strategies of shipping companies.

Jareño et al. (2016) uses the quantile regression approach to investigate the sensitivities of U.S. companies included in the S&P 500 index to interest rate changes over the period 2003 to 2013. By dividing the companies into sector portfolios they find the effect of both nominal and real interest rate and inflation to differ across the industrial sectors, where the impact is more evident in extreme market conditions. From the previous discussion, we propose the following testable hypothesis:

Hypothesis 5: There is a negative relation between changes in the interest rate and shipping stock returns. Since the shipping industry is highly leveraged, an increase in interest rate can lead to liquidity problems and variations in future cash flow – particularly during depressed shipping markets.

3. Empirical methodology

To examine the risk profile of shipping stocks divided into the sectors: container, dry bulk, and tanker, we use a set of pre-specified macroeconomic factors. By utilising the quantile regression method, we are able to model the effect of the risk factors on shipping stock returns under different market conditions. Furthermore, by using the ordinary least squares (OLS) regression as a benchmark for comparison, we accentuate the increased comprehension of the risk-return relationship achieved by the use of quantile regression. In the following, we will present the models we apply in the empirical analysis.

The standard multivariate linear model is given by the equation:

$$r_{it} = \alpha_i + \beta_{i1} dW.ret_t + \beta_{i2} dOil_t + \beta_{i3} VIX_t + \beta_{i4} d\$exch.r_t + \beta_{i5} d10Y.r + \varepsilon_{it} \quad (1)$$

where r_{it} is the excess return on stock portfolio i at time t, α_i is the intercept and $\beta_{i1}, \beta_{i2}, \dots, \beta_{i5}$ is the sensitivity of risk factor $1,2, \dots ,5$ for portfolio i. $dW.ret_t$ is the excess return of the MSCI All Country World Index at time t, $dOil_i$ is the log change of the WTI crude oil price at time t, VIX_t is the levels of the CBOE Volatility Index at time t, $d\$exch.r_t$ is the log change of Trade-Weighted U.S. Dollar Index: Major currencies at time t, and $d10Y.r_t$ is the log change of the 10-year Treasury Rate at time t. The errors ϵ_{it} are random variables that are independent and identically distributed (i.i.d.) with mean equal to zero.

The standard linear regression efficiently models the conditional mean and variance of the dependent variables, by finding the betas that minimise the sum of the squared residuals (Alexander, 2008). Hence, information about the tails of the distribution of the dependent variable is lost. For the regression coefficients to be the best linear unbiased estimators

(BLUE), the residual assumptions must hold[1]. If one or more of the classical properties do not hold, the beta coefficients are no longer BLUE (Studenmund, 2014). To address this issue, the quantile regression method developed by Koenker and Bassett (1978), present a more flexible approach giving a complete picture of the joint distribution of the data. The approach is non-parametric since it requires no distributional assumptions to optimally estimate the parameters. The method is far more robust to outliers and non-normality than the OLS regression, and provides more accurate and precise estimates (Brooks, 2014).

We use the following qth quantile linear regression model to describe the dependence between the risk factors and the stock portfolio returns, where the intercept and the regression coefficients depends on q, letting $q \in (0,1)$:

$$r_{it}^{(q)} = \alpha_i^{(q)} + \beta_{i1}^{(q)} dW.ret_t + \beta_{i2}^{(q)} dOil_t + \beta_{i3}^{(q)} VIX_t + \beta_{i4}^{(q)} d\$exch.r_t + \beta_{i5}^{(q)} d10Y.r + \varepsilon_{it}^{(q)} \quad (2)$$

where $r_{it}^{(q)}$ is the excess return on stock portfolio i at time t for quantile q, $\alpha_i^{(q)}$ is the intercept for quantile q and $\beta_{i1}^{(q)}, \beta_{i2}^{(q)}, \dots, \beta_{i5}^{(q)}$ is the sensitivity of risk factor $1,2,\dots,5$ for portfolio i for quantile q. The distribution $\varepsilon_{it}^{(q)}$ is left unspecified[2]. The quantile regression approach models the entire conditional distribution of returns given the associated risk factors, by examining the shape of the distribution in addition to location and scale. The method minimises the sum of the absolute values of the residuals, and finds the different quantiles by weighting the residuals. To obtain the standard errors for the estimated coefficients, we use the pairs bootstrapping procedure proposed by Buchinsky (1995). By using this procedure, the standard errors are asymptotically valid under heteroscedasticity and misspecifications of the quantile regression function. If the intercept and regression coefficients vary with q, the model identifies a form of heteroscedasticity in the conditional return distribution. Hence, model presented in equation (2) will add more information about the risk-return profile of the shipping stocks, than the conditional mean regression in equation (1). Additionally, deviations between the mean and median estimates indicate asymmetry in the error distribution (Brooks, 2014).

By inserting the estimated values for the intercept and regression coefficients for a given value of q, using the last observed values for the risk factors, in equation (2), we can

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[1] Assumptions for using OLS include: 1. $E(u_t) = 0$, 2. $var(u_t) = \sigma^2 < \infty$, 3. $cov(u_i, u_j) = 0 \; for \; i \neq j$, 4. $u_t \sim N(0, \sigma^2)$ (Brooks, 2014).

[2] The distribution of the standard error term is not required to meet the same criteria as those in the OLS regression model.

calculate VaR for each stock portfolio. VaR is simply a particular conditional quantile on the distribution and is a risk measure for the loss level that is expected to be exceeded with probability $q \in (0,1)$ if the portfolio is held over some time (Alexander, 2009).

4. Data

The focus in our empirical work is on the container, dry bulk, and tanker sectors as these represent the majority of cargo capacity of the global merchant fleet (Alizadeh and Nomikos, 2009). Our data sample consists of 34 shipping companies, where the sample period ranges from from 1st August, 2001 to 31st December, 2015. Four of the companies are included in two or three of the sectors. Our portfolios consist of the companies used by Drobetz et al. (2010), with the exception of companies that; lack sufficient length of historical data[3], is acquired by or merged with other companies[4], or is excluded for other reasons[5]. As a result, our sample is smaller than the original by Drobetz et al. (2010). There is a possibility that the results are driven by sample selection bias. Possible causes for that are; our sample selection includes fewer companies, large companies are excluded due to lack of historical data, and some of the included companies are involved in other business areas in addition to the shipping industry. These aspects could potentially lead to estimation biases, and as a consequence the selected macroeconomic factors may not be entirely representative for the actual risk facing this industry. However, we believe that our sample is representative for the shipping market, as it is based on a prominent source in the area of shipping research. We do not regard the issue of having a smaller sample size to be of great importance; for instance, Grammenos and Arkoulis (2002) use a sample selection of no more than 36 companies. In the Appendix A we present a list of our selected shipping companies in tables A1-A3.

Daily stock prices for each of the companies are collected from Thomson Reuters Datastream, denominated in USD and adjusted for stock splits and dividends. The portfolios are constructed by weighting each company in accordance to its market value. We find the portfolio weights for the individual companies by dividing the market capitalization of each company on the sum of total market capitalization for the companies combined. For each day, the portfolio weights are recalculated. Finally, the weights are always positive and sum to one.

[3] China Shipping Container Line (CSCL), Euronav, Hanjin Shipping Co., Pacific Basin Shipping, Ship Finance Intl., Sinotrans Ltd., Tsakos Energy Navigation and Overseas Shipholding Group (OSG).
[4] Knightsbridge Tankers Ltd., Shinwa Kaiun and Brostrom.
[5] Dampskibsselskabet “Torm” A/S (D/S Torm) (faulted data series), Trailer Bridge Inc. (unable to find), Alexander & Baldwin (main industry listed as real estate).

We calculate the daily logarithmic excess returns for each portfolio, where the 1-month U.S. Treasury rate is used as the risk-free rate. That is:

$$ER_{it} = \ln\left(\frac{P_{it}}{P_{i(t-1)}}\right) - r_f \quad (4)$$

where ER_{it} is the excess return of portfolio i at time t, $P_{i,t}$ is the price of stock portfolio i at time t, $P_{i,t-1}$ is the price of stock portfolio i at time , $t-1$, and r_f is the 1-month U.S. Treasury rate. The excess return of each portfolio serves as our dependent variables, denoted; 'Container', 'Dry Bulk' and 'Tanker'.

The global macroeconomic factors, which serve as our independent variables, are expressed as the daily log changes of the data time series, except for the Morgan Stanley Capital International (MSCI) All Country World Index (ACWI) and the volatility index. To calculate the excess return for the MSCI ACWI we use formula (4). VIX is expressed in levels. We use the following formula to calculate the daily log changes:

$$c_{it} = \ln\left(\frac{V_{it}}{V_{i(t-1)}}\right) \quad (5)$$

Where c_{it} is the daily log change of variable i at time t, V_{it} is the value of variable i at time t, and $V_{i(t-1)}$ is the value of variable i at time $t-1$.

As a proxy for the world market portfolio, we use the MSCI ACWI. The index covers around 85% of the global investment opportunities and include a sample of large and medium capitalisation companies across 23 developed markets and 23 emerging markets countries[6]. The excess return of the variable is denoted '$dW.ret$'. The oil price variable is set by the West Texas Intermediate (WTI) crude oil spot price, measured in USD per barrel of crude oil. The WTI crude oil price is closely related to the bunker fuel price (Alizadeh and Nomikos, 2009). The daily log change of this variable is denoted '$dOil$'. Levels of the Chicago Board Options Exchange Volatility Index (VIX) is denoted as 'VIX'[7]. To capture the exchange rate risk, we use the variable Trade-Weighted U.S. Dollar Index, which is a weighted average of the foreign exchange value of the USD against major currencies, including the Euro Area,

[6] Previous literature investigating the impact of the world return on shipping stock returns use the MSCI World Equity Index as a proxy for the world market portfolio (see e.g. Grammenos and Arkoulis, 2002; Drobetz et al., 2010). However, we believe that the MSCI ACWI serves as a better proxy, as the shipping industry is affected by changes in the economy in both developed and emerging countries. Furthermore, the three dependent variables exhibit stronger correlations with the MSCI ACWI than the MSCI World Equity Index. For further detail on the MSCI ACWI, see the MSCI factsheet:
https://www.msci.com/resources/factsheets/index_fact_sheet/msci-acwi.pdf

[7] VIX provides an estimate of the expected future realised for the SPX index for 30 calendar days, and is based on the bid and ask prices of the cross-section of S&P 500 index options. The index is a widely used measure of the level of investor fear in the market.

Table 1: Descriptive statistics

	Container	Dry Bulk	Tanker	dW.ret	dOil	VIX	d$exch.r	d10Y.r
Mean	0.0234 %	-0.0002 %	-0.0145 %	0.0083 %	0.0086 %	20.314 %	-0.0038 %	-0.0216 %
Std. Dev.	3.400 %	2.459 %	3.170 %	1.033 %	2.385 %	9.163 %	0.466 %	1.950 %
Max.	39.520 %	14.781 %	24.983 %	8.903 %	21.277 %	80.860 %	2.155 %	8.923 %
Min.	-22.144 %	-19.542 %	-20.882 %	-7.371 %	-17.217 %	9.890 %	-4.107 %	-18.497 %
Skewness	0.666	-0.263	0.023	-0.375	-0.003	2.122	-0.243	-0.098
Kurtosis	14.790	8.820	9.027	11.256	8.577	9.487	6.690	7.005
JB	22 063*	5 351*	5 693*	10 770*	4 874*	9 415*	2 170*	2 520*
ADF	-63.815*	-57.065*	-62.077*	-42.667*	-64.865*	-3.634*	-62.417*	-45.687*
N	3 761	3 761	3 761	3 761	3 761	3 761	3 761	3 761

Note: The table presents descriptive statistics for excess return of the three portfolios and the world return, the VIX and log change for the remaining independent variables. Data running from 1st August, 2001 to 31st December, 2015. The table includes the test statistic of the Jarque-Bera (JB) test for the normality assumption, and the empirical statistics of the Augmented Dickey-Fuller (ADF) unit root test. N is the number of observations. * and ** indicate the rejection of the null hypothesis at the 1% and 5% levels, respectively.

Canada, Japan, United Kingdom, Switzerland, Australia and Sweden. The log change of this variable is denoted '$d\$exch.r$'. Finally, the long-term rate is given by the 10-Year Constant Maturity Treasury Rate, where the log changes of is denoted '$d10Y.r$'. The daily data for the independent variables are collected from two sources, over the period 1st August, 2001 to 31st December, 2015. We use Thomson Reuters Datastream to obtain data for MSCI ACWI, WTI crude oil price and VIX, while Trade-Weighted U.S. Dollar Index, 1-month and 10-year Treasury Rates are collected from Federal Reserve Bank of St. Louis (see Appendix A, table A4). For missing data points in the time series, i.e. not announced data, we insert the value from the previous day.

4.1 Descriptive statistics

Table 1 lists the descriptive statistics for the variables under consideration. The mean excess returns of the shipping stock portfolios vary across the sectors. The container portfolio exhibits a positive average excess return – accompanied by the highest standard deviation, as well as the highest maximum and minimum values (measured in absolute values) relative to the excess return of the other shipping portfolios and MSCI ACWI. The dry bulk and tanker portfolios have negative mean excess returns, where dry bulk exhibits the lowest mean excess return of all variables. The mean excess return for the MSCI ACWI is positive. Drobetz et al. (2010) find the container, dry bulk and tanker portfolio to all exhibit positive mean excess return. Our dissimilar findings may be caused by the selected sample time period. However, our results correspond to Drobetz et al. (2010) when addressing variance as a measure of risk, namely that the variance for all shipping stock portfolios is higher than the variance of market portfolio. During our sample period there has been a rise in the oil price, which leads to a positive mean return, in addition to a relatively high standard deviation. Our study covers a period of a clearly declining interest rate, which is shown by the highly negative mean change in the 10-year Treasury Rate. The mean change in exchange rate is negative and relatively low in absolute value, implying that over the period the USD has generally depreciated slightly against the currencies included in the currency basket. VIX exhibits the highest standard deviation and maximum value compared to the other data series in the sample. VIX reached particularly high values in 2008-2009, around the time of the recent financial crisis (see Appendix C, figure C2).

All risk factors exhibit kurtosis, leading to rejection of the Jarque-Bera test of normality for the unconditional distribution of all the series. Additionally, all series show negative skewness, except the VIX, and the tanker and container portfolio returns – which all have positive skewness. This indicates that the quantile regression method will provide more accurate parameter estimates than OLS regression, as the method is more robust to outliers and non-normality. We test the null hypothesis of a unit root using augmented Dickey and Fuller (1979) (ADF) statistics. We let the Schwarz criterion determine the optimum lag length (max 30) included in the ADF-test. The results of the ADF-test show that all return series are stationary.

4.2 Correlations

Table 2 presents the correlation structure of our dependent and independent variables. The correlations between the shipping portfolios and the risk factors are varying. The excess returns of the shipping portfolios exhibit moderate correlation with the excess return of MSCI ACWI, where the correlation is highest for the dry bulk portfolio. Changes in oil price and exchange rate show, respectively, weak positive and negative correlation with the shipping portfolios. Change in the 10-year Treasury Rate has weak positive correlations with both the container and tanker portfolio; while for the dry bulk portfolio there is little, if any, correlation. There are barely any correlations between VIX and the three shipping portfolios.

Table 2: Correlation between dependent and explanatory variables

	Container	Dry Bulk	Tanker	dW.ret	dOil	VIX	d$exch.r	d10Y.r	VIF
Container	1.000								
Dry Bulk	0.399	1.000							
Tanker	0.398	0.424	1.000						
World Return	0.462	0.495	0.490	1.000					
Oil	0.218	0.222	0.288	0.292	1.000				1.401
VIX	-0.070	-0.093	-0.087	-0.155	-0.066	1.000			1.147
Exchange Rate	-0.331	-0.322	-0.248	-0.343	-0.256	0.032	1.000		1.026
10Y Rate	0.184	0.131	0.204	0.369	0.197	-0.069	0.002	1.000	1.203

Note: The table presents the correlation matrix between the excess return for the three portfolios, the levels for VIX and log changes for the remaining independent variables. Data running from 1st August, 2001 to 31st December, 2015. VIF-values for the independent variables are all below two.

The correlations between the independent variables are generally weak. The highest correlation (0.369) is measured between the excess return of MSCI ACWI and changes in 10-year Treasury Rate. With a weak correlation structures between the independent variables, and VIF-values below two, multicollinearity does not present a problem in our analysis. The absence of multicollinearity is crucial in our search for an understanding of how the various variables influence the different shipping portfolio returns. High multicollinearity distorts the standard errors, and thus the significance of the findings in regression analysis.

5. Empirical results and discussion

Tables 3-5 report the estimates from the OLS and quantile regressions for the regressed excess return of the three shipping sectors on the set of pre-specified risk factors. Equation (1) estimates the OLS regression, where we use Newey-West standard errors with autocorrelation, also called HAC (heteroscedasticity and autocorrelation consistent).[8] The quantile regression results are given by equation (2). In order to estimate the covariance matrix of the parameter estimates, we employ the pairs bootstrapping procedure (Buchinsky, 1995), with maximum iterations set to 10,000. We present numerical estimates for the conditional mean and seven quantiles from 0.05 to 0.95 in table 3-5. Figure 1-3 illustrate graphically the results for all the estimated conditional quantiles for each of the portfolio excess returns.

[8] The assumptions for using the OLS do not hold for any of the sectors, indicating that the beta coefficients are no longer BLUE. See Appendix B, tables B1-B3 for specification of the diagnostic tests.

Table 3: OLS and quantile regression estimates for the container sector

	OLS	Q(0.05)	Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)	Q(0.95)
α	0.000	-0.007**	-0.008*	-0.001	0.000	0.003	0.010*	0.013*
	(0.171)	(-2.053)	(-2.869)	(-0.604)	(0.172)	(1.371)	(4.663)	(3.504)
$\beta_{dW.ret}$	1.205*	1.213*	1.187*	1.176*	1.172*	1.261*	1.407*	1.266*
	(15.681)	(7.465)	(10.826)	(13.457)	(17.114)	(12.893)	(14.458)	(6.485)
β_{dOil}	0.078*	0.063	0.097**	0.050***	0.057*	0.080*	0.073***	0.023
	(3.257)	(1.536)	(2.249)	(1.816)	(2.522)	(3.034)	(1.740)	(0.324)
β_{VIX}	-0.001	-0.171*	-0.115*	-0.072*	-0.004	0.061*	0.105*	0.146*
	(-0.085)	(-8.796)	(-7.234)	(-6.940)	(-0.540)	(5.017)	(9.126)	(7.997)
$\beta_{d\$exch.r}$	-1.402*	-1.029*	-1.115*	-1.180*	-1.280*	-1.357*	-1.198*	-1.343*
	(-10.608)	(-4.292)	(-5.900)	(-9.075)	(-11.630)	(-8.649)	(-6.127)	(-3.331)
$\beta_{d10Y.r}$	0.066**	0.096	0.076	0.052	0.041	0.079**	0.093***	0.235*
	(2.408)	(1.414)	(1.556)	(1.556)	(1.560)	(2.144)	(1.896)	(2.564)
R^2/ Pseudo R^2	0.252	0.239	0.203	0.167	0.143	0.149	0.184	0.195

Note: This table present OLS and quantile estimates for the container sector given by equitation (1) and (2). For the OLS and quantile regressions, the numbers in parentheses are HAC and bootstrap standard errors, respectively. *, ** and *** denotes statistical significance at the 1, 5, and 10% levels.

Table 4: Quantile regression estimates for the dry bulk sector

	OLS	Q(0.05)	Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)	Q(0.95)
α	0.001	-0.014*	-0.008*	-0.005*	0.001	0.005*	0.010*	0.017*
	(0.921)	(-5.495)	(-5.213)	(-4.057)	(0.851)	(3.642)	(5.583)	(5.721)
$\beta_{dW.ret}$	1.040*	1.048*	1.072*	0.957*	0.870*	0.998*	1.262*	1.295*
	(14.791)	(7.836)	(11.782)	(19.328)	(15.788)	(16.060)	(14.845)	(9.368)
β_{dOil}	0.064*	0.077**	0.041***	0.048*	0.052*	0.037**	0.050**	0.055
	(3.765)	(2.041)	(1.802)	(2.731)	(4.333)	(2.232)	(1.947)	(1.200)
β_{VIX}	-0.005	-0.087*	-0.075*	-0.033*	-0.007	0.029*	0.066*	0.080*
	(-1.003)	(-6.856)	(-9.308)	(-5.101)	(-1.278)	(4.554)	(6.421)	(5.544)
$\beta_{d\$exch.r}$	-0.822*	-0.740*	-0.685*	-0.803*	-0.879*	-0.809*	-0.610*	-0.833*
	(-8.631)	(-3.367)	(-5.276)	(-10.278)	(-10.407)	(-7.136)	(-4.337)	(-3.739)
$\beta_{d10Y.r}$	-0.055*	-0.110**	-0.085**	-0.041***	-0.028	-0.015	0.004	-0.044
	(-8.631)	(-2.044)	(-2.403)	(-1.658)	(-1.284)	(-0.598)	(0.097)	(-0.635)
R^2/ Pseudo R^2	0.276	0.231	0.201	0.156	0.133	0.136	0.158	0.180

Note: See table 2.

Table 5: Quantile regression estimates for the tanker sector

	OLS	Q(0.05)	Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)	Q(0.95)
α	0.000	-0.023*	-0.014*	-0.002	0.000	0.004*	0.012*	0.024*
	(0.374)	(-7.940)	(-5.578)	(-1.448)	(0.365)	(2.889)	(4.215)	(7.322)
$\beta_{dW.ret}$	1.273*	1.289*	1.177*	1.133*	1.145*	1.190*	1.433*	1.528*
	(15.281)	(8.549)	(12.981)	(16.092)	(17.585)	(14.073)	(11.030)	(10.424)
β_{doil}	0.193*	0.146*	0.191*	0.204*	0.166*	0.156*	0.124*	0.192*
	(7.379)	(2.603)	(5.379)	(9.415)	(6.663)	(6.102)	(2.574)	(3.164)
β_{VIX}	-0.003	-0.096*	-0.079*	-0.063*	-0.004	0.046*	0.090*	0.093*
	(-0.625)	(-5.927)	(-6.926)	(-8.379)	(-0.545)	(5.935)	(6.580)	(5.766)
$\beta_{d\$exch.r}$	-0.467*	-0.747*	-0.376	-0.145	-0.294**	-0.546*	-0.439***	-0.460
	(-3.563)	(-2.868)	(-1.593)	(-1.322)	(-2.175)	(-5.024)	(-1.783)	(-1.329)
$B_{d10y.r}$	0.035	0.013	0.055	0.060**	0.061**	0.068**	0.064	-0.021
	(1.285)	(0.162)	(0.991)	(2.028)	(2.153)	(2.413)	(1.149)	(-0.235)
R^2/ $PseudoR^2$	0.267	0.206	0.188	0.161	0.124	0.125	0.142	0.158

Note: See table 2.

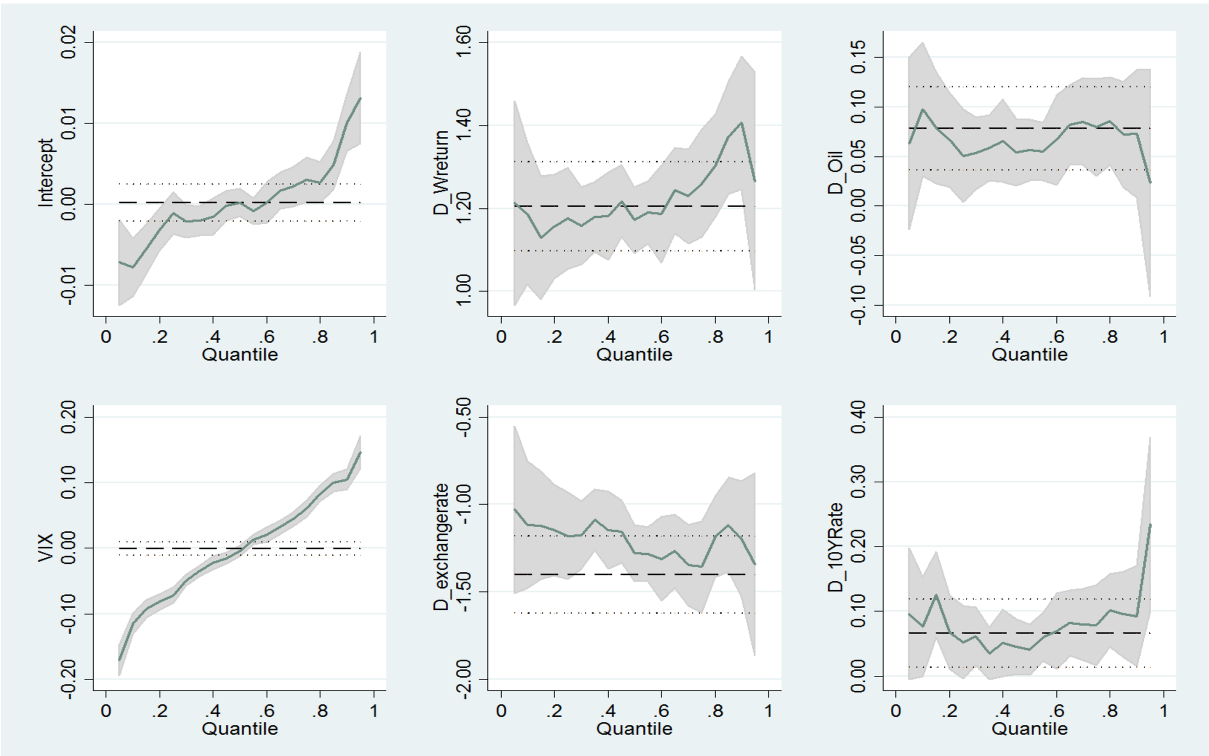

Figure 1: Graphical illustration of the OLS and quantile regression estimates for the container sector.

Note: The figure presents the OLS and quantile regression estimates for the intercept, the world return, the change in oil price, the VIX, the change in exchange rate and the change in the 10-year rate. The stippled line represents the beta coefficient provided by OLS regression. The solid line represents the beta coefficients given by quantile regression, for quantiles between 0 and 1. The grey area is the 90% point-wise confidence band.

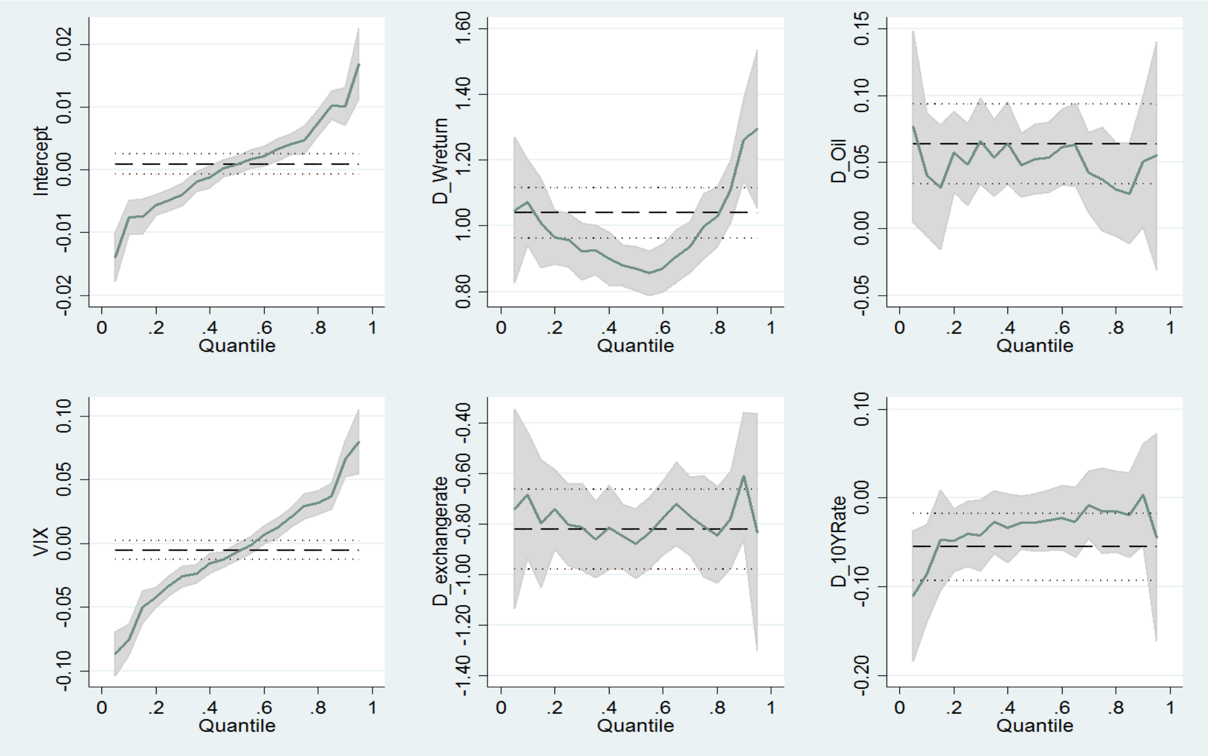

Figure 2: Graphical illustration of the OLS and quantile regression estimates for the dry bulk sector
Note: See figure 1.

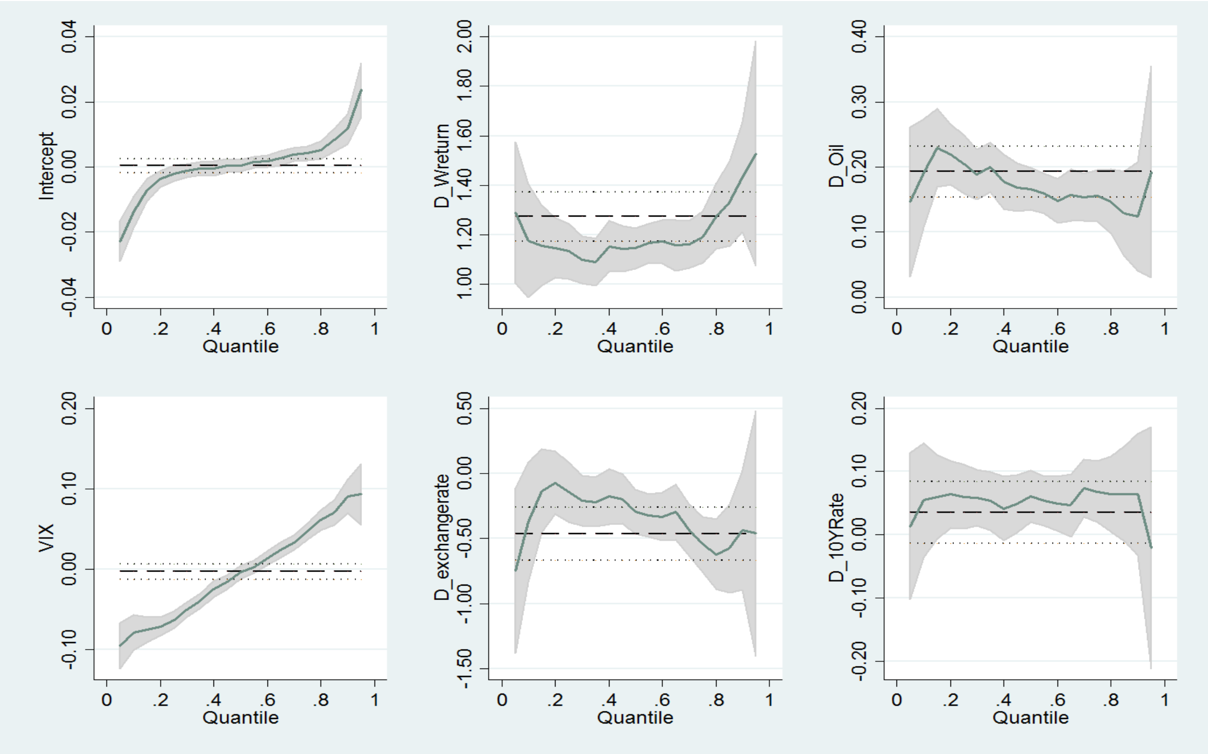

Figure 3: Graphical illustration of the OLS and quantile regression estimates for the tanker sector
Note: See figure 1.

5.1 The dependence structure between excess return of shipping stocks and excess return of the world market portfolio

The effect of the world market portfolio, represented by MSCI ACWI, is positive and significant at the 1% level for the entire return distribution in all sectors (see tables 3-5). The beta coefficient of the OLS regression is significant and greater than one for all sectors, where the container and tanker sectors exhibit the highest beta values. The estimated beta coefficients from the quantile regression show that the impact of the market return varies across quantiles, and is higher than unity for the entire return distribution for both the container and tanker sectors. Figure 1 shows a weak increasing trend in the relation between market risk and the container portfolio return. This is not the case for dry bulk and tanker sectors (see figure 2 and 3). For the dry bulk sector, the impact of the world market portfolio return fluctuates across the quantiles, where the effect is smaller than one for the intermediate (0.25-0.75) quantiles. In the lower and upper tails, the impact is greater than one, indicating a stronger tail dependence. The quantile regression shows that for all the sector alike, the dependence is higher in the upper (0.90-0.95) quantiles than the lower (0.05-0.10) and intermediate quantiles, indicating that the global economy has a stronger influence in bullish than bearish markets. The OLS regression underestimates the sensitivity of market risk at the upper quantiles for all sectors.

The empirical analysis confirms hypothesis 1, as we find that the shipping industry exhibit higher systematic risk than the market[9], excluding the intermediate quantiles of the dry bulk sector. The finding is not in line with the research of Kavussanos and Marcoulis (1997) and Drobetz et al. (2010), as they both provide evidence of a beta lower than one for the U.S.-listed water transportation sector and global shipping stocks, respectively. Nonetheless, these results are anticipated considering the capital-intensive nature of the shipping industry – characterised by business cycles and volatile earnings (Alizadeh and Nomikos, 2009). It is reasonable that a well-performing global economy, reflected in higher global equity returns, will increase the demand for shipping transportation. A healthy world economy may lead to a higher demand for manufactured consumer goods and increased industrial activity, which in turn increases the demand for goods and commodities used directly or as energy input in the production. Consequently, the demand for both container, dry bulk and tanker transportation

[9] Furthermore, when comparing the explanatory power of our five-factor model with a one-factor model including only the return of the market portfolio using the OLS regression, we find the market risk to be the most important factor in explaining the variations in shipping stock returns. This finding is similar to the research of Ferson and Harvey (1994) and Kavussanos et al. (2002). For the one-factor model, R^2 for the container, dry bulk and tanker portfolio returns are 0.213, 0.245 and 0.240, respectively.

increase. Since supply is ponderous and slow to change in the shipping industry (Stopford, 2009), the increased demand will lead to higher freight rates, resulting in higher shipping stock returns. Furthermore, the results from the quantile regression show that the dependence between the returns of shipping stocks and the world market portfolio may be asymmetrical; making OLS regression inadequate to describe their relation – an observation supported by the previous research of Barnes and Hughes (2002).

5.2 The dependence structure between excess return of shipping stocks and changes in the oil price

The relationship between shipping stock returns and changes in the oil price is positive across the entire distribution for all of the three segments. However, the level of dependence varies to some degree between quantiles, but more prominently between the segments. Furthermore, OLS overestimates the dependence relative to the majority of the quantiles, including the median, in all three shipping sectors.

In both the container and dry bulk segments, beta coefficients are stable throughout the distribution, with only small fluctuations between quantiles. Furthermore, both segments exhibit signs of tail independence. In the tanker segment, influence is found to be stronger than in the other segments, and significant over the entire distribution. There is a vague negative trend in the value of the beta coefficients across quantiles, but the decrease does not follow a consistent pattern. Nevertheless, as a general trend it may imply that oil price fluctuations have slightly less impact on tanker stock returns in bullish than bearish markets.

In light of hypothesis 2, our results present evidence that the effect of oil price changes on shipping stock returns is positive. This finding reflects the study by Drobetz et al. (2010), and what Poulakidas and Joutz (2009) find in the tanker segment. It contradicts, however, the findings of Grammenos and Arkoulis (2002). The positive relationships given by our results imply that the effect of oil as a proxy for the state of the world economy is superior to the effect of oil as a major part of transportation costs. Further, the impact of oil price changes being stronger on tanker stock returns than in the other two segments is unsurprising, considering the explanation of Poulakidas and Joutz (2009) – who find that tanker demand is derived from the demand for oil.

When it comes to the dependence structure, beta values are relatively stable throughout the conditional distribution. The container sector exhibits tail independence in both the upper and lower quantiles, which supports the findings of Mensi et al. (2014) who find the same pattern investigating stock market returns in BRICS countries. The pattern of decreasing dependency in the upper tail in the dry bulk sectors is in line with what Reboredo and Ugolini (2016) find in their research. However, an important note is that the insignificance may stem from few observations in the outermost quantiles.

5.3 The dependence structure between excess return of shipping stocks and the volatility index (VIX)

The impact of VIX on shipping stock returns evolves from negative to positive as the quantiles increase across the return distribution for all sectors. For container, dry bulk and tanker portfolios alike, VIX is negatively related to excess return in the lower tail (0.05-0.25), with positive relation in the upper tail (0.75-0.95), where the beta coefficients are significant at the 1% level in all quantiles. The impact is insignificant for both the median and the conditional mean. A reason for insignificant results in the OLS estimation may be that the negative and positive impacts cancel each other out. The absolute value of the beta coefficient for the VIX is higher in the 0.05 than the 0.95 quantile for the container sector, whereas for dry bulk and tanker the difference is less evident[10].

The results given by our empirical analysis do not completely support hypothesis 3, which postulate a negative relationship between VIX and shipping stock returns. We fail to find evidence of an asymmetric relation between VIX and the dry bulk and tanker portfolio returns. However, there is indication that the asymmetric volatility phenomenon is present in the container sector. The postulated negative relation appears in the lower tail for all sectors alike, but in the upper tail the relations are positive. Though not in line with our hypothesis, this finding is in line with the empirical study of Chiang and Li (2012). Hence, we can use the economic explanation provided by their research to describe the changing volatility-return relation across quantiles. As the return distribution in the lower quantiles represent pessimistic market conditions, the negative relation is caused by increased uncertainty among investors when volatility is rising, causing shipping stock prices to fall. Conversely, during an optimistic shipping market (upper quantiles), increased volatility levels drive stock prices up, as investors expect to be compensated with higher returns.

5.4 The dependence structure between excess return of shipping stocks and changes in the USD exchange rate

The effect of changes in the exchange rate, represented by the Trade Weighted U.S. Dollar Index, is negative for all shipping sectors – implying that an appreciation of the USD has a

[10] Using an unconditional quantile regression model, regressing only the return of each shipping stock portfolio on the volatility index, we find a more pronounced asymmetric relation. Measured in absolute value, the impact of VIX is higher in the lower tail than the upper tail for all sectors – indicating the presence of the asymmetric volatility phenomenon. This finding can be explained by the leverage hypothesis of Black (1976) and the volatility feedback hypothesis of French et al. (1987).

negative effect on stock returns. The OLS regression tends to overestimate the impact of exchange rate fluctuations, most prominently in the container segment, where the OLS estimate is more negative than what is found in any of the estimated quantiles.

The impact of changes in the exchange rate on container stock returns is significant at the 1%-level in all quantiles. Furthermore, the effect is slightly increasing throughout the conditional distribution, with more negative beta values in higher quantiles, i.e. in bullish markets. An implication of this is that exchange rate risk may be higher in good market conditions. We note, however, that the variations between quantiles are not great. The influence of exchange rate fluctuations on dry bulk stock returns does not appear to depend on market conditions, as the values of beta remain relatively stable throughout the conditional distribution. Also in the dry bulk portfolio the relationship is negative and significant at the 1%-level across the whole distribution. In the tanker sector we observe fewer significant quantiles, and generally lower beta values – implying that changes in the exchange rate have a lesser impact on tanker stock returns. The strongest dependence is found in the lowermost quantile (0.05), with scattered significance for the rest of the distribution. No obvious trend is observable regarding the dependence structure throughout the distribution.

Hypothesis 4 states that the effect of exchange rate fluctuations on stock returns can be either positive or negative. Our results provide evidence of the latter, as all segments exhibit clear negative dependencies, in all conditional quantiles of the distribution. In other words, when the USD appreciates, shipping stock returns decrease. This may be explained by higher U.S. denominated costs than revenues for non-U.S. companies. Another explanation is that, as U.S. quoted goods become more expensive, demand for these goods decrease, i.e. an indirect effect (McConville, 1999). Our findings support previous literature in shipping, such as Drobetz et al. (2010) and Grammenos and Arkoulis (2002), who also find a negative relationship.

Although some fluctuations occur, we are unable to detect any clear differences in dependence between bullish or bearish markets. We do, however, see that exchange rate fluctuations have a stronger influence on stock returns in the container segment than in the tanker and dry bulk segments. The container segment carries manufactured goods, and consequently goods of higher value (Stopford, 2009). This can explain the stronger impact of changes in the USD on container stock returns, through the indirect exchange rate effect (McConville, 1999). A USD appreciation increases the price of an expensive good more than a cheaper good in units of local currency, consequently decreasing the demand for shipping services of these goods. Additionally, it seems reasonable to assume that the demand for manufactured consumer goods are more price elastic than, say, the price of fuel and grain.

5.5 The dependence between excess return of shipping stocks and changes in the 10-year rate

The effect of the interest rate risk, represented by the 10-year Treasury Rate, differs across both the conditional return distribution and the three sectors. For the dry bulk sector, the effect of changes in the long-term rate is negative and significant only in the lower tail of the distribution. The beta coefficient provided by the OLS estimation is significantly negative, and overestimates the dependence relative to the 0.05-0.25 quantile. For the other segments, the impact of changes in the interest rate is positive and significant in the upper tail for the container portfolio and intermediate quantiles for the tanker sector. The conditional mean underestimates the effect of the interest rate relative to the significant quantiles for both sectors.

The empirical analysis shows that only the dry bulk portfolio return is supported by hypothesis 5. The detected negative relation is in line with the study of El-Masry et al. (2010). Since the shipping industry is highly leveraged, it is expected that the relation is evident in a depressed market as changes in interest rate can lead to severe liquidity problems and fluctuations in future cash flow. Jareño et al. (2016) also find the impact of interest rate to be more evident in extreme market conditions. Surprisingly, the container and tanker portfolio returns are positively related to the interest rate risk. The finding may be explained by the fact that one of the drivers behind interest rates is the state of the economy. Rates tend to rise during periods of expansions, while they may fall in depressed economic periods. Hence, an increase in the interest rate makes riskier investments more favourable, indicating higher demand for shipping stocks as the industry is well-known for being a ‘low-return, high-risk’ business (Stopford, 2009). It is, however, surprising that this effect is evident for the container and tanker sectors, while not for the dry bulk sector.

5.6 Summary of main results

The impact of the market portfolio return is significant and positive for all sectors, where the dependence is stronger in the upper tail of the return distribution. Changes in oil price have a stronger influence on returns in the tanker sector than for the container and dry bulk sectors. The impact is positive in all sectors, however, both the dry bulk and container sectors exhibit weaker tail dependence than the tanker portfolio. Furthermore, the OLS regression tends to overestimate the influence of oil price changes. Regarding VIX, the beta coefficients change signs from negative to positive around the median with increased impact towards the outer quantiles, for all sectors. Thus, OLS regression fails to describe the relationship between market volatility and shipping stock returns, as the negative and positive impacts in the tails cancel each other out. Fluctuations in the U.S. exchange rate are significantly negative for all sectors, but have the strongest impact on the container portfolio, followed by dry bulk and tanker. OLS overestimates the dependence throughout the entire conditional distribution in the container portfolio. Finally, the effect of changes in the 10-year rate is inconsistent between the segments. While we find a positive relationship with the container portfolio, the impact is found to be negative on tanker and dry bulk portfolio returns. Moreover, the dependence is quite weak and only significant in the upper tail for the container portfolio, lower tail for the dry bulk portfolio, and intermediate quantiles for the tanker portfolio. The explanatory powers of the OLS regressions are similar over the three sectors, with values fluctuating around 25%, meaning that large parts of changes in the shipping portfolio returns remain unexplained. The pseudo R^2 is also low and relatively similar between the segments, although slightly higher in the lower tails than in the remainder of the distributions.

5.7 Value-at-Risk estimation

In this section we illustrate how the quantile regression estimates can be directly implemented in a non-parametric VaR analysis to forecast the next-day level of tail risk. The last observations of the five risk factors in our sample period serve as the baseline in our VaR analysis for the container, dry bulk and tanker segments (see figure 4-6). Estimated values of the intercept and regression coefficients for a given quantile are inserted in equation (2), in addition to the last observed values for each of the five risk factors. As it is the tails that are of interest for investors in long and short positions, we focus our discussion on the 5% and 95% VaR.

There is a clear sign of risk asymmetry, as the downside risk is clearly higher than the upside risk in all segments. In the dry bulk segment, we see that there is a 5% probability that an investor in a long position will endure a loss of 3.5% or more over a one-day period. For an investor in a short position, however, there is a 5% probability that the loss will exceed 2.2%. For the investors in the container portfolio, the losses that may be exceeded with a 5% probability is almost twice as high for a long investor than for a short investor, as the 5% VaR is -4.9% and the 95% VaR is 2.5%. The 5% VaR in the tanker portfolio is -4.9%, against a 95% VaR of 3.2%.

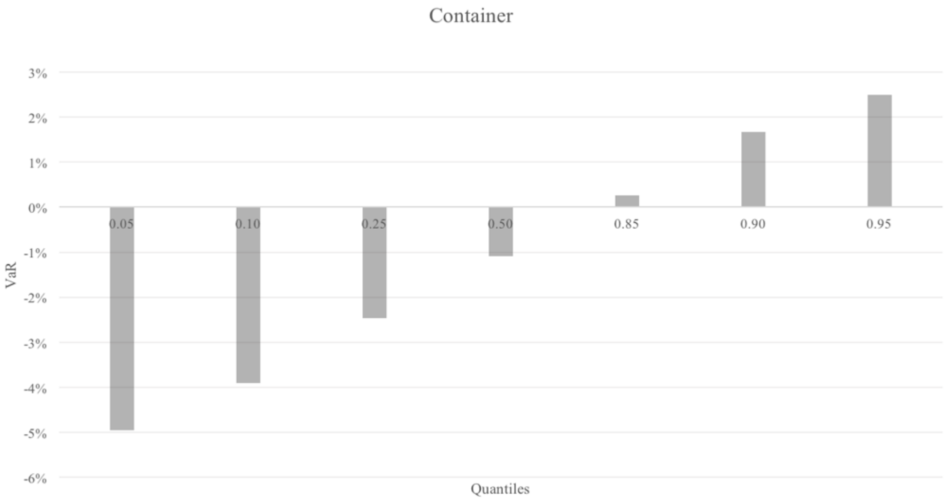

Figure 4: VaR values for the excess return for the container portfolio

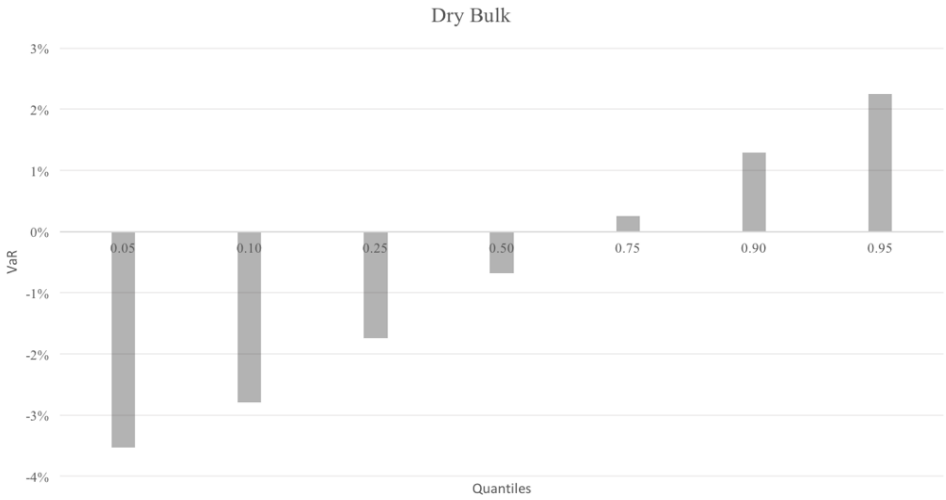

Figure 5: VaR values for the excess return of the dry bulk portfolio

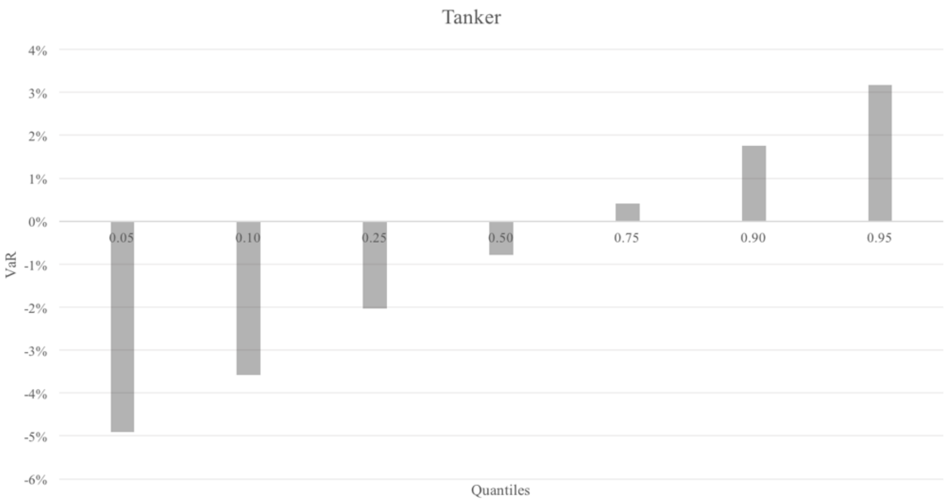

Figure 6: VaR values for the excess return of the tanker portfolio

Table 6: One-day 5% and 95% VaR estimates from the parametric VaR and non-parametric VaR using quantile regression estimates

	Container		Dry Bulk		Tanker	
	Parametric	*QR*	*Parametric*	*QR*	*Parametric*	*QR*
$VaR_{5\%}$	-5.57%	-4.94%	-4.11%	-3.53%	-5.28%	-4.91%
$VaR_{95\%}$	5.57%	2.49%	4.11%	2.25%	5.28%	3.18%

Note: The table presents the parametric VaR and quantile regression (QR) VaR measures for each shipping sector.

From table 6, it is clear that the non-parametric VaR estimation calculated directly from the quantile regression yields different risk estimates than the parametric VaR[11]. Generally, the parametric VaR appears to overestimate the one-day tail risk. An explanation for the deviations between the two approaches is that the parametric VaR relies on several assumptions, for instance constant volatility and normal distribution. It is particularly vulnerable to high kurtosis. From the statistics presented in table 1, it is apparent that our three shipping portfolios exhibit both skewness and high kurtosis, and consequently are not normally distributed. As a result, the parametric VaR may overestimate the actual risk present in the 5% and 95% quantiles.

5.8 Scenario analysis

We use the 5% and 95% VaR estimates to carry out a scenario analysis for each risk factor. This allows us to predict the VaR-levels for the next day, given changes in a risk factor, *ceteris paribus*, in the upper and lower tails, based on historical observations. For each risk factor we let the value fluctuate between the minimum and maximum observed value in our sample period (see table 1). Figures 7-11 show graphs for each risk factor, where the lines represent changes in the 5% and 95% VaR for the container, dry bulk, and tanker portfolios over a spectre of historically observed values for the given risk factor.

In figure 7, we see that as the value of the world excess return decreases (increases), the minimum loss that is expected with a 5% probability increases for an investor who is long (short) in the investment. The 95% VaR in the container and dry bulk portfolios will be affected more or less identically by changes in the world excess return. When it comes to the 5% VaR, there is a slightly bigger deviation between the container and dry bulk portfolios. We see that a reduction in world excess return will have a stronger impact on the 5% VaR in the container portfolio, implying that the container portfolio becomes riskier than the dry bulk portfolio for reduced levels of world excess return. The tanker portfolio is more sensitive to

[11] To calculate the parametric VaR, we use the formula: $Var_{5\%} = VaR_{95\%} = Mean - (Std.Dev * Z_{0.05})$

these changes, reflected by the steeper line. We see that all three portfolios have a 5% VaR of 0 when the daily world excess return is around 3%. The 95% VaR is 0 when the daily world excess return is approximately -3%.

VaR levels of shipping portfolios are generally less sensitive to changes in oil return than they are to the world excess return, illustrated by the flatter lines in figure 8. The tanker portfolio stands out, especially for the 95% VaR, where an increased positive change in the oil price will increase the risk for a short investment notably more than what is the case for the container and dry bulk portfolios. As the daily logarithmic change of oil price goes from 0% to 2.5%, the 95% VaR rises from approximately 3% to 8% in the tanker portfolio. The one-day 95% VaR for the container portfolio remains relatively stable around 2%, while it rises from 1% to 3% for the dry bulk portfolio. The container and dry bulk portfolios are more sensitive to decreased changes in oil price when it comes to the 5% VaR, although the tanker portfolio still exhibits the strongest sensitivity.

As we saw in the analysis of the quantile regression outputs, VIX has a positive impact on shipping returns above the median and a negative impact below the median. This connection is also represented by the positive and negative slopes (see figure 9) for the 95% and 5% VaR, respectively. The sensitivities are similar in the 5% and 95% VaR, and the container portfolio exhibits the strongest sensitivity to changes in VIX, followed by tanker and dry bulk. When VIX is 0.8, as it was at the peak around the 2008 financial crisis, the one-day 5% VaR is approximately -15% for the container portfolio, -11% for the tanker portfolio and -8% for the dry bulk portfolio.

For the exchange rate (see figure 10), the minimum loss that is expected with a probability of 5% increases for a long (short) position, as the change in the exchange rate increases (decreases). The risk is slightly higher in the short position than in the long position, recognised by the higher values of 95% VaR for given values of exchange rate changes. For the extreme levels of exchange rate, the highest risk is found in the container segment. This is the case both for the 5% and 95% VaR, but the difference from the tanker and dry bulk segments is larger in the 95%. Here, if the change in exchange rate is -5%, the one-day 95% VaR is almost 10% for container, 7% for dry bulk and 6% for the tanker portfolio.

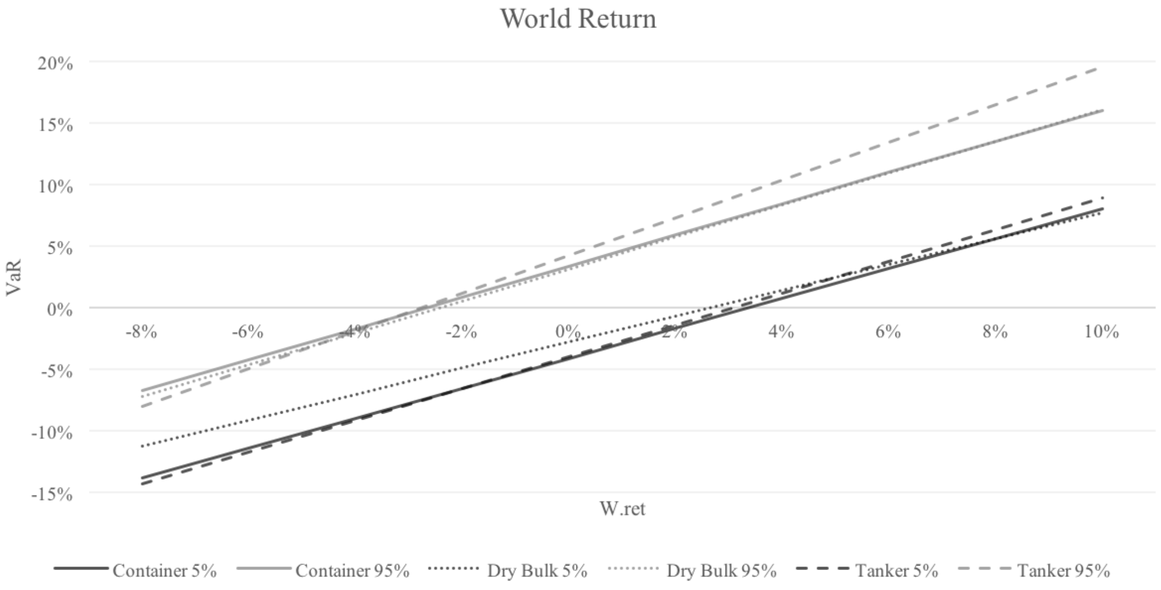

Figure 7: Scenario analysis of change in 5% and 95% VaR in response to changes in the excess return of the world market portfolio, ceteris paribus, for all three sectors.

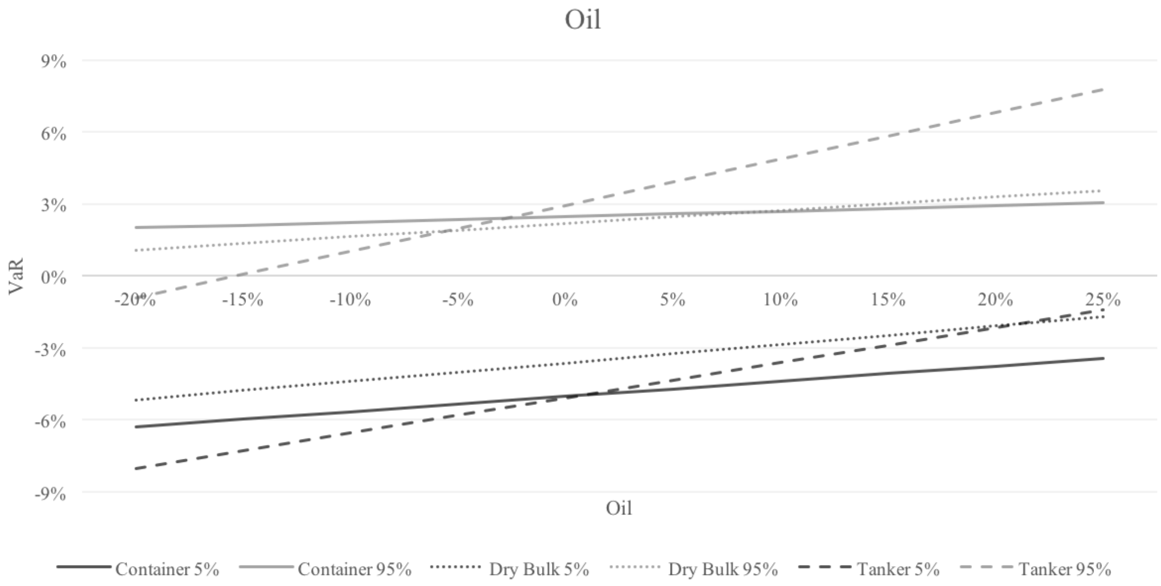

Figure 8: Scenario analysis of change in 5% and 95% VaR in response to changes in oil price return, ceteris paribus, for all three sectors.

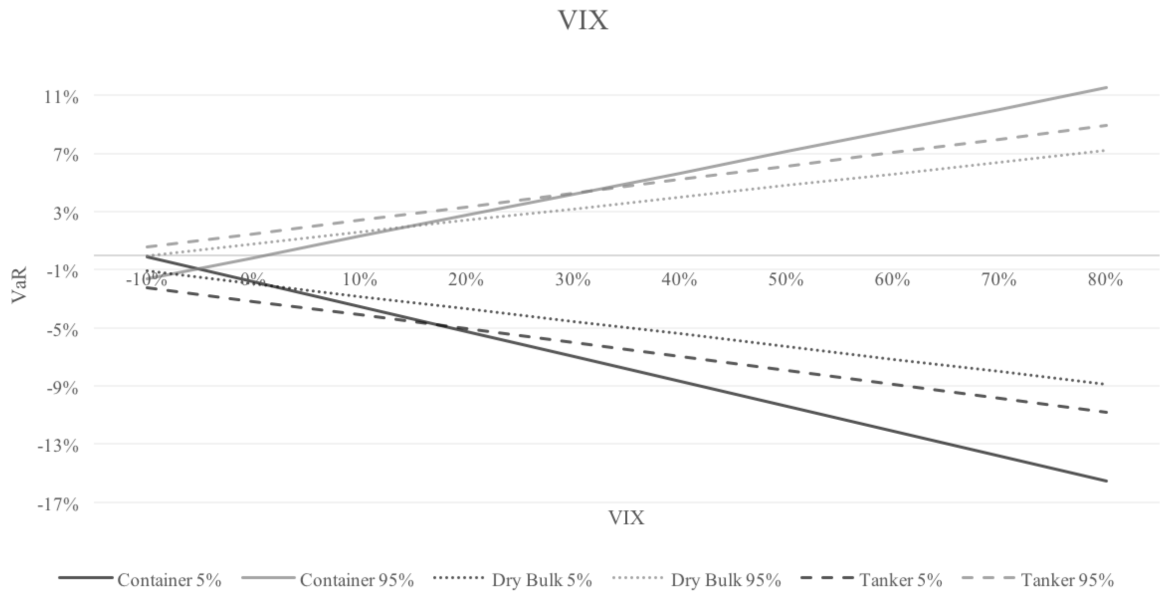

Figure 9: Scenario analysis of change in 5% and 95% VaR in response to changes in VIX, ceteris paribus, for all three sectors.

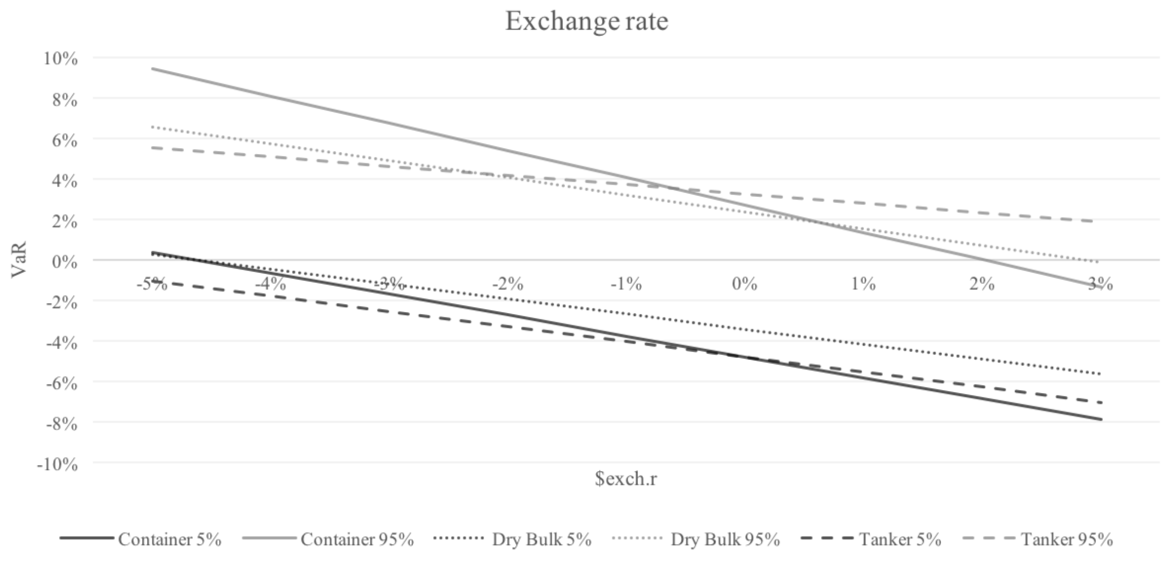

Figure 10: Scenario analysis of change in 5% and 95% VaR in response to changes in USD exchange rate return, ceteris paribus, for all three sectors.

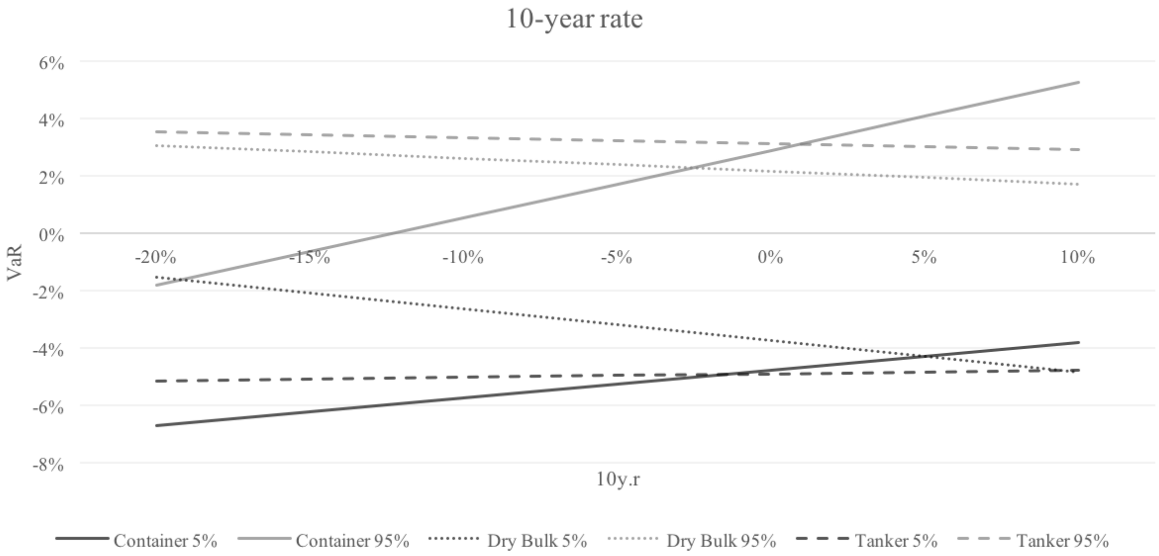

Figure 11: Scenario analysis of change in 5% and 95% VaR in response to changes in 10-year Treasury Rate rerun, ceteris paribus, for all three sectors.

When it comes to the influence of changes in the 10-year rate on the tail risk in the three portfolios, we observe that the reaction is quite different across the sectors (see figure 11). In the upper tail (95%), the dry bulk and tanker portfolios have negative relationships with changes in the interest rate, as we see slightly decreasing curves, indicating a lower tail risk for increased changes in the 10-year rate. In great contrast to this, the VaR is rapidly increasing for the container portfolio for elevated levels of interest rate changes. When the change in interest rate is negative, the dry bulk and tanker segments exhibit a much higher risk than the container segment. For positive interest rate changes, however, the container portfolio holds higher risk than the other two portfolios. In the lower tail it is the dry bulk portfolio that stands out, as the risk increases when the change in interest rate moves from negative towards positive. The opposite is true for the container and tanker portfolios, where the long position becomes riskier for more negative changes in the 10-year rate. To sum up, for the long and short positions alike, the container segment holds the highest risk for both negative and positive changes in the interest rate.

Our analysis shows how the estimation of VaR and the accompanying scenario analysis provide a useful comprehension of asymmetry and differences in tail dependency across risk factors and shipping segments. By comparing the extreme values of the 5% and 95% VaR for each macroeconomic variable, we further get an idea of which risk factors have the potential to inflict the biggest losses. We find, considering the range of values observed throughout our sample period for each risk factor, that the world excess return cause the highest one-day VaR-levels in the upper and lower tails, followed by VIX. For extreme values the world excess return, the one-day VaR levels are around -14% and 19% in the lower and upper tail respectively, compared to -15% and 11% for VIX. The three remaining factors have lower impact on tail risk, where changes in the exchange rate and oil follow with quite similar impact, and lastly the changes in the 10-year rate affects the least of all.

The results from the scenario analysis also reveal which of the shipping sectors experience the highest levels of tail loss in the event of extreme values in the risk factors. The container portfolio is more exposed to both upper and lower tail risk than the two other portfolios when it comes to VIX, and the upper tail risk of the exchange rate and the 10-year rate. The tanker portfolio is the shipping segment that shows the strongest tail risk, both upper and lower, for the world excess return and the oil price. The container and tanker segments exhibit similar values of 5% VaR for extreme levels of changes in the exchange rate and 10-year rate.

6. Conclusion

This study models the risk profile of shipping stocks by focusing on market weighted portfolios for the container, dry bulk and tanker sectors. We use the quantile regression methodology, which enables us to investigate the impact of macroeconomic risk factors across the entire conditional return distribution of shipping stock portfolios. The beta coefficients from the quantile regression are directly used to calculate Value-at-Risk (VaR); an advantageous approach to forecast risk, as no assumption regarding the underlying distribution is necessary. The 5% and 95% VaR estimates are further stress tested in a scenario analysis for each of the five risk factors, finding how tail risk is expected to respond to changes in macroeconomic variables. Our research serves as an extension to existing research, as we are the first to apply quantile regression to model the risk profile of shipping stocks. In doing so, the risk-return relation is modelled not only at the conditional mean, but also in the tails of the distribution.

The shipping industry is characterised by volatile earnings and business cycles, caused by imbalances between supply and demand. Macroeconomic factors will influence the global shipping market through their strong impact on demand, as they reflect the current economic climate and future economic prospects. As the changes in the supply-demand ratio cause freight rates, and consequently stock prices, to fluctuate, it is crucial to identify the risk factors that negatively affect the expected cash flow. Based on previous empirical literature examining the risk-return profile of shipping stocks, and economic intuition, we investigate how the market risk, the volatility index and the changes in oil price, exchange rate, and interest rate will impact shipping stock returns.

Our empirical findings suggest that the quantile regression method provides a more complete picture of the dependence structure between shipping stock returns and the risk factors. The impact of the market portfolio return is positive for all sectors and quantiles, where the influence is more evident in the upper tails of the distribution. Changes in oil price have a stronger influence on the tanker portfolio return than the dry bulk and container sectors, and is positive across the entire distribution for all segments. The impact of the VIX evolves from negative to positive for increasing conditional quantiles, changing signs at the median, for all sectors alike. All segments exhibit a clear negative dependence with changes in exchange rate, where the influence is strongest for the container sector, followed by the dry bulk and tanker sector. This indicates that a U.S. dollar appreciation causes shipping stock returns to decrease. Changes in the long-term interest rate is negatively related to the dry bulk sector, whereas for the container and tanker portfolios the impact is positive.

The VaR analysis shows that all shipping segments exhibit asymmetric risk exposure, with a higher risk in the lower tail compared to the upper tail. The scenario analysis shows that the three segments respond differently to changes in the five risk factors, and that sensitivities might differ between the upper (95%) and the lower (5%) tail. The most evident differences in sensitivities are found in the interest rate factor. Here, the VaR levels in the container portfolio increase rapidly for higher levels of interest rate changes, most prominently in the in the upper tail. The world excess return cause the highest one-day VaR-levels in both tails, followed by VIX, changes in the exchange rate, changes in the oil price and, lastly, changes in the interest rate. Finally, we reveal that for extreme values in the risk factors, the container and tanker segments experience the highest levels of tail risk.

Our findings have implications for investors who want to take into account the state of the shipping market in their investment decisions. As we uncover factor sensitivities and how these vary between shipping segments and across the return distribution, risk and portfolio managers can benefit from the insight provided by our study in asset allocation and portfolio optimisation. Our illustration of risk forecasting using VaR can further be used by risk managers to meet risk exposure requirements.

Since the VaR and scenario analyses are based on the beta coefficients from the quantile regression, weaknesses in our analysis may occur if parameters are sub-optimally estimated. In the case of few observations in the outermost (0.05 and 0.95) quantiles, the beta estimations may be inaccurate, leading to an inexact estimation of the 5% and 95% VaR.

This, in addition to possible insignificant parameter estimates, will result in incorrect VaR measures and consequently bias in our scenario analysis. Possible non-linear relations between the portfolios and the risk factors will also make our results unreliable. To extend our study, a non-linear quantile regression analysis using copulas may be applied. We use daily frequencies in order to gain a sufficient amount of observations for estimation of all quantiles. However, the disadvantage is that we exclude macroeconomic factors that only provide data at lower frequencies. A natural extension for further research may therefore be to use monthly data series, including more risk factors in hope of raising the explanatory power of the model. Another strategy for a follow-up study may be to back test the volatility forecast provided by the quantile regression methodology, or compare the VaR measures with other estimation techniques.

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Appendix

A. *Companies and independent variables included in the sample*

Table A1: Container companies

Container companies	Marked	Datastream symbol
AP Moeller Maersk B	Denmark	DK:DSA
AP Moeller Mearsk A	Denmark	DK:DSB
Compania Sud Americana De Vapores S.A. (CSAV)	Chile	CL:VPR
Evergreen Marine	Taiwan	TW:EVE
Finnlines	Helsinki	M:FINL
Heung-A Shipping Co. Ltd.	South Korea	KO:HHB
Hyundai Merchant Marine Co. Ltd.	South Korea	KO:HMA
Kawasaki Kisen Kaisha (K-Line)	Japan	J:KK@N
MISC Berhad	Malaysia	L:MISC
Mitsui OSK Lines (MOL)	Japan	J:MO@N
Neptune Orient Lines (NOL)	Singapore	T:NOLS
Nippon Yusen Kabushiki Kaisha (NYK)	Japan	J:NY@N
Orient Overseas Intl.	Hong Kong	K:OROC
Regional Container Line (RCL)	Thailand	Q:RCCT
Samudera Shipping Line	Singapore	T:SAMU
Wan Hai Lines	Taiwan	TW:WHL
Wilh. Wilhelmsen Holding ASA (WWH)	Norway	N:WWI
Yang Ming Marine Transport Corp.	Taiwan	TW:YMM

Table A2: Dry bulk companies

Dry bulk companies	Marked	Datastream symbol
Cosco Corp.	Singapore	T:COSC
Dampskibsselskabet "NORDEN" A/S (D/S Norden)	Denmark	DK:DNO
Golden Ocean Group Ltd.	United States	@GOGL
Great Eastern Shipping	India	IN:GES
Mitsui OSK Lines (MOL)	Japan	J:MO@N
Precious Shipping	Thailand	Q:PSL
U-Ming Marine Transport	Taiwan	TW:UMM

Table A7: Tanker companies

Tanker companies	Marked	Datastream symbol
Concordia Maritime	Sweden	W:CNBF
Dampskibsselskabet "NORDEN" A/S (D/S Norden)	Denmark	N:FRO
Frontline Ltd.	Norway	N:FRO
Great Eastern Shipping	India	U:NAT
I.M. Skaugen ASA	Norway	N:IMSK
James Fisher & Sons	United Kingdom	FSHR
Jinhui Shipping & Transportation Ltd.	Norway	N:JIN
Mitsui OSK Lines (MOL)	Japan	J:MO@N
Neptune Orient Lines (NOL)	Singapore	T:NOLS
Nordic American Tanker Shipping	United States	U:NAT
NS United Kaiun Kaisha	Japan	J:NSUK
Odfjell "A"	Norway	N:ODF
Stolt Nielsen	Norway	N:SIN
Teekay Corporation	United States	U:TK

Table A4:Independent variables

Variables	Collected from / Datastream symbol
WTI Crude Oil Spot price	Datastream / CRUDOIL
CBOE Volatility Index	Datastream : CBOEVIX
MSCI ACWI	Datastream : MSACWF$
10-Month Treasury Constant Maturity Rate	https://research.stlouisfed.org/fred2/series/DGS10#
Trade Weighted U.S. Dollar Index: Major Currencies	https://research.stlouisfed.org/fred2/series/DTWEXM
1-Month Treasury Constant Maturity Rate	https://research.stlouisfed.org/fred2/series/DGS1MO#

B. Assumptions for using OLS

Table B1: Test of assumptions for using OLS – Container sector

Assumptions	Test	Critical values (5%)	Test statistic
$E(u_t) = 0$			0
$var(u_t) = \sigma^2 < \infty$	White's test	1.57	4.940
$cov(u_i, u_j) = 0$ for $i \neq j$	Breusch-Godfrey test	1.00	1.381
$u_t \sim N(0, \sigma^2)$	Jarque-Bera test	5.99	47 759

Note: The White's test, tests for heteroscedasticity in the residuals. F-version of the test statistic is presented, indicating the presence of heteroscedasticity. To test the residuals for autocorrelation, we use the Breusch-Godfrey test with 250 lags of the residuals. F-statistics is presented, indicating the presence of autocorrelation. We use the heteroscedasticity and autocorrelation consistent (HAC) standard errors which adjusts standard errors for heteroscedasticity and autocorrelation. Jarque-Bera tests for normality in the residuals. The test statistic is χ^2 distributed, where H_o states that the residuals are normally distributed.

Table B2: Test of assumptions for using OLS – Dry bulk sector

Assumptions	Test	Critical values (5%)	Test statistic
$E(u_t) = 0$			0
$var(u_t) = \sigma^2 < \infty$	White's test	1.57	21.540
$cov(u_i, u_j) = 0$ for $i \neq j$	Breusch-Godfrey test	1.00	1.562
$u_t \sim N(0, \sigma^2)$	Jarque-Bera test	5.99	4 233

Note: See table B1.

Table B3: Test of assumptions for using OLS – Tanker sector

Assumptions	Test	Critical values (5%)	Test statistic
$E(u_t) = 0$			0
$var(u_t) = \sigma^2 < \infty$	White's test	1.57	23.624
$cov(u_i, u_j) = 0$ for $i \neq j$	Breusch-Godfrey test	1.00	1.219
$u_t \sim N(0, \sigma^2)$	Jarque-Bera test	5.99	2 422

Note: See table B1.

C. *Graphs of the developments in dependent and independent variables*

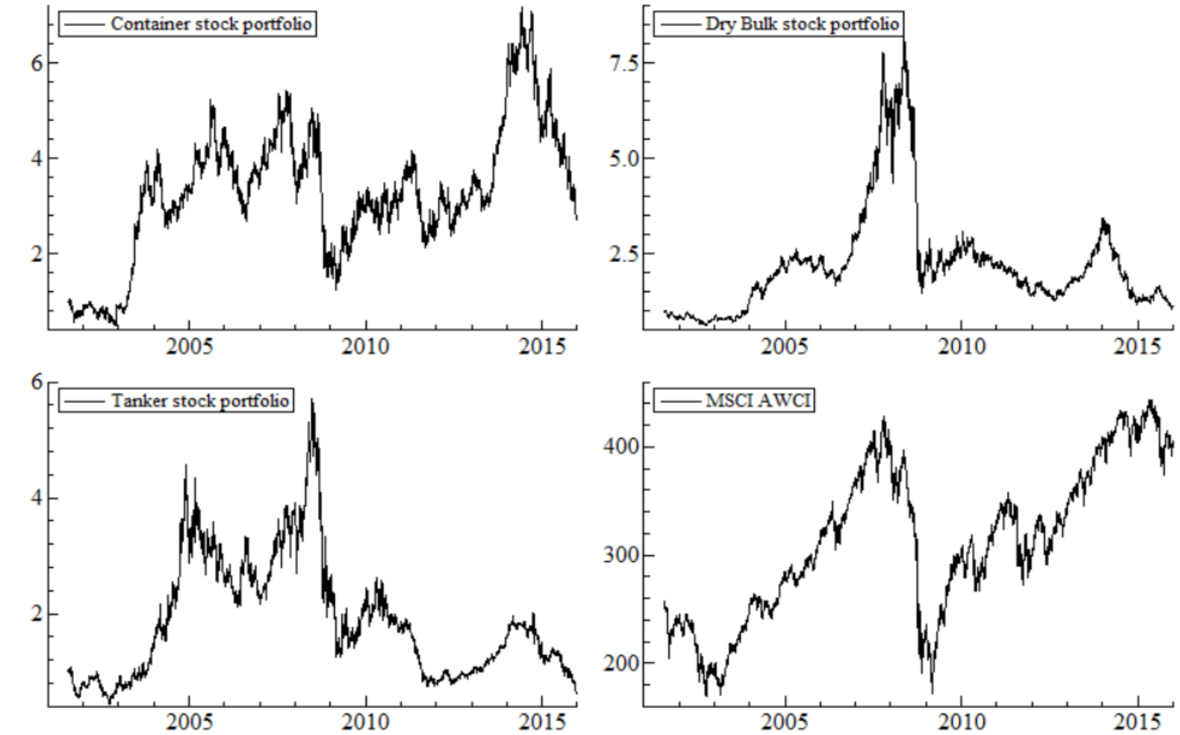

Figure C1: The figure shows the development of the container, dry bulk and tanker stock portfolio, and the MSCI ACWI from 1st August, 2001 to 31st December, 2015. All the shipping stock portfolios are indexed, August 1st, 2001=1.

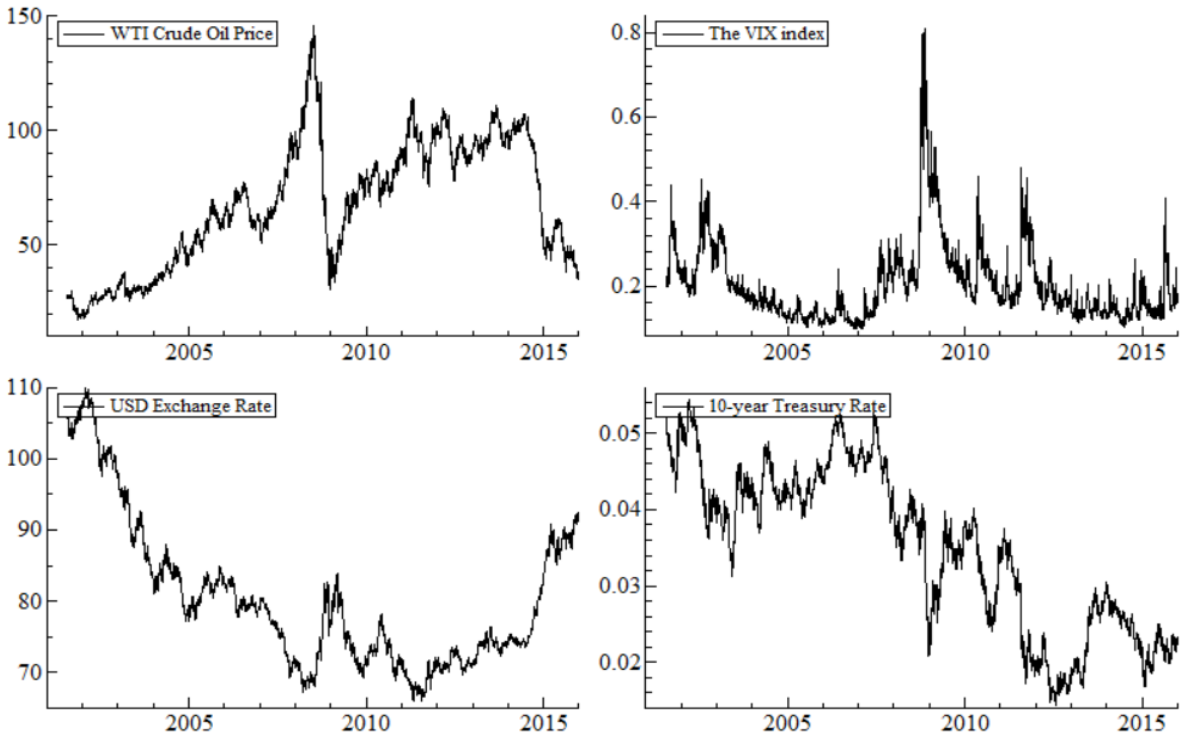

Figure C2: The figure shows the development of the WTI crude oil price, the volatility index, USD exchange rate and 10-year Treasury rate from August 1st, 2001 to December 31st, 2015. The VIX index shows the development in implied volatility, in decimals. The USD exchange rate is a trade-weighted index describing the effects of dollar appreciation and deprecation against foreign currencies.