



Article

Modelling Stock Returns and Risk Management in the Shipping Industry

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Abstract: We estimate the impact of macroeconomic risk factors on shipping stock returns, using a quantile regression (QR) model. We regress the excess return of a portfolio for the container, dry bulk, chemical/gas, oil tanker, and diversified shipping sectors on the world market portfolio excess return, volatility index, and changes in the oil price, exchange rate, and interest rate. The sensitivities of stock returns to the risk factors differ across quantiles and shipping segments and are found to be significant for the volatility index, world market portfolio return, exchange rate, and changes in long-term interest rate with variation over quantiles. This provides evidence of asymmetric and heterogeneous dependence between stock returns and certain macroeconomic risk variables. The results of the study also suggest that standard OLS regression is inadequate to uncover the risk-return relation.

Keywords: shipping stocks; ordinary least square; quantile regression; conditional distribution; asymmetric dependence

JEL Classification: C32; G10; C22



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1. Introduction

The international shipping industry is the lifeblood of the globalized economy, as it transports the majority of all raw materials, semi-finished goods, and finished goods that move around the globe. International trade is facilitated by specialized ships that operate in largely distinct freight markets for tankers (oil, gas, and chemicals), bulk carriers (raw materials, such as iron ore, coal, and grain), and container carriers (finished goods). Shipping is also one of the most cyclical industries associated with a number of idiosyncratic characteristics such as the cyclicity and seasonality of the demand for shipping services, freight rates, fragmented structure of the shipping industry as well as capital intensity (e.g., Alexandridis et al. 2018).

Given the long-observed positive correlation between ocean freight rates and economic activity (e.g., Klovland 2004; Tinbergen 1959), freight rate indices have been used to measure the component of worldwide real activity that drives the demand for industrial commodities in global markets. Given this close relationship between macroeconomic factors and the state of the shipping industry, analysis of the risk factors that affect shipping stock returns can shed light on the mechanisms by which macro variables have an impact on equity performance in the general market. Even though oil is often included as a risk

factor, the oil price is simultaneously a significant input cost in manufacturing, an indicator of global demand as well as an indicator of energy supply risks (e.g., spare oil production capacity, storage levels, or supply disruptions due to sanctions). This characteristic results in a complex and dynamic feedback loop among the oil market, the real economy, and equity markets, which is likely conditional on the oil price process itself (e.g., demand destruction may occur at high prices). The net effect can be observed, however, in the demand for seaborne transportation and, therefore, in the earnings and stock returns of shipping companies. By analyzing the impact of oil price changes across the range of shipping firms and the distribution of quantiles of their stock returns, we can indirectly explore the impact of oil price changes on demand in the various subsectors of the shipping industry. Similarly, by testing the impact of USD exchange rates on the share performance of different types of shipping service providers, we can shed light on the US dollar's impact on shipping industry returns.

In addition to shipping's role as a gauge for global trade and economic conditions, the industry has unique characteristics that make shipping industry an interesting candidate for empirical research on factor models in its own right (e.g., [Alexandridis et al. 2018](#)). First, it is often taken as a textbook example of a perfectly competitive industry, with fragmented ownership, very low taxation, and light regulatory burden. The latter characteristics are a natural consequence of having truly mobile assets (ships) that operate largely in international waters. In addition, although building ships are highly capital intensive, easy access to asset-backed financing means that barriers to entry are relatively low. Second, the combination of uncertain demand, the long lifespan of assets, and a lagged supply response function due to the time-to-build creates highly cyclical, asymmetric, and volatile earnings, giving the industry a reputation as a "low-return, high-risk" business (e.g., [Stopford 2009](#)). However, empirical studies do not support this and give rise to the "shipping return paradox"; the market betas are relatively low, often under unity (e.g., [Makrominas 2018](#)). [Syriopoulos and Bakos \(2019\)](#) find investor herding behavior in shipping and ask if herding is a reason behind volatility spillover between market segments in shipping. [Michail and Melas \(2020\)](#) examine the impact of Covid-19 pandemic on shipping freight rates. They find that the pandemic has directly affected the freight rates in bulk and dirty tanker segments.

Given the capital intensity of the shipping industry and volatility and cyclical nature of shipping stock returns, it is clearly of interest for investors and corporate managers to understand that the success or failure of a shipping company will be determined by macroeconomic forces as well as industry and company-specific risk factors under adverse market conditions.

The shipping finance literature provides empirical evidence that macroeconomic factors have significant impact on shipping stock risks and returns on the basis of ordinary least square (*hereafter*, OLS) regression models (e.g., [Drobetz et al. 2010](#); [El-Masry et al. 2010](#); [Grammenos and Arkoulis 2002](#); [Kavussanos and Marcoulis 2000](#)). We extend previous research by modeling the relationship between shipping stock returns and a set of financial and macroeconomic risk factors across the distribution of quantiles of conditional returns, following the quantile regression (*hereafter*, QR) analysis developed by [Koenker and Bassett \(1978\)](#). QR analysis provides a more comprehensive picture of the effect of the predictors on the response variable by modeling the relationship between a set of predictor variables and specific percentiles (or quantiles) of the response variable (e.g., [Bassett and Chen 2001](#); [Baur and Schulze 2005](#); [Baur et al. 2012](#); [Koenker 2004](#); [Lin et al. 2013](#); [Mensi et al. 2014](#)). QR analysis has been employed in the finance literature to model dependence between equity returns and other financial variables (e.g., [Meligkotsidou et al. 2009](#); [Mensi et al. 2014](#); [Reboredo and Ugolini 2016](#)). If the stock returns are normally distributed, there will be a direct link between volatility and quantiles/value at risk. This is not case for the shipping stock returns. Return distributions tend to have fat tails and are skewed. Using quantile regression approach. we can model directly how value at risk (quantiles) at lower tail (e.g., 1%, 5%) and upper tail (e.g., 95%, 99%) relates to the risk factors.

In this study, we use a sample of equity returns for 102 listed shipping companies for the data period from 5 January 2001 to 30 December 2016. Results of our QR analysis show that sensitivities of stock returns are significant for volatility index, world market portfolio return, exchange rate, and changes in long-term interest rate, and they do vary across quantiles and shipping segments. These results provide evidence of asymmetric dependence between stock returns and certain macroeconomic risk variables that standard OLS regression approach is not adequate to uncover such relationship.

Results of our analysis show that sensitivities of stock returns to the risk factors differ across quantiles and shipping segments and are significant for the volatility index, world market portfolio return, exchange rate, and changes in long-term interest rate with variation over quantiles. These results provide evidence of asymmetric and heterogeneous dependence between stock returns and certain macroeconomic risk variables that standard OLS regression is not adequate to uncover this finding.

Our study makes three major contributions to the literature. First, we use the dependence between economic activity and shipping market performance to explore the mechanism through which macroeconomic variables including changes in oil price affect the various parts of the industrial complex. The results help explain some of the inconsistencies reported in the finance literature. Second, this is the first study to use the QR method to determine the impact of macroeconomic risk factors on shipping stock returns, thereby uncovering new dependence structures between shipping stock returns and macroeconomic risk variables across the conditional return distributions. Third, we find there is a difference between the factors that are important for the OLS regression versus QR methods. The quantile regression analysis also displays significant results where a median or OLS regression does not. For example, QR results show that the volatility index VIX tend to magnify the returns of the shipping segments on a positive return day, while the same decreases on a negative return day. This implies that shipping stocks returns are sensitive to volatility in stock markets. The VIX volatility is not endogenous because it is taken from the general stock market, where shipping stocks have a minor market capital weight. A standard OLS regression is a regression contingent on the mean where positive and negative symmetric effects cancel out, which in turn may yield zero effect. This is exemplified in our empirical results section.

The remainder of this paper is organized as follows. Section 2 presents a review of the relevant literature and testable hypotheses. Section 3 contains the empirical methodology and data, and Section 4 provides the empirical results. Finally, Section 5 provides summary and concludes with some limitations of our study and avenues for further research.

2. Literature Review

Prior studies have used multifactor asset pricing model to assess the impact of systematic risk factors such as market, firm size, book-to-value, profitability, and investment (e.g., Fama and French 1993; Elyasiani et al. 2011; Fama and French 2016) as well as the effects of macroeconomic risk variables such as interest risk, exchange rate risk, oil price risk on stock returns of firms (e.g., Narayan and Sharma 2011; Mohanty and Nandha 2011; Sanusi and Ahmad 2016). There is little consensus, however, regarding which risk factors should be included in multifactor models to explain the additional risks that influence stock returns.

Barnes and Hughes (2002) examine whether CAPM holds at points of the distribution other than the mean. Using the QR 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. Reboredo and Ugolini (2016) use the QR analysis to test the impact of oil price risk on the return distribution in BRICS countries (Brazil, Russia, India, China, and South Africa) and three developed economies (US, UK, and EU). They find that oil prices have a stronger impact on stock returns in the lower tail, but a 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 for

the 1997–2013 period using the QR approach. They find that the risk–return relationship evolves from negative to positive as the quantile increases. For quantiles below the median, the excess return is negatively related to risk and vice versa.

A number of studies have examined the performance of factor models for shipping company equities, typically using some combination of the macroeconomic variables and systematic risk variables. For example, Kavussanos and Marcoulis (1997) and Drobetz et al. (2010) focus on the estimation of market betas, using the seemingly unrelated regression (SUR) approach and find that shipping companies generally exhibit a market beta that is lower than unity. 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 for the period from 1997 to 2005. They find that the exposure to fluctuations in short- and long-term interest rates is significant for only 14 firms (9.79% of all firms in the sample) and negative in 12 of these cases. Grammenos and Arkoulis (2002) investigate the impact on shipping stocks of oil prices, industrial production, inflation, and changes in USD exchange rates during the 1989–1998 period using the multivariate least squares method. Their study documents that changes in oil prices negatively affect shipping stock returns. Drobetz et al. (2010) hypothesize that oil prices can have both a negative and a positive influence on shipping stock returns, as oil serves as a proxy for the global economic environment but also represents a cost for shipping companies. Their findings indicate that changes in oil prices have a significant positive impact on stock returns in the container sector only. The latter highlights how oil price could have an asymmetric impact on different parts of the global economy and, hence, different market segments of ocean transportation. Several studies examine the impact of foreign exchange risk on stock returns of shipping industry. Several studies including Loudon (1993), Leggate (1999) and Akatsuka and Leggate (2001) find that the exchange rate significantly influences the performance of shipping companies. Studies by Grammenos and Arkoulis (2002) and Drobetz et al. (2010) document that the USD exchange rate is negatively related to shipping stock returns. Finally, Ekrem and Kristensen (2016) use the QR analysis to investigate the effects of various macroeconomic risk factors such as stock market volatility, oil price risk, exchange rate risk and interest rate risk on shipping stock returns. Their findings suggest that risk exposures vary across conditional quantiles. They also do vary under different market conditions. For a comprehensive review of literature in shipping finance and investments, please refer to Alexandridis et al. (2018).

3. Methodology and Data

3.1. Methodology

Consistent with the empirical evidence in the literature, we argue that the excess returns of a portfolio of shipping stocks are likely to be influenced by the following four macroeconomic factors: excess return on the market portfolio ($R_{Mt} - R_{Ft}$), return on the West Texas Intermediate (WTI) oil price (OIL_t), change in the trade-weighted USD Index (FX_t), and change in the 10-year US treasury rate (UST_t). In addition, we include a fifth risk factor, the CBOE Volatility Index (VIX_t), as an explanatory variable in our model. VIX reflects the implied volatility of the S&P 500 Index for a 30-day period. VIX is a widely used measure of the level of investor fear in the stock market and has been found to influence US stock market returns in a number of empirical studies (see, e.g., Badshah 2013; Chiang and Li 2012; Dennis et al. 2006; Fleming et al. 1995; Mensi et al. 2014). The volatility in US stock market returns is also likely to have an impact on global stock market returns.

In addition, we include the four financial factors proposed by Fama and French (2016) that capture portfolio returns from sorts by company size (market capitalization), book-to-market-value, investments, and profitability. Following their original notation, we will refer to SMB_t as the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks, the difference between the return on diversified portfolio of high and low book-to-market value stocks as HML_t , the difference between the return on diversified portfolio of stocks with robust and weak profitability as RMW_t , and the difference between the return on a diversified portfolio of stocks with conservative and

aggressive investment as CMA_t . WML_t is the difference between the return on a diversified portfolio of stocks that are winners and those that are losers. To assess the importance of shipping sector variables, we also include return of indices that reflect the state of the freight markets, notably, the Baltic Dry Index (BDI_t), the Harpex Container Freight Index (HPX_t), and a Bunker Fuel Index (BFI_t). For the purposes of estimation, all variables refer to daily logarithmic changes, except VIX_t , which is stationary in levels. See Appendix A for a detailed variable description.

With our dependent variable $R_{it} - R_{Ft}$ as the excess return of shipping equity portfolio i at time t , our most comprehensive factor model is thus given by

$$R_{it} - R_{Ft} = \alpha_i + \beta_{i1}(R_{Mit} - R_{Ft}) + \beta_{i2}OIL_t + \beta_{i3}FX_t + \beta_{i4}UST_t + \beta_{i5}VIX_t + \beta_{i6}SMB_t + \beta_{i7}HML_t + \beta_{i8}RMW_t + \beta_{i9}CMA_t + \beta_{i10}WML + \beta_{i11}BDI_t + \beta_{i12}HPX_t + \beta_{i13}BFI_t + \varepsilon_{it}$$

where $\beta_{i1}, \beta_{i2}, \dots, \beta_{i13}$ is the sensitivity of risk factor 1, 2, ..., 13 or shipping portfolio i .

We have five portfolios, one for each market segment: bulk, tank, container, chemical and diverse shipping firms. Individual names of firms in each segment are provided in the Appendix B. Equation (1) is estimated base on both standard OLS regression and the QR method developed by [Koenker and Bassett \(1978\)](#). The notation in Equation (1) might lead some readers to think this is a panel data regression model. It is not, because we are estimating a separate time series regression for each market segment. In the dataset, the right-hand side variables only vary over time, not across firms as indicated by the index t . The left-hand side returns vary over each firm, but we have constructed a market weighted return index for each segment, bulk, tanker, container, and diversified firms.

We have collected all listed shipping firms we could find under the industry code Marine Transportation in Datastream. The names of the firms are listed in the Appendix B. We are not aware of any other listed shipping firm. Our sample size of firms is twice as large as the sample used by [Drobetz et al. \(2010\)](#). Our dataset should therefore be a valid representation of the universe of listed global shipping firms. There are additional private firms, but their stocks are not publicly traded, and therefore, they are not included in our sample. The selection of firms into each segment is based on the verbal description of each firm in the Datastream database. A firm with an overweight of containerships would be classified as a container shipping firm. Some firms had ships more evenly distributed across market segments and were characterized as diverse segment. Although this segmentation is subjective, as any listing under a specific industry code is, we think our results show different effects from various risk factors on each segment which is consistent with our a priori hypothesis. Our segmentation of firms represents the specific risk in a market segment such as bulk. Shipping is also characterized by a different rate development between segments. For example, bulk and tank segments may behave differently due to different supply and demand considerations.

The nonparametric QR method requires no distributional assumption to optimally estimate the parameters and, therefore, gives a more complete picture of the joint distribution of the data. The latter method is also far more robust to outliers and non-normality in the distribution of residuals than is the OLS regression approach and, thus, provides more accurate and precise estimates of parameters ([Brooks 2014](#)). When Equation (1) is estimated, using OLS, the errors ε_{it} are assumed to be independent and identically distributed (i.i.d.) with a mean equal to zero, whereas it is left unspecified in the quantile regression.

To obtain the standard errors for the estimated coefficients when using the QR method, we use the paired bootstrapping procedure proposed by [Buchinsky \(1995\)](#). By using this procedure, standard errors are asymptotically valid under heteroscedasticity and misspecification of the QR function. If the intercept and regression coefficients vary with q , the model identifies a form of heteroscedastic conditional return distribution. Hence, the QR estimates will add more information about the risk-return profile of the shipping stocks than will the conditional mean regression in the OLS case. In addition, 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 quantile q and using the last observed values for the risk factors in Equation (2), we can calculate VaR for each stock portfolio. VaR is a particular conditional quantile on the distribution and is a risk measure for the loss level that is expected to exceed with probability $q \in (0, 1)$, if the portfolio is held over some time (e.g., Alexander 2009).

3.2. Data and Descriptive Statistics

We use a sample of 102 listed shipping companies for the period 5 January 2001 to 30 December 2016 (see Appendices B.1–B.5 for details, including names of shipping firms for each segment). We survey the listed firms under the industry code Maritime Transportation. Our sample contains all firms that are classified as shipping firms. We exclude logistics firms, warehousing firms, and passenger transport like cruise liners. Our sample represents the majority of listed shipping firms that serve manufacturing industry with needs for raw materials. Sample firms are classified into five market-weighted portfolios that represent the major sub-sectors (segments) of the shipping industry: container, dry bulk, chemicals/gas, tanker, and “others” (e.g., owners with diversified fleets). Daily stock prices for each of the companies are obtained from Eikon Datastream, denominated in USD and adjusted for stock splits. The portfolios are constructed by weighting each company in accordance with its market value, whereby the weights reflect the market capitalization of each company divided by the sum of total market capitalization within each market segment for all firms in the portfolio. The one-month US Treasury rate is used as the risk-free rate. The excess logarithmic return of each portfolio serves as our dependent variables. Figure 1 shows the price development of our five value-weighted shipping sector portfolios over the sample period (indexed to 100 at the start of the sample).

As a proxy for the world market portfolio, we use the Morgan Stanley Capital International (MSCI) All Country World Index (ACWI). The index covers approximately 85% of the global investment opportunities and includes a sample of large and medium capitalization companies across 23 developed markets and 23 emerging market countries. For details on the MSCI ACWI, please see <https://www.msci.com/acwi> (accessed on 5 April 2021).

We note that previous research (Drobetz et al. 2010; Grammenos and Arkoulis 2002) uses the MSCI World Equity Index, consisting of developed markets only. The shipping industry, however, is clearly influenced also by developing markets, notably, Brazil, India, and China, such that the ACWI should be a more appropriate choice. The trade-weighted US Dollar Index is a weighted average of the foreign exchange value of the USD against major currencies, including those of the Euro area, Canada, Japan, United Kingdom, Switzerland, Australia, and Sweden. Figure 2 shows the MSCI world stock market index versus bunker fuel cost and the trade-weighted USD basket index over the sample period. Figure 3 exhibits the co-movement between Baltic Dry Index and Harpex Container Freight Index.

Daily data for the independent variables are collected for the period 1 August 2001 to 31 December 2016, using Eikon Datastream (MSCI ACWI, WTI crude oil price, VIX, and 10-year Treasury Rates). Table 1 presents the descriptive statistics for the variables under consideration. We note that average excess returns for the equity portfolios and world market proxy are positive, except for the dry bulk market. We must be careful however interpreting the mean values as the large volatility in the mean return is very sensitive to the sample size.

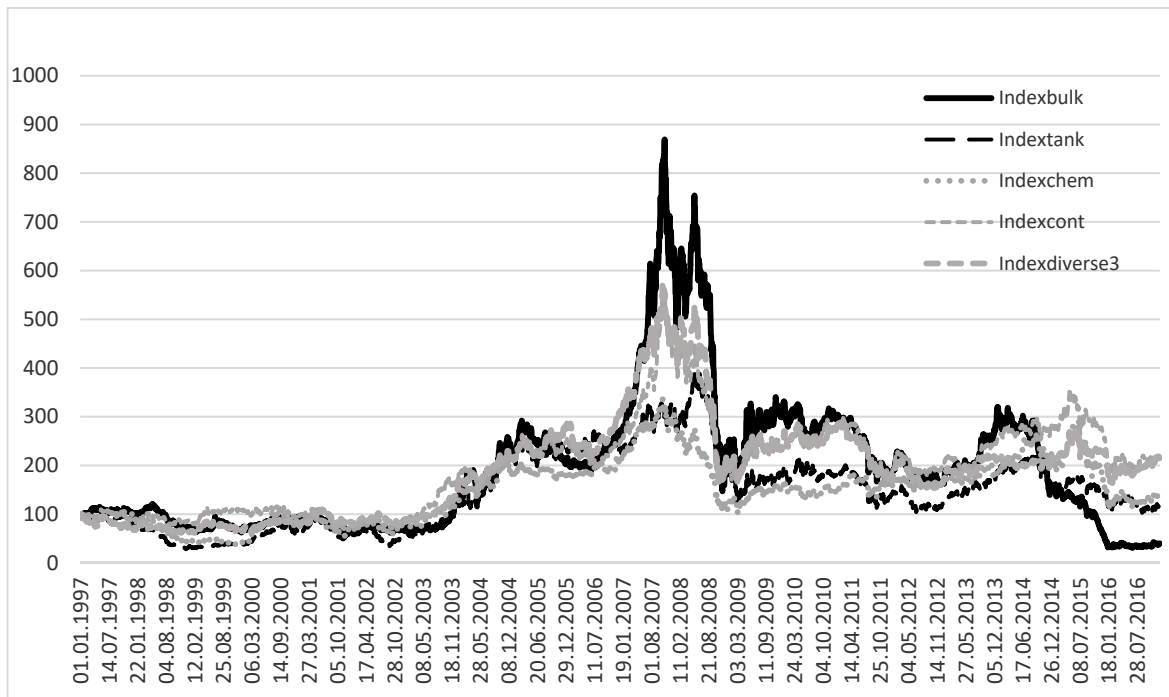


Figure 1. Shipping market segments index values. Note: IndexBulk = A level index created from the returns for the bulk segment, starting at 100; IndexTank = A level index created from the returns for the tanker segment, starting at 100; IndexChem = A level index created from the returns for the chemical/gas segment, starting at 100; IndexBulk = A level index created from the returns for the bulk segment, starting at 100; IndexContainer = A level index created from the returns for the container segment, starting at 100; IndexDiverse = A level index created from the returns for the diverse segment, starting at 100; IndexMarket = A level index created from the global market returns.

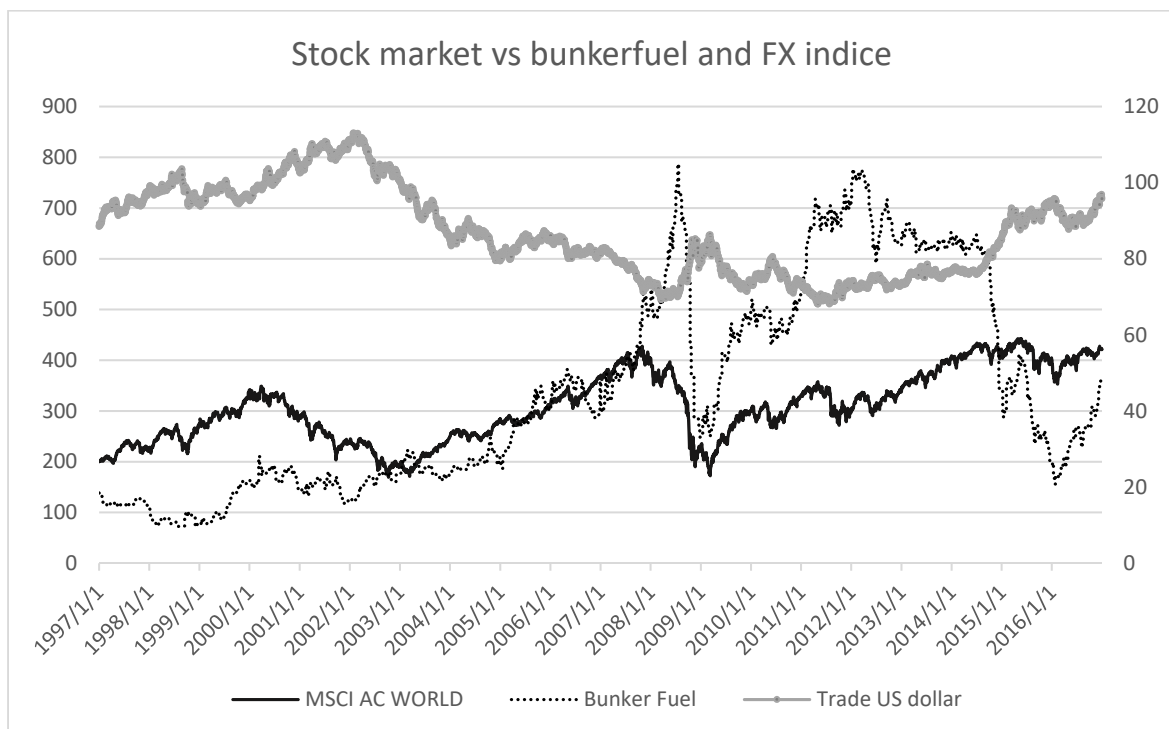


Figure 2. Stock market index versus fuel cost and USD basket index. Note: Bunker Fuel and FX (Foreign Exchange) indexes are on the right-hand side axis. Morgan Stanley Capital International (MSCI) All Country World Index (ACWI) is on the left-hand side axis.

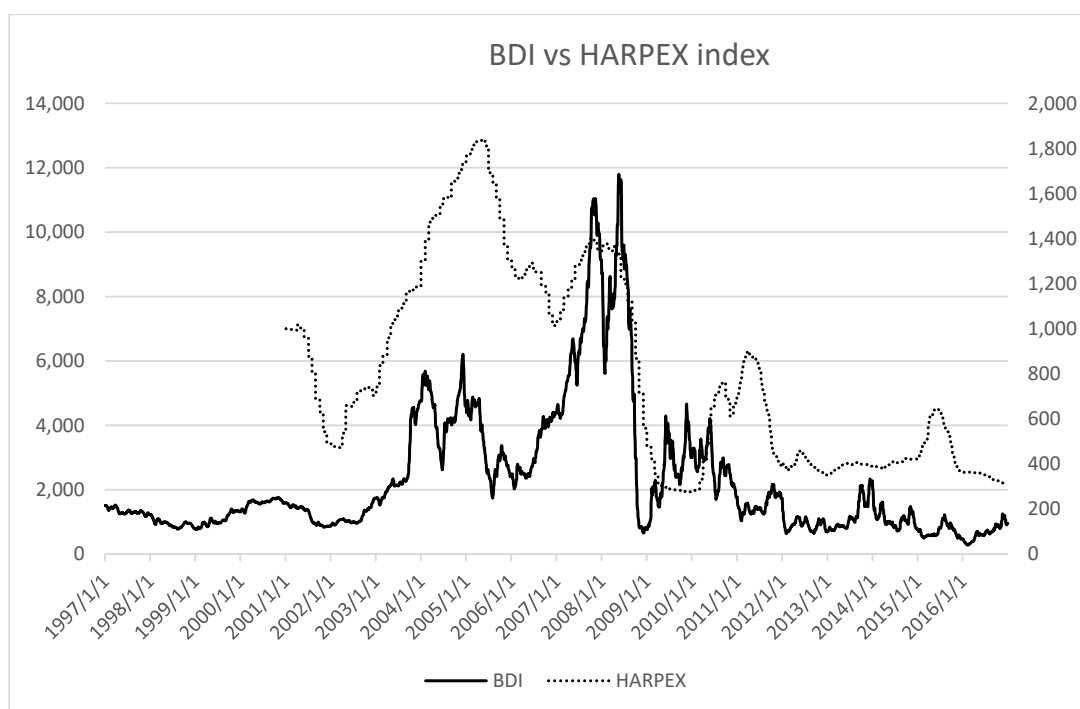


Figure 3. Baltic Dry Index versus Harpex Container Freight Index. Note: BDI, the Baltic Exchange Dry Index, is on the left-hand axis, and Harpex, the container freight index, is on the right-hand axis.

Table 1. Descriptive statistics.

| Variable | Obs | Mean | Std. Dev. | Min | Max | Skew | Kurtosis |
|-------------|------|--------|-----------|--------|-------|--------|----------|
| Ret Bulk | 4171 | −0.002 | 1.912 | −10.84 | 11.09 | −0.115 | 6.674 |
| Ret Tank | 4171 | 0.033 | 1.987 | −11.19 | 12.80 | −0.49 | 6.564 |
| Ret Chem | 4171 | 0.026 | 1.714 | −10.10 | 9.76 | −0.178 | 5.927 |
| Ret Cont | 4171 | 0.028 | 1.326 | −11.75 | 8.13 | −0.389 | 7.319 |
| Ret Diverse | 4171 | 0.034 | 1.450 | −9.05 | 8.77 | −0.163 | 5.926 |
| OIL | 4171 | 0.000 | 0.024 | −0.17 | 0.16 | −0.075 | 7.435 |
| VIX | 4171 | 20.177 | 8.885 | 9.89 | 80.86 | 2.137 | 9.837 |
| (Rm-Rf) | 4171 | 0.020 | 0.987 | −6.67 | 9.20 | −0.229 | 10.539 |
| UST | 4171 | −0.001 | 0.059 | −0.51 | 0.25 | −0.006 | 5.741 |
| FX | 4171 | −0.002 | 0.389 | −3.39 | 2.37 | −0.237 | 6.656 |
| SMB | 4171 | 0.011 | 0.432 | −3.96 | 2.37 | −0.704 | 10.685 |
| HML | 4171 | 0.018 | 0.343 | −3.02 | 2.24 | 0.052 | 8.908 |
| RMW | 4171 | 0.015 | 0.271 | −1.69 | 1.51 | −0.047 | 5.595 |
| CMA | 4171 | 0.016 | 0.285 | −2.51 | 1.72 | 0.03 | 10.533 |
| WML | 4171 | 0.021 | 0.668 | −4.89 | 4.32 | −0.68 | 9.264 |
| BDI | 4171 | −0.012 | 1.992 | −12.07 | 13.66 | 0.088 | 7.914 |
| HPX | 4171 | −0.028 | 1.407 | −24.37 | 28.87 | 0.117 | 144.42 |
| BFI | 4171 | 0.022 | 1.888 | −26.95 | 18.96 | −1.618 | 47.544 |

Note: RetBulk = Portfolio return on the dry bulk segment is constructed by weighting each company in accordance with its market value, for which the weights reflect the market capitalization of each company divided by the sum of total market capitalization within each market segment for all firms in the portfolio. RetTank = similar to RetBulk for the Tank segment; RetChem = similar to RetBulk for the Chemical/gas segment; RetCont = similar to RetBulk for the Container segment; RetDiverse = similar to RetBulk for the Diverse segment; OIL = log of WTI Oil Spot price changes from $t - 1$ to t ; VIX = Volatility Index of S&P 500; Rm-Rf = excess return on MSCI Global; UST = change in 10-Year US Treasury bond yield from $t - 1$ to t ; FX = change in the levels of the Trade Weighted US Dollar Index from $t - 1$ to t ; SMB = return on diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks based on Fama-French (hereafter, FF) factor; HML = difference between the return on diversified portfolio of high and low book-to-market value stocks based on FF factor; RMW = difference between the return on diversified portfolio of stocks with robust and weak profitability based on FF factor; CMA = difference between the return on diversified portfolio of stocks with conservative and aggressive investments based on FF factor; WML = difference between the return on diversified portfolio of stocks of winners minus losers based on momentum factor; BDI = log of Baltic Exchange Dry Index price changes from $t - 1$ to t ; HPX = log of Harpex Shipping Index price changes from $t - 1$ to t ; BFI = log of Bunker Fuel price changes from $t - 1$ to t .

The tanker equity segment is the most volatile, followed by dry bulk and chemicals/gas, with diversified shipping and container companies as showing the lowest standard deviation. This is consistent with the view that raw material transportation exhibits the highest demand volatility compared to the transportation of intermediate inputs and finished goods.

All risk factors exhibit kurtosis, leading to rejection of the Jarque-Bera test of normality for the unconditional distribution of all of the series. The distributions also show varying skewness, with the VIX, container, tanker, and container portfolio returns as having positive skewness and the remaining distributions as having negative skewness. This indicates that the QR method will provide more accurate parameter estimates than will OLS regressions, as the QR method is more robust to outliers and non-normality. We test the null hypothesis of a unit root, using Augmented Dickey–Fuller (ADF) statistics (Dickey and Fuller 1979) statistics. We use three control lags in the ADF regression. The results of the ADF test show that all return series are stationary.

Table 2 presents the correlation matrix of our dependent and independent variables. The excess returns of the shipping portfolios exhibit a moderate correlation with the excess return of the MSCI ACWI, with the highest correlations for the tanker and dry bulk equity portfolios. Oil price and interest rate changes show a weak positive correlation with portfolio returns across shipping equity segments, while VIX and changes in the USD exchange rate exhibits weak negative correlations. Overall, the low magnitude of correlations across the matrix suggests the absence of multicollinearity.

Table 2. Correlation between dependent and explanatory variables.

| | Ret Bulk | Ret Chem | Ret Cont | Ret Tank | Ret Diver | OIL | VIX | Rm-Rf | UST | FX | SMB | HML | RMW | CMA | WML | BDI | HPX | BFI | |
|------------|----------|----------|----------|----------|-----------|-------|-------|-------|-------|-------|-------|-------|------|-------|-------|------|------|------|--|
| Ret Bulk | 1.00 | | | | | | | | | | | | | | | | | | |
| Ret Chem | 0.49 | 1.00 | | | | | | | | | | | | | | | | | |
| Ret Cont | 0.50 | 0.52 | 1.00 | | | | | | | | | | | | | | | | |
| Ret Tank | 0.43 | 0.33 | 0.42 | 1.00 | | | | | | | | | | | | | | | |
| Ret Diver. | 0.41 | 0.27 | 0.38 | 0.65 | 1.00 | | | | | | | | | | | | | | |
| OIL | 0.27 | 0.30 | 0.32 | 0.20 | 0.17 | 1.00 | | | | | | | | | | | | | |
| VIX | −0.10 | −0.10 | −0.10 | −0.12 | −0.10 | −0.07 | 1.00 | | | | | | | | | | | | |
| Rm-Rf | 0.53 | 0.59 | 0.56 | 0.47 | 0.40 | 0.32 | −0.15 | 1.00 | | | | | | | | | | | |
| UST | 0.19 | 0.24 | 0.21 | 0.10 | 0.08 | 0.17 | −0.07 | 0.33 | 1.00 | | | | | | | | | | |
| FX | −0.21 | −0.22 | −0.18 | −0.29 | −0.23 | −0.23 | 0.03 | −0.31 | 0.06 | 1.00 | | | | | | | | | |
| SMB | −0.13 | −0.25 | −0.21 | −0.04 | 0.06 | −0.12 | 0.00 | −0.54 | −0.30 | −0.06 | 1.00 | | | | | | | | |
| HML | 0.14 | 0.15 | 0.12 | 0.15 | 0.12 | 0.14 | −0.05 | 0.08 | 0.04 | −0.13 | 0.04 | 1.00 | | | | | | | |
| RMW | −0.20 | −0.22 | −0.22 | −0.12 | −0.11 | −0.04 | 0.08 | −0.39 | −0.25 | −0.04 | 0.18 | −0.20 | 1.00 | | | | | | |
| CMA | −0.28 | −0.21 | −0.21 | −0.23 | −0.22 | −0.18 | 0.06 | −0.36 | −0.13 | 0.10 | 0.17 | 0.40 | 0.03 | 1.00 | | | | | |
| WML | −0.20 | −0.22 | −0.20 | −0.12 | −0.11 | −0.12 | 0.02 | −0.41 | −0.23 | 0.07 | 0.40 | −0.04 | 0.42 | 0.35 | 1.00 | | | | |
| BDI | 0.19 | 0.03 | 0.05 | 0.11 | 0.12 | 0.02 | −0.06 | 0.01 | 0.00 | −0.03 | 0.03 | −0.03 | 0.01 | −0.05 | 0.02 | 1.00 | | | |
| HPX | −0.04 | 0.00 | −0.02 | 0.02 | 0.02 | −0.02 | −0.08 | −0.02 | −0.07 | 0.00 | 0.01 | 0.00 | 0.01 | 0.03 | 0.02 | 0.00 | 1.00 | | |
| BFI | 0.02 | 0.01 | 0.03 | 0.03 | 0.02 | 0.01 | −0.06 | 0.04 | 0.01 | −0.02 | −0.02 | 0.02 | 0.01 | −0.03 | −0.01 | 0.04 | 0.00 | 1.00 | |

Note: Variable definitions are explained in the text of Table 1.

4. Empirical Results and Discussion

Tables 3–7 present the estimates obtained across our five shipping equity sectors, using OLS regression (Specification 1) and the QR approach (seven quantiles from 5% through 95%, Specifications 2 through 8). These results are also presented graphically for the bulk segment in Figure 4. The OLS estimates significance have been confirmed by Newey–West robust standard errors that account for autocorrelation and heteroscedasticity in error terms. To estimate the covariance matrix of the parameter estimates in the QR case, we employ the paired bootstrapping procedure (Buchinsky 1995), with maximum iterations set to 1000 as a robustness control.

Table 3. Ordinary least square (OLS) and quantile regression estimates for the dry bulk segment.

| Model | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|-------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| | Bulk OLS | Bulk 05 | Bulk 10 | Bulk 25 | Bulk 50 | Bulk 75 | Bulk 90 | Bulk 95 |
| OIL | 5.624 *** 5.310 | 7.299 * 2.470 | 7.185 *** 3.900 | 5.487 *** 4.260 | 3.956 *** 4.250 | 3.735 ** 2.790 | 4.989 * 2.220 | 7.661 ** 2.600 |
| VIX | 0.002 0.700 | −0.054 *** 7.240 | −0.035 *** 7.350 | −0.016 *** 4.810 | 0.000 *** 0.070 | 0.017 *** 4.980 | 0.040 *** 6.940 | 0.052 *** 6.860 |
| Rm-Rf | 1.074 *** 28.720 | 1.029 *** 9.870 | 1.135 *** 17.450 | 1.050 *** 23.090 | 0.972 *** 29.570 | 1.045 *** 22.090 | 1.132 *** 14.26 | 1.146 *** 11.02 |
| UST | 1.263 ** 2.890 | 0.398 0.330 | 0.886 1.170 | 1.041 1.960 | 1.821 *** 4.740 | 1.519 ** 2.500 | 1.269 1.370 | 2.215 1.820 |
| FX | 0.128 1.840 | 0.218 1.130 | 0.206 1.700 | 0.073 0.870 | 0.040 0.650 | 0.137 1.560 | 0.158 1.080 | 0.288 1.500 |
| SMB | 0.869 *** 12.140 | 1.031 *** 5.170 | 0.990 *** 7.950 | 0.850 *** 9.760 | 0.764 *** 12.140 | 0.741 *** 8.180 | 0.774 *** 5.090 | 0.791 *** 3.980 |
| HML | 0.824 *** 10.120 | 0.933 *** 4.120 | 0.777 *** 5.490 | 0.820 *** 8.280 | 0.870 *** 12.150 | 0.975 *** 9.470 | 0.771 *** 4.460 | 0.692 ** 3.060 |
| RMW | 0.160 1.510 | −0.032 −0.110 | 0.057 0.310 | 0.144 1.110 | −0.049 −0.520 | 0.144 1.070 | 0.362 1.600 | 0.513 1.740 |
| CMA | −1.023 *** −9.530 | −1.131 *** −3.780 | −0.749 *** −4.010 | −0.773 *** −5.920 | −0.808 *** −8.570 | −0.976 *** −7.190 | −1.217 *** −5.340 | −1.219 *** −4.090 |
| WML | 0.026 0.580 | 0.184 1.490 | 0.147 1.910 | 0.069 1.280 | 0.084 * 2.160 | 0.038 0.680 | −0.056 −0.590 | −0.207 −1.680 |
| BDI | 0.171 *** 14.460 | 0.168 *** 5.110 | 0.155 *** 7.560 | 0.160 *** 11.150 | 0.162 *** 15.620 | 0.169 *** 11.310 | 0.213 *** 8.510 | 0.275 *** 8.380 |
| HPX | −0.033 −1.950 | −0.083 −1.790 | −0.041 −1.420 | −0.021 1.040 | −0.008 −0.540 | −0.030 −1.430 | −0.044 −1.240 | −0.035 −0.750 |
| BFI | −0.014 −1.100 | −0.029 −0.840 | −0.002 −0.100 | −0.002 −0.130 | 0.002 0.220 | −0.001 −0.080 | −0.054 * −2.030 | −0.083 * −2.400 |
| C | −0.071 −1.200 | −1.236 *** −7.460 | −1.035 *** −10.01 | −0.536 *** −7.400 | −0.055 *** −1.050 | 0.406 *** 5.400 | 0.921 *** 7.290 | 1.424 *** 8.620 |
| N | 4170 | 4170 | 4170 | 4170 | 4170 | 4170 | 4170 | 4170 |

Note: Model 1 is OLS regression; Models 2–8 are quantile regression for quantile 5% to 95% for the Dry bulk segment; ***, **, * indicate significance level at 1%, 5%, and 10%, respectively. Variable definitions are explained in Appendix A.

The effect of the world market portfolio, represented by the excess market return ($R_{Mt} - R_{Ft}$) variable for global stocks, constructed by Fama and French, differs across sectors, with tanker, dry bulk, and chemical/gas transportation equities generally showing betas greater than 1 and container and diversified shipping portfolios as having betas below 1. Although the volatility in freight rates and shipping stock price return can be high compared to the general stock market (see descriptive statistics), the market beta is remarkably low for the contingent mean regression. All the median (50% quantile) regressions have stock market beta less than unity except for the tanker segment, which is 1.083, only slightly above unity. This tells a story of shipping as a unique asset class with descriptive statistics for shipping stocks unlike the common stock market. We can conclude that shipping stocks are characterized by high un-systematic risk and conversely low systematic risk. The graphical representation in Figure 4 shows a tendency for a U-shaped market return sensitivity with higher market betas for very low and very high shipping portfolio returns, similar to the bulk segment. This indicates a stronger tail dependence on the market factor and implies that OLS regression underestimates the sensitivity of market risk at the lower and upper quantiles of the return distribution. This effect is particularly obvious for the tanker and dry bulk sectors. Interestingly, our expanded factor model (both in terms of covariates and sample period) differs in this regard from earlier research (Drobetz et al. 2010; Kavussanos and Marcoulis 1997), which finds empirical evidence of

market betas lower than unity. Indeed, the relatively high betas for the tanker and dry bulk segments better reflect what we would expect, given the high volatility of earnings and sensitivity to demand cycles (Alizadeh and Nomikos 2009).

Table 4. Ordinary least square (OLS) and quantile regression estimates for the tanker segment.

| Model | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | | | |
|-------|-----------------|------------------|-----------------|-----------------|-----------------|-----------------|-----------------|----------------|-----------------|-----------------|------------------|
| | Tank OLS | Tank 05 | Tank 10 | Tank 25 | Tank 50 | Tank 75 | Tank 90 | Tank 95 | | | |
| OIL | 7.693 7.000 | *** 9.060 | ** 2.900 | 10.040 4.840 | *** 7.848 | *** 6.240 | *** 7.010 | *** 3.580 | *** 6.472 | ** 2.920 | 7.498 1.810 |
| VIX | 0.001 −0.460 | −0.042 −5.210 | *** −0.037 | *** −6.980 | *** −6.150 | *** 0.320 | *** 5.820 | *** 0.019 | *** 0.037 | *** 6.580 | 0.057 5.400 |
| Rm-Rf | 1.182 30.460 | *** 1.340 | *** 12.140 | *** 16.260 | *** 26.600 | *** 32.360 | *** 24.590 | *** 15.210 | *** 1.190 | *** 1.611 | 1.202 8.220 |
| UST | 1.821 4.020 | *** 2.541 | * 1.970 | 2.394 2.800 | ** 5.000 | *** 2.297 | *** 5.870 | *1.260 | *1.760 | 1.611 1.760 | 1.436 0.840 |
| FX | 0.032 −0.440 | 0.134 −0.650 | 0.036 −0.260 | 0.162 −1.970 | * −2.040 | * 0.127 | * −0.920 | * 0.075 | * −0.500 | 0.073 −1.060 | −0.288 −1.060 |
| SMB | 0.392 5.270 | *** 0.811 | *** 3.840 | 0.657 4.690 | *** 6.610 | *** 6.610 | *** 5.570 | * 2.190 | * 1.460 | 0.219 1.460 | 0.335 1.200 |
| HML | 0.620 7.340 | *** 0.579 | 0.638 2.410 | *** 4.010 | *** 4.448 | *** 4.640 | *** 8.480 | *** 8.730 | *** 0.816 | *** 0.816 | 1.217 3.820 |
| RMW | 0.135 1.230 | 0.449 1.430 | 0.031 0.150 | 0.048 0.380 | −0.074 0.780 | 0.160 0.780 | 0.160 1.290 | 0.364 1.640 | 0.660 1.100 | 0.458 1.100 | |
| CMA | −0.345 3.100 | ** 0.207 | 0.740 0.650 | −0.155 0.740 | −0.240 1.880 | −0.582 6.060 | *** 0.097 | *** 4.550 | *** 2.040 | * 0.061 | −0.566 1.350 |
| WML | 0.078 1.700 | 0.106 0.810 | 0.102 1.170 | 0.078 1.470 | 0.097 2.440 | * 2.440 | * 1.780 | 0.093 0.660 | 0.061 0.660 | −0.081 0.460 | |
| BDI | 0.021 1.740 | −0.003 0.070 | 0.037 1.590 | 0.022 1.580 | 0.029 2.770 | ** 1.830 | ** 1.830 | 0.025 1.210 | 0.030 1.210 | 0.032 0.700 | |
| HPX | 0.019 1.070 | 0.007 0.150 | 0.005 0.150 | 0.009 0.470 | 0.014 0.900 | −0.004 0.900 | −0.004 0.220 | 0.043 1.240 | −0.003 0.050 | −0.003 0.050 | |
| BFI | −0.021 1.620 | −0.025 0.680 | −0.026 1.050 | −0.019 1.310 | −0.021 1.920 | −0.021 1.920 | −0.034 2.320 | * 0.620 | −0.016 0.620 | −0.033 0.670 | |
| C | −0.029 0.470 | −1.637 9.320 | *** −1.019 | *** −0.457 | *** −0.030 | *** 0.550 | *** 0.484 | *** 6.930 | *** 0.981 | *** 7.890 | 1.403 6.030 |
| N | 4168 | 4168 | 4168 | 4168 | 4168 | 4168 | 4168 | 4168 | 4168 | 4168 | |

Note: Model 1 is based on OLS regression; Models 2–8 are based on quantile regression for quantile 5% to 95% for the Tanker segment; ***, **, * indicate significance level at 1%, 5%, and 10%, respectively. Variable definitions are explained in Appendix A.

Table 5. Ordinary least square (OLS) and quantile regression estimates for the chemical segment.

| Model | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | | | |
|-------|-----------------|------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|---------------|---------------|
| | Chem OLS | Chem 05 | Chem 10 | Chem 25 | Chem 50 | Chem 75 | Chem 90 | Chem 95 | | | |
| OIL | 7.693 7.000 | *** 16.210 | *** 5.670 | 10.670 5.890 | *** 8.602 | *** 7.600 | *** 9.400 | *** 7.910 | *** 11.540 | *** 5.530 | 15.23 5.47 |
| VIX | 0.001 0.460 | −0.028 3.850 | *** 5.350 | *** 3.930 | *** 0.000 | *** 0.000 | ** 4.840 | ** 3.130 | ** 0.017 | ** 3.130 | 0.02 3.48 |
| Rm-Rf | 1.182 30.460 | *** 1.222 | *** 12.110 | *** 17.650 | *** 23.760 | *** 29.080 | *** 22.380 | *** 12.950 | *** 9.954 | *** 9.90 | 0.97 9.90 |
| UST | 1.821 4.020 | *** −0.034 | 0.596 0.030 | 0.517 1.110 | 0.601 1.610 | 0.601 1.610 | 0.973 1.900 | 0.553 0.640 | −0.03 0.03 | −0.03 0.03 | |
| FX | 0.032 0.440 | 0.300 1.600 | 0.211 1.780 | 0.176 2.370 | * 3.100 | ** 0.184 | ** 0.261 | ** 0.255 | ** 1.870 | ** 2.42 | 0.44 2.42 |
| SMB | 0.392 5.270 | *** 0.795 | *** 4.120 | 0.638 5.210 | *** 6.020 | *** 6.320 | *** 4.400 | *** 3.030 | ** 0.428 | ** 3.030 | 0.29 1.55 |
| HML | 0.620 7.340 | *** 0.144 | 0.475 3.410 | *** 6.100 | *** 0.531 | *** 6.830 | *** 3.550 | *** 2.030 | * 0.326 | * 2.030 | 0.45 2.09 |
| RMW | 0.135 1.230 | −0.444 1.550 | 0.024 0.130 | −0.098 0.860 | 0.072 0.790 | 0.015 0.120 | −0.019 0.090 | 0.29 1.04 | −0.019 0.090 | 0.29 1.04 | |
| CMA | −0.345 3.100 | ** −0.147 | −0.301 1.640 | −0.374 3.260 | ** 4.510 | ** 4.510 | *** 2.280 | * 1.320 | −0.280 1.320 | * 0.46 | −0.13 0.46 |
| WML | 0.078 1.700 | 0.284 2.370 | * 2.300 | * 2.850 | ** 2.250 | * 2.250 | * 1.340 | −0.047 0.530 | −0.047 0.530 | −0.12 0.99 | |
| BDI | 0.021 1.740 | 0.050 1.590 | 0.030 1.510 | 0.025 2.020 | * 2.440 | * 2.440 | * 3.130 | ** 1.570 | 0.037 1.570 | 0.04 1.37 | |
| HPX | 0.019 1.070 | −0.083 1.830 | 0.007 0.240 | 0.008 0.470 | 0.005 0.340 | −0.003 0.340 | −0.003 0.140 | −0.006 0.190 | −0.006 0.190 | −0.02 0.55 | |
| BFI | −0.021 1.620 | 0.019 0.570 | 0.005 0.220 | 0.003 0.230 | −0.003 0.270 | −0.003 0.270 | −0.021 1.470 | −0.004 0.150 | −0.004 0.150 | 0.00 0.10 | |
| C | −0.029 0.470 | −1.680 10.460 | *** −1.040 | *** −0.494 | *** −0.012 | *** 0.240 | *** 6.280 | *** 10.550 | *** 1.237 | *** 10.550 | 1.66 10.59 |
| N | 4168 | 4156 | 4156 | 4156 | 4156 | 4156 | 4156 | 4156 | 4156 | 4156 | |

Note: Model 1 is based on OLS regression; Models 2–8 are based on quantile regression for quantile 5% to 95% for the Chemical segment; ***, **, * indicate significance level at 1%, 5%, and 10%, respectively. Variable definitions are explained in Appendix A.

Table 6. Ordinary least square (OLS) and quantile regression estimates for the container sector.

| Model | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|-------|----------------|------------|------------|------------|------------|------------|------------|------------|
| | Contain OLS | Cont 05 | Cont 10 | Cont 25 | Cont 50 | Cont 75 | Cont 90 | Cont 95 |
| OIL | −0.646 | −0.405 | 0.618 | −0.207 | −1.296 | −0.481 | −1.381 | −1.192 |
| | 0.84 | 0.18 | 0.41 | 0.23 | 1.71 | 0.56 | 0.90 | 0.50 |
| VIX | 0.00 | −0.05 *** | −0.04 *** | −0.02 *** | 0.00 | 0.02 *** | 0.03 *** | 0.03 *** |
| | 0.91 | 8.16 | 9.37 | 9.43 | 0.09 | 7.69 | 7.34 | 5.41 |
| Rm-Rf | 0.77 *** | 0.90 *** | 0.83 *** | 0.79 *** | 0.75 *** | 0.71 *** | 0.69 *** | 0.68 *** |
| | 28.44 | 11.28 | 15.47 | 24.37 | 27.78 | 23.38 | 12.84 | 8.05 |
| UST | 0.00 | 0.14 | 0.28 | −0.01 | 0.34 | 0.29 | 0.54 | 0.29 |
| | 0.00 | 0.15 | 0.44 | 0.02 | 1.08 | 0.82 | 0.86 | 0.29 |
| FX | −0.20 *** | 0.01 | 0.03 | −0.12 * | −0.19 *** | −0.28 *** | −0.27 ** | −0.37 * |
| | 3.88 | 0.07 | 0.26 | 2.05 | 3.89 | 4.89 | 2.72 | 2.35 |
| SMB | 0.76 *** | 0.99 *** | 0.86 *** | 0.73 *** | 0.68 *** | 0.66 *** | 0.62 *** | 0.65 *** |
| | 14.60 | 6.46 | 8.38 | 11.79 | 13.14 | 11.47 | 6.01 | 4.01 |
| HML | 0.62 *** | 0.88 *** | 0.68 *** | 0.54 *** | 0.53 *** | 0.59 *** | 0.71 *** | 0.87 *** |
| | 10.48 | 5.03 | 5.80 | 7.60 | 8.97 | 8.99 | 6.06 | 4.72 |
| RMW | 0.37 *** | 0.21 | 0.25 | 0.29 ** | 0.35 *** | 0.36 *** | 0.28 ** | 0.20 |
| | 4.86 | 0.94 | 1.66 | 3.15 | 4.65 | 4.17 | 1.84 | 0.84 |
| CMA | −0.66 *** | −0.64 ** | −0.71 *** | −0.55 *** | −0.54 *** | −0.53 *** | −0.69 *** | −1.17 *** |
| | 8.52 | 2.79 | 4.62 | 5.89 | 6.99 | 6.10 | 4.44 | 4.82 |
| WML | 0.08 * | 0.22 * | 0.17 ** | 0.11 ** | 0.05 | 0.02 | 0.10 | 0.24 * |
| | 2.49 | 2.29 | 2.73 | 2.93 | 1.66 | 0.64 | 1.62 | 2.36 |
| BDI | 0.06 *** | 0.06 * | 0.05 ** | 0.03 ** | 0.04 *** | 0.05 *** | 0.08 *** | 0.09 *** |
| | 7.08 | 2.54 | 2.75 | 3.20 | 5.01 | 5.06 | 4.73 | 3.48 |
| HPX | 0.02 * | 0.10 ** | 0.07 ** | 0.03 ** | 0.03 * | 0.02 | 0.00 | 0.00 |
| | 2.01 | 2.72 | 2.75 | 1.76 | 2.43 | 1.59 | 0.05 | 0.00 |
| BFI | 0.00 | 0.00 | 0.01 | 0.01 | 0.01 | 0.00 | 0.00 | −0.02 |
| | 0.16 | 0.08 | 0.66 | 0.73 | 0.57 | 0.46 | 0.08 | 0.78 |
| C | 0.03 | −0.78 *** | −0.49 *** | −0.17 ** | 0.00 | 0.26 *** | 0.64 *** | 1.06 *** |
| | 0.77 | 6.16 | 5.69 | 3.27 | 0.04 | 5.42 | 7.49 | 7.94 |
| N | 4149 | 4149 | 4149 | 4149 | 4149 | 4149 | 4149 | 4149 |

Note: Model 1 is OLS regression; Models 2–8 are quantile regression for quantile 5% to 95% for the Container segment; ***, **, * indicate significance level at 1%, 5%, and 10%, respectively. Variable definitions are explained in Appendix A.

Table 7. Ordinary least square (OLS) and quantile regression estimates for the diversified segment.

| Model | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|-------|----------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|
| | Diverse OLS | Diverse 05 | Diverse 10 | Diverse 25 | Diverse 50 | Diverse 75 | Diverse 90 | Diverse 95 |
| OIL | −0.062 | 0.813 | 0.306 | 0.071 | −0.206 | 0.385 | −1.619 | −2.854 |
| | 0.070 | 0.360 | 0.200 | 0.070 | 0.230 | 0.340 | 0.860 | 1.370 |
| VIX | 0.000 | −0.051 *** | −0.039 *** | −0.024 *** | −0.001 *** | 0.020 *** | 0.043 *** | 0.059 *** |
| | 0.190 | 8.950 | 10.100 | 8.960 | 0.280 | 7.050 | 8.960 | 11.100 |
| Rm-Rf | 0.821 *** | 0.794 *** | 0.777 *** | 0.776 *** | 0.775 *** | 0.806 *** | 0.898 *** | 0.980 *** |
| | 27.060 | 10.000 | 14.420 | 20.990 | 24.720 | 20.300 | 13.440 | 13.290 |
| UST | 0.043 | 0.148 | 0.015 | 0.072 | −0.453 | 0.480 | −0.161 | 0.157 |
| | 0.120 | 0.160 | 0.020 | 0.170 | 1.240 | 1.030 | 0.210 | 0.180 |
| FX | 0.030 | 0.145 | 0.091 | 0.097 | 0.088 | 0.101 | 0.010 | 0.186 |
| | 0.530 | 0.990 | 0.910 | 1.410 | 1.520 | 1.370 | 0.080 | 1.360 |
| SMB | 1.213 *** | 1.303 *** | 1.065 *** | 1.059 *** | 1.105 *** | 1.251 *** | 1.255 *** | 1.243 *** |
| | 20.890 | 8.570 | 10.320 | 14.950 | 18.420 | 16.460 | 9.820 | 8.810 |
| HML | 0.570 *** | 0.790 *** | 0.664 *** | 0.615 *** | 0.490 *** | 0.657 *** | 0.553 *** | 0.674 *** |
| | 8.630 | 4.570 | 5.660 | 7.640 | 7.190 | 7.600 | 3.800 | 4.200 |
| RMW | 0.374 *** | 0.232 | 0.376 * | 0.428 *** | 0.297 *** | 0.304 ** | 0.212 | 0.541 ** |
| | 4.350 | 1.030 | 2.460 | 4.080 | 3.340 | 2.700 | 1.120 | 2.590 |
| CMA | −0.710 *** | −0.786 *** | −0.683 *** | −0.680 *** | −0.604 *** | −0.683 *** | −0.889 *** | −0.931 *** |
| | 8.160 | 3.450 | 4.420 | 6.410 | 6.720 | 6.000 | 4.640 | 4.400 |
| WML | −0.004 | 0.198 * | 0.153 * | 0.022 | −0.045 | −0.048 | 0.043 | 0.047 |
| | 0.120 | 2.110 | 2.390 | 0.510 | 1.220 | 1.020 | 0.540 | 0.540 |
| BDI | 0.075 *** | 0.069 ** | 0.056 ** | 0.044 *** | 0.061 *** | 0.070 *** | 0.099 *** | 0.145 *** |
| | 7.870 | 2.770 | 3.290 | 3.730 | 6.170 | 5.610 | 4.680 | 6.240 |
| HPX | 0.031 * | −0.025 | 0.007 | 0.032 | 0.016 | 0.016 | 0.052 | 0.056 |
| | 2.280 | 0.710 | 0.280 | 1.910 | 1.170 | 0.900 | 1.740 | 1.690 |
| BFI | 0.000 | −0.015 | −0.010 | −0.013 | 0.001 | 0.007 | 0.026 | 0.004 |
| | 0.030 | 0.570 | 0.540 | 1.070 | 0.130 | 0.500 | 1.150 | 0.160 |
| C | 0.010 | −0.840 *** | −0.585 *** | −0.228 *** | −0.012 | 0.266 *** | 0.571 *** | 0.772 *** |
| | 0.210 | 6.650 | 6.830 | 3.870 | 0.240 | 4.220 | 5.370 | 6.580 |
| N | 4161 | 4161 | 4161 | 4161 | 4161 | 4161 | 4161 | 4161 |

Note: Model 1 is OLS regression; Models 2–8 are quantile regression for quantile 5% to 95% for the Diverse segment; ***, **, * indicate significance level at 1%, 5%, and 10%, respectively. Variable definitions are explained in Appendix A.

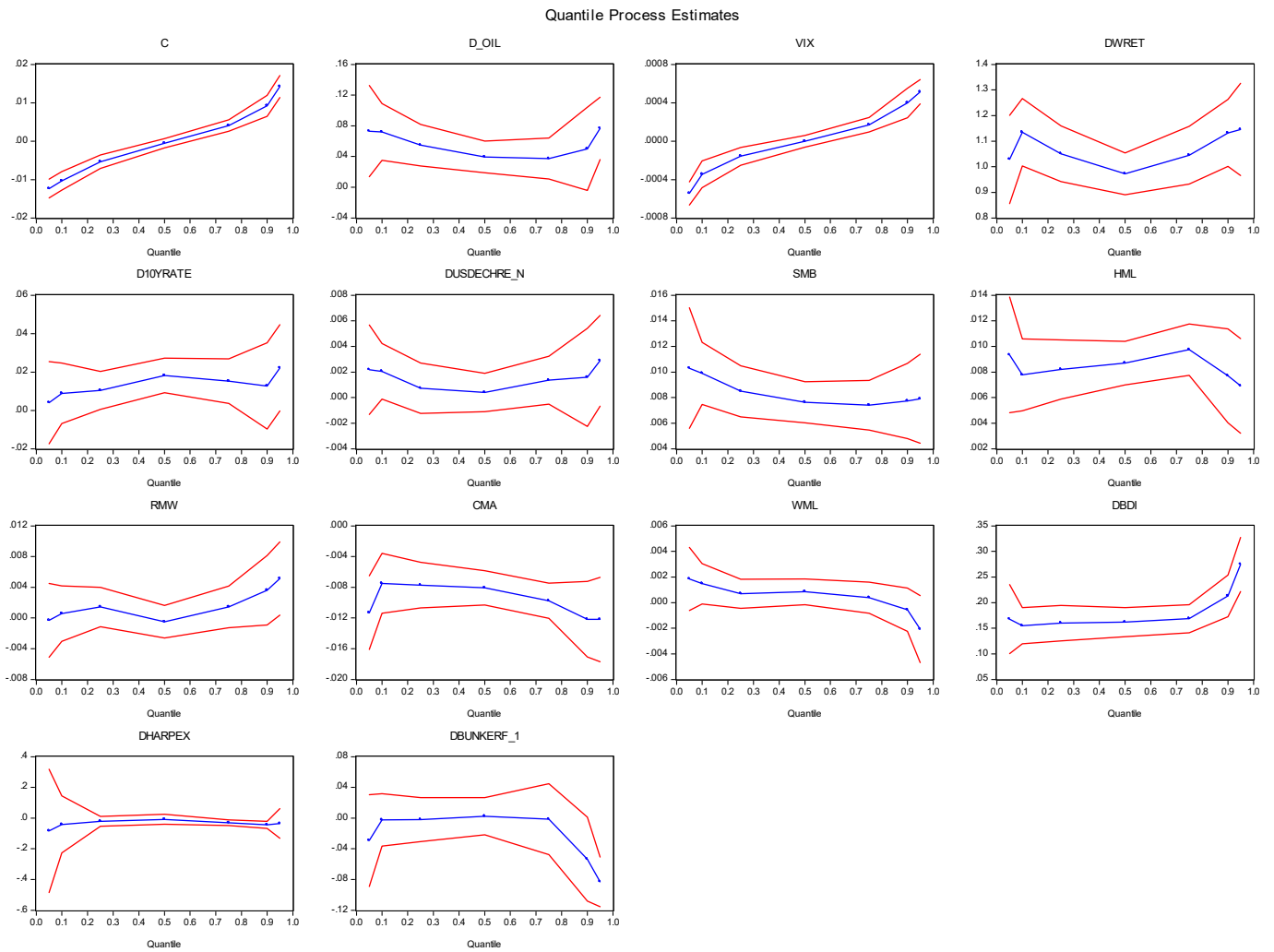


Figure 4. Graphical illustration of the quantile regression (QR) estimates for the bulk sector.

The relationship between shipping stock returns and changes in the oil price is positive across virtually the entire distribution for the tanker, bulk, and chemical/gas sectors and insignificant for containers and diversified shipping. For the former sectors, we again see a clear U-shape, with a greater sensitivity to large negative and positive oil price changes, particularly so for the chemical transportation market. One possible explanation for the latter observation, given that oil is a major input in petrochemical production, is that large oil-price movements affect the margins of chemical producers and consumers, creating dislocations in the supply chain and the corresponding need for transportation. Overall, our results present evidence that the effect of oil price changes on shipping stock returns is positive, in line with Poulakidas and Joutz (2009) and Drobetz et al. (2010) but in contrast to Grammenos and Arkoulis (2002). The positive relationship implies 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 and chemical/gas stock returns than on the other segments is not surprising, considering that the tanker segment is driven by the demand for oil and its chemical derivatives. Certainly, our sample contains the period May 2003–December 2008, when oil prices increased from \$27 per barrel to \$144 per barrel due to an increase in global demand for oil (e.g., Mohanty and Nandha 2011).

The impact of VIX (here we use level and not relative level changes) on shipping stock returns is rather symmetric (the negative sensitivities at low levels are in absolute values, which are not very different from the positive sensitivities at high levels). The impact of

volatility from the OLS (mean) regression and median QR is insignificant. The results of our empirical analysis do not fully support the leverage effect hypothesis, which states that the volatility increases more when prices fall than when prices rise.

The changing volatility–return relationship across quantiles is consistent with the findings of [Chiang and Li \(2012\)](#). As the return distribution in the lower quantiles represents pessimistic market conditions, the negative relationship 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.

The effect of changes in the exchange rate, represented by the Trade-Weighted US Dollar Index, is negative for the container segment, implying that appreciation of the USD has a negative effect on stock returns. The impact of changes in the exchange rate on container stock returns is significant at the 1% level in all quantiles. For this segment, there is a tendency for a higher effect (more negative values) at low and high quantiles. For the other segments, there is little effect. In other words, when the USD appreciates, shipping stock returns decrease. A likely explanation is that, as US-quoted goods become more expensive, demand for these goods decreases, i.e., an indirect trade effect ([Mcconville 1999](#)). Our findings support the previous research in shipping, such as that of [Grammenos and Arkoulis \(2002\)](#) and [Drobetz et al. \(2010\)](#), who also find a negative relationship. However, we do not find any relation between exchange rates and shipping stock returns for all but the container and chemical segment. The container sector 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. In addition, it seems reasonable to assume that the demand for manufactured consumer goods is more price elastic than, say, the price of fuel and grain.

The effect of the interest rate risk, represented by the 10-year Treasury Rate, differs across both the conditional return distribution and the shipping sectors. In many cases, it is not significant. For the dry bulk sector, there are several quantiles with a significant and positive effect, with no specific pattern over quantiles. For the tanker segment, we have a significant and positive effect for all quantiles. The detected positive relation is not in line with the work of [El-Masry et al. \(2010\)](#). Because the shipping industry is highly leveraged, it might be expected that the relationship would be evident in a depressed market, as changes in the interest rate could lead to severe liquidity problems and fluctuations in future cash flow. However, a higher return on shipping stocks when the interest rate increases could be a product of higher demand for ship transport during strong economic periods when interest rates tend to rise.

[Jareño et al. \(2016\)](#) also find the impact of the interest rate to be more evident in extreme market conditions.

The small-minus-big (SMB) factor has a significant and positive impact on the shipping returns. The average market capitalization of S&P 500 firms is 20.5 billion USD, with the median firm (DollarTree, #250) at 20.6 billion USD (<https://www.slickcharts.com/sp500> (accessed on 31 December 2015)) at the end of the year 2015. The data reported in Table 8 show that combined market value of 102 firms included in the sample at the end of calendar year, 2015, was 98,072.1 million USD with an average market value of 961 million USD per company. This is about 1/20 of the median S&P 500 company market value. The small average size can explain why the SMB factor is positive and significant. The market cap varies between the market segments. The bulk companies have an average of 288 million USD, while the tanker companies have an average of 555.6 million USD. The container shipping companies have the largest market value of 1527.8 million USD per company.

Table 8. Size of companies in each market segment.

| Segment | Market Values (MV) | Number of Companies | Average MV per Company |
|-----------|--------------------|---------------------|------------------------|
| | Mill. USD | | |
| Bulk | 6051 | 21 | 288.15 |
| Tanker | 3889 | 7 | 555.58 |
| Chemical | 10,824 | 17 | 636.71 |
| Container | 61,110 | 40 | 1527.75 |
| Diverse | 16,198 | 17 | 952.82 |
| Sum | 98,072 | 102 | 961.49 |

Source: <https://www.slickcharts.com/sp500>, (accessed on 31 December 2015).

The coefficients that pertain to the “value premium” (HML) are positive and statistically significant. These results are consistent with findings of a previous study (Elyasiani et al. 2011) that uses the Fama and French (1993) model for a sample of industrial companies. This supports the notion that the valuation risk premium is important, and its effect is consistent with the model’s expectations.

Fama and French (2016) suggest that negative risk premia for robust-minus-weak (RMW) profitability and conservative-minus-aggressive (CMA) investment are more likely to be associated with unprofitable firms with aggressive investments. Our results show that the risk premium associated with RMW is not significant, whereas the CMA factor is negative and statistically significant. That is, the shipping return-generating process behaves like the returns of firms with a neutral profit expectation that invest aggressively. The coefficient that pertains to the momentum factor (WML) is not statistically significant, indicating that the shipping companies are not likely to be perceived by investors as the typical momentum stock.

Even though we control for the standard Fama and French (2016) risk factors, it is important that we also control for industry-specific factors. The Baltic Dry Index is positive and significant for the bulk, container, and diversified segments. It is also significant for the 50% and 75% quantile for the chemical/gas segment. This validates shipping as an asset class different from other classes.

In addition, there are other segment-specific factors that may drive equity returns.

For instance, the coefficient that pertains to the HPX container freight index is significant for container and diversified shipping segment. In contrast, the coefficient of BFI (Bunker Fuel) is not significant except for the tanker segment. It is important, however, to control for BFI in our model because the omitted BFI variable may correlate with other explanatory variables and, thus, make other coefficient estimates biased.

Tables 9 and 10 summarize the impact of macroeconomic risk factors on equity returns at the sector level for each of the five segments when using the QR and the OLS approach, respectively. We can observe that the results based on the QR method significantly differ from those that are reported based on the traditional OLS regression method.

Table 9. Summary of significant effects from factor by shipping segment (OLS regression).

| Factors | Segment | | | | |
|----------|---------|--------|----------|-----------|---------|
| | Bulk | Tanker | Chemical | Container | Diverse |
| Constant | | | | | |
| OIL | + | + | + | | |
| VIX | | | | | |
| Rm-Rf | + | + | + | + | + |
| UST | + | + | + | | |
| FX | | | | | |
| SMB | + | + | + | + | + |
| HML | + | + | + | + | + |
| RMW | | | | + | + |
| CMA | - | - | - | - | - |
| WML | | | | | |
| BDI | + | + | | + | + |
| HPX | | | | + | + |
| BFI | | | | | |

Note: A minus sign indicates significant negative effect, while a plus sign indicates a significant positive effect. A blank indicates no significant effect.

Table 10. Summary of significant effects from factor by shipping segment (quantile regression).

| Factors | Segment | | | | |
|----------|---------|--------|----------|-----------|---------|
| | Bulk | Tanker | Chemical | Container | Diverse |
| Constant | +/- | +/- | +/- | +/- | +/- |
| OIL | + | + | + | | |
| VIX | +/- | +/- | +/- | +/- | +/- |
| Rm-Rf | + | + | + | + | + |
| UST | + | + | | | |
| FX | | | | - | |
| SMB | + | + | + | + | + |
| HML | + | + | + | + | + |
| RMW | | | | + | + |
| CMA | - | - | - | - | - |
| WML | | | | + | |
| BDI | + | + | + | + | + |
| HPX | | | | + | |
| BFI | | - | | | |

Note: A minus sign indicates significant negative effect, while a plus sign indicates a significant positive effect. A blank indicates no significant effect.

5. Robustness Test

The shipping industry is unique in the sense that it differs from other industrial and manufacturing firms by having mobile assets that constantly move around the globe. Drobetz et al. (2010) suggest that shipping stocks belong to a separate asset class because they exhibit low stock market beta, and their risk-return profile differs from other industry indices. The shipping industry is generally asset-heavy, relatively more capital intensive with lower profit margin than other industries. The shipping industry revenue and cash-flows are relatively more volatile compared to other industries due to uncertain demand and supply for sea transport (Drobetz et al. 2016). Shipping firms in general exhibit higher leverage compared with other industrial firms (e.g., Drobetz et al. 2013). Shipping industry exhibits distinct investment and financing patterns which significantly differ from industrial and manufacturing firms. (e.g., Drobetz et al. 2016). Furthermore, the value of a shipping firm is tightly linked to asset specificity of the ship (e.g., Drobetz et al. 2016). Thus, we argue that shipping stocks belong to a separate asset class which differs from the other industrial firms. In order to support this view, we run a regression with the same independent variables using a non-shipping stock index as the dependent variable. We use

S&P 1200 Industrial stock index as our control portfolio of industrial stocks. We regress the excess returns on S&P1200 Industrial stock index against the independent variables using both OLS and QR methods. Regression results reported in Table 11 show that the sensitivities to risk factors in the case of S&P 1200 stock index in general, are different from the sensitivities in the various shipping segments. For OIL, the effect is negative, while for most shipping segments the effect is positive. VIX has a negative effect for low quantiles and a positive effect for high quantiles. The same is found for all shipping segments, but the effect is stronger for shipping stocks than non-shipping S&P 1200 stock index. The market beta (Fama and French excess market return) of S&P1200 Industrial stock index is around 1.1 for all quantiles, indicating that industrial firms on average is riskier than average S&P 500 stock. The bulk and tanker market have betas close to these values. For the rest of the shipping segments, the market betas are lower. The market betas also vary more across quantiles for the shipping segments than that of S&P 1200 Industrial stock index. Regarding UST, we have a significant positive effect for some quantiles for S&P 1200 stock index. Tank and Bulk segments show significant positive effect for most quantiles, where for other shipping segments, UST has had no significant effect. FX has a significant effect for all quantiles for S&P1200 stock index. When compared with the non-shipping stock index, the effect of FX on shipping sectors is less significant. In the container segment, there is a negative effect. Of all the Fama and French factors SMB, HML, RMV, CMA, WML, the latter three have significant effects on S&P1200 stock index, whereas for the shipping segments the opposite is true with only SMB and HML being significant. The shipping-specific factors BDI, HPX, BFI have no significant effect on the general stock market, while for certain shipping segments, these factors are important. These results demonstrate that sensitivities differ substantially between non-shipping firms (industrial S&P 1200 companies) and shipping firms. These findings are also consistent with the previous studies (e.g., [Drobetz et al. 2010, 2016](#)) indicating that risk-return profile of shipping industry significantly differs from that of non-shipping firms. Therefore, the shipping industry needs to be considered as a separate asset class.

In the next section, we provide the robustness check for the stability of our models' parameter estimates by splitting the data period in two equal subperiods (first half and second half of the sample period). Although we conduct the subperiod analysis for all five shipping sectors, for the sake of brevity, we only report OLS and QR estimates for the tanker segment. Tables 12 and 13 present results for the first and the second subperiods, respectively. We compare the OLS and QR regression results reported in Table 12 with those of Table 13 and find them to be qualitatively similar. The effect of VIX is roughly the same in both periods. The market betas are also similar, although we observe slightly higher values in the second period. OIL in the second subperiod tends to be more positive and significant than the first subperiod. UST seems to have the same positive effect in both periods, while FX seems to be slightly more significant in the second period. In case of the Fama and French factors (SMB, HML, RMW, CMA, and WML), it is hard to detect any significant difference in risk sensitivity between the two subperiods. For the shipping-specific factors BDI, HPX, and BFI, we have little significance in both periods for the tanker segment. Overall, we find that the parameter estimates and signs are relatively stable over the two subperiods.

Table 11. The performance model applied to S&P (SP) 1200 Industrial firms index.

| Model | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|-------|------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| | SP1200 OLS | 5% | 10% | 25% | 50% | 75% | 90% | 95% |
| OIL | -1.94 *** | -1.01 | -1.42 *** | -1.60 *** | -1.88 *** | -2.26 *** | -2.51 *** | -2.21 *** |
| VIX | -7.37 | -1.53 | -3.27 | -5.79 | -8.19 | -8.20 | -5.69 | -3.74 |
| | 0.00 ** | -0.02 *** | -0.02 *** | -0.01 *** | 0.00 | 0.01 *** | 0.01 *** | 0.02 *** |
| | -2.15 | -12.91 | -14.29 | -10.96 | (-1.47) | -9.90 | -12.53 | -13.25 |
| Rm-Rf | 1.10 *** | 1.13 *** | 1.12 *** | 1.11 *** | 1.11 *** | 1.12 *** | 1.13 *** | 1.09 *** |
| | -119.08 | -48.43 | -73.37 | -113.63 | -137.28 | -115.18 | -72.47 | -52.40 |
| UST | 0.38 *** | 0.28 | 0.35 | 0.33 *** | 0.41 *** | 0.41 *** | 0.35 | 0.26 |
| | -3.52 | -1.04 | -1.93 | -2.89 | -4.32 | -3.56 | -1.90 | -1.06 |
| FX | 0.11 *** | 0.15 *** | 0.14 *** | 0.13 *** | 0.11 *** | 0.10 *** | 0.11 *** | 0.09 ** |
| | -6.18 | -3.35 | -5.09 | -6.93 | -7.38 | -5.76 | -3.84 | -2.30 |
| SMB | 0.04 ** | 0.07 | 0.03 | 0.03 | 0.02 | 0.02 | 0.04 | 0.00 |
| | -2.39 | -1.67 | -1.02 | -1.34 | -1.15 | -0.95 | -1.39 | -0.11 |
| HML | 0.04 | -0.02 | 0.02 | 0.05 ** | 0.05 *** | 0.03 | 0.09 *** | 0.11 ** |
| | -1.80 | -0.47 | -0.59 | -2.42 | -2.80 | -1.38 | -2.78 | -2.44 |
| RMW | 0.18 *** | 0.16 ** | 0.20 *** | 0.21 *** | 0.19 *** | 0.17 *** | 0.17 *** | 0.05 |
| | -6.65 | -2.39 | -4.68 | -7.64 | -8.45 | -6.17 | -3.75 | -0.92 |
| CMA | 0.14 *** | 0.26 *** | 0.20 *** | 0.17 | 0.15 *** | 0.19 *** | 0.20 *** | 0.12 ** |
| | -5.33 | -3.87 | -4.63 | -5.96 | -6.30 | -6.82 | -4.42 | -2.07 |
| WML | -0.11 *** | -0.12 *** | -0.11 *** | -0.10 *** | -0.09 *** | -0.08 *** | -0.10 *** | -0.08 *** |
| | -10.38 | -4.41 | -5.80 | -8.83 | -9.05 | -6.99 | -5.39 | -3.22 |
| BDI | 0.00 | 0.01 | 0.01 *** | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| | -0.70 | -1.57 | -2.80 | -2.00 | -0.36 | -1.07 | -0.44 | -0.26 |
| HPX | 0.00 | -0.02 | -0.01 | 0.00 | 0.00 | 0.00 | 0.00 | -0.01 |
| | -0.45 | -1.91 | -1.53 | -0.10 | -0.89 | -0.64 | -0.52 | -0.91 |
| BFI | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 |
| | -0.06 | -0.68 | -0.03 | -1.11 | -0.38 | -1.40 | -0.15 | -0.81 |
| C | 0.02 | -0.09 ** | -0.07 *** | -0.04 | 0.01 | 0.03 ** | 0.07 *** | 0.10 *** |
| | -1.17 | -2.31 | -2.71 | -2.84 | -0.46 | -2.12 | -3.01 | -3.06 |
| N | 4170 | 4170 | 4170 | 4170 | 4170 | 4170 | 4170 | 4170 |

Note: Model 1 is based on OLS regression; Models 2–8 are based on quantile regression for quantile 5% to 95% for the dry bulk segment; ***, ** indicate significance level at 1%, and 5%, respectively. RetSP1200 = The excess return on S&P 1200 industrial firms stock index. For other variable definitions, see the text of Table 1.

Table 12. OLS and quantile regression estimates Tanker shipping firms First Subperiod (2001–2008).

| Model | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|-------|----------|--------------|-----------|-----------|-----------|----------|----------|----------|
| | Tank OLS | Ret Tank 05% | Tank 10% | Tank 25% | Tank 50% | Tank 75% | Tank 90% | Tank 95% |
| IL | 4.50 ** | 9.21 | 4.43 | 5.30 * | 2.32 | 1.95 | 0.85 | 7.64 |
| | 2.45 | 1.74 | 1.23 | 2.21 | 1.36 | 0.90 | 0.19 | 1.68 |
| VIX | 0.00 | -0.06 *** | -0.03 ** | -0.02 *** | 0.01 | 0.03 *** | 0.04 ** | 0.04 ** |
| | -0.56 | -3.74 | -2.93 | -2.88 | -1.06 | -4.62 | -2.89 | -3.04 |
| Rm-Rf | 1.21 *** | 1.19 *** | 1.21 *** | 1.18 *** | 1.05 *** | 1.26 *** | 1.19 *** | 1.27 *** |
| | -16.87 | -5.77 | -8.60 | -12.61 | -15.73 | -14.84 | -6.80 | -7.17 |
| UST | 2.18 *** | 3.43 | 3.09 | 2.68 | 1.99 ** | 1.40 | 1.95 | -0.47 |
| | -2.92 | -1.60 | -2.11 | -2.75 | -2.88 | -1.59 | -1.07 | -0.25 |
| FX | 0.05 | -0.12 | -0.08 | 0.03 | 0.10 | 0.37 ** | -0.02 | 0.26 |
| | -0.41 | -0.32 | -0.34 | -0.16 | -0.88 | -2.51 | -0.07 | -0.84 |
| SMB | 0.50 *** | 0.70 | 0.49 | 0.69 *** | 0.29 ** | 0.39 ** | 0.32 | 0.28 |
| | -3.85 | -1.88 | -1.91 | -4.08 | -2.42 | -2.56 | -1.02 | -0.89 |
| HML | 0.53 *** | -0.39 | 0.29 | 0.52 ** | 0.74 *** | 0.71 *** | 0.46 | 0.85 ** |
| | -3.31 | -0.86 | -0.91 | -2.50 | -5.02 | -3.79 | -1.17 | -2.16 |
| RMW | 0.14 | -0.02 | 0.19 | 0.18 | -0.05 | 0.32 | 0.16 | 0.17 |
| | -0.81 | -0.03 | -0.56 | -0.76 | -0.29 | -1.55 | -0.38 | -0.38 |
| CMA | -0.07 | 0.80 | -0.04 | -0.10 | -0.38 | -0.22 | -0.18 | -0.45 |
| | -0.42 | -1.66 | -0.12 | -0.46 | -2.41 | -1.13 | -0.44 | -1.08 |
| WML | 0.30 *** | 0.63 ** | 0.65 *** | 0.22 ** | 0.36 *** | 0.26 ** | 0.37 | 0.32 |
| | -3.48 | -2.55 | -3.82 | -1.96 | -4.52 | -2.58 | -1.75 | -1.48 |
| BDI | 0.05 | 0.04 | 0.09 | 0.07 | 0.07 ** | 0.05 | 0.06 | 0.07 |
| | -1.61 | -0.49 | -1.48 | -1.72 | -2.29 | -1.48 | -0.85 | -0.88 |
| HPX | 0.03 | -0.02 | 0.01 | 0.02 | 0.00 | 0.01 | 0.04 | -0.01 |
| | -0.91 | -0.25 | -0.16 | -0.35 | -0.06 | -0.28 | -0.51 | -0.17 |
| BFI | -0.03 | -0.06 | -0.05 | -0.03 | -0.02 | -0.04 | -0.05 | 0.04 |
| | -1.26 | -0.99 | -1.22 | -0.97 | -0.89 | -1.49 | -1.00 | -0.81 |
| C | -0.02 | -1.55 *** | -1.44 *** | -0.55 *** | -0.06 *** | 0.44 ** | 1.00 *** | 2.12 *** |
| | -0.19 | -4.41 | -6.01 | -3.45 | -0.53 | -3.07 | -4.51 | -7.03 |
| N | 2001 | 2001 | 2001 | 2001 | 2001 | 2001 | 2001 | 2001 |

Note: Model 1 is based on OLS regression; Models 2–8 are based on quantile regression for quantile 5% to 95% for the dry bulk segment; ***, **, * indicate significance level at 1%, 5%, and 10%, respectively. Variable definitions are explained in the text of Table 1.

Table 13. OLS and quantile regression estimates Tanker shipping firms Second Subperiod (2009–2016).

| Model | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|-------|-----------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| | Tank OLS | Ret Tank 05% | Ret Tank 10% | Ret Tank 25% | Ret Tank 50% | Ret Tank 75% | Ret Tank 90% | Ret Tank 95% |
| OIL | 8.77 *** | 10.43 *** | 9.06 *** | 8.51 *** | 9.13 *** | 6.41 *** | 7.27 *** | 14.43 *** |
| | -6.84 | -2.95 | 3.90 | 5.87 | 8.13 | 4.00 | 3.41 | 4.01 |
| VIX | 0.00 | -0.04 *** | -0.04 *** | -0.02 *** | 0.00 | 0.01 *** | 0.03 *** | 0.05 *** |
| | -0.03 | -5.46 | -7.40 | -6.67 | -0.86 | -3.84 | -7.28 | -6.85 |
| Rm-Rf | 1.09 *** | 1.14 *** | 1.15 *** | 1.10 *** | 1.09 *** | 0.99 *** | 0.97 *** | 1.01 *** |
| | -25.84 | -9.82 | -14.96 | -23.11 | -29.34 | -18.79 | -13.86 | -8.52 |
| UST | 1.24 ** | 2.19 | 1.73 | 2.50 *** | 2.18 *** | 1.47 ** | 0.60 | -0.47 |
| | -2.35 | -1.50 | -1.80 | -4.20 | -4.72 | -2.22 | -0.69 | -0.31 |
| FX | 0.12 | 0.20 | 0.33 ** | 0.26 *** | 0.23 ** | 0.08 | 0.08 | 0.06 |
| | -1.47 | -0.88 | -2.24 | -2.88 | -3.18 | -0.82 | -0.57 | -0.27 |
| SMB | 0.14 | 0.70 ** | 0.54 *** | 0.25 *** | 0.15 * | -0.06 | -0.25 | 0.17 |
| | -1.70 | -3.00 | -3.55 | -2.59 | -2.04 | -0.62 | -1.80 | -0.73 |
| HML | 0.17 | 0.13 | 0.22 | 0.11 | 0.25 *** | 0.29 ** | 0.22 | 0.07 |
| | -1.64 | -0.43 | -1.14 | -0.88 | -2.69 | -2.18 | -1.24 | -0.22 |
| RMW | -0.38 *** | -0.56 | -0.77 ** | -0.52 *** | -0.35 *** | -0.37 ** | -0.55 ** | -0.56 |
| | -2.67 | -1.44 | -3.02 | -3.26 | -2.79 | -2.08 | -2.33 | -1.41 |
| CMA | -0.66 *** | 0.07 | -0.35 | -0.36 ** | -0.81 *** | -0.75 *** | -0.63 ** | -0.85 ** |
| | -4.49 | -0.18 | -1.29 | -2.16 | -6.24 | -4.09 | -2.58 | -2.05 |
| WML | -0.15 *** | -0.27 | -0.14 | -0.14 * | -0.04 | -0.12 | -0.16 | -0.37 ** |
| | -2.85 | -1.81 | -1.39 | -2.32 | -0.80 | -1.78 | -1.81 | -2.45 |
| BDI | 0.01 | 0.02 | 0.04 | 0.03 * | 0.01 | 0.02 | 0.02 | 0.02 |
| | -1.02 | -0.78 | -1.73 | -2.22 | -0.72 | -1.17 | -1.06 | -0.47 |
| HPX | 0.01 | 0.01 | 0.02 | 0.01 | 0.02 | -0.01 | 0.03 | 0.00 |
| | -0.49 | -0.23 | -0.71 | -0.46 | -1.06 | -0.63 | -1.16 | -0.01 |
| BFI | -0.02 | 0.00 | -0.02 | -0.02 | -0.02 | -0.02 | -0.03 | -0.01 |
| | -1.40 | -0.05 | -0.91 | -1.44 | -1.67 | -1.01 | -1.15 | -0.33 |
| C | -0.05 | -1.07 *** | -0.67 *** | -0.33 *** | -0.01 | 0.44 *** | 0.70 *** | 0.81 *** |
| | -0.71 | -6.00 | -5.77 | -4.50 | -0.10 | -5.46 | -6.49 | -4.48 |
| N | 2168 | 2168 | 2168 | 2168 | 2168 | 2168 | 2168 | 2168 |

Note: Model 1 is based on OLS regression; Models 2–8 are based on quantile regression for quantile 5% to 95% for the dry bulk segment; ***, **, * indicate significance level at 1%, 5%, and 10%, respectively. Note: Variable definitions are explained in the text of Table 1.

6. Summary and Conclusions

We estimate the impact of macroeconomic risk factors on shipping stock returns, using a quantile regression model. We regress the excess return of a portfolio for the container, dry bulk, chemical/gas, oil tanker, and diversified shipping sectors on the world market portfolio excess return, volatility index, and changes in the oil price, exchange rate, and interest rate. Our results show that return sensitivities are significant for the volatility index, world market portfolio return, exchange rate, and changes in the long-term interest rate with variation over quantiles. Oil price changes and exchange rate fluctuations are more stable across the quantiles. Changes in the oil price are likely to have a significant and negative impact on all three sectors. In the case of the tanker sector, the impact of oil price changes is most significant. The impact of fluctuation in the US exchange rate is significantly negative for all sectors and has the strongest impact on the container sector, followed by the dry bulk and tanker sectors.

Our results suggest that the standard OLS regression method cannot reveal the risk-return relation for different quantiles for shipping stocks; it shows only the estimates calculated at the mean of the independent variables. The QR analysis captures stock return sensitivities to various risk factors. The results show that risk sensitivities differ across quantiles and shipping segments, implying that risk exposures vary under different market conditions. The results also provide evidence of asymmetric and heterogeneous dependence between shipping stock returns and certain macroeconomic risk variables. This is especially noticeable for the VIX. For example, the OLS estimates for the VIX variable is insignificant, while the QR model captures tail dependence. In the QR model, the VIX factor has a significant and negative return on stock returns below the median, while it has a positive impact on stock returns above the median. In case of market and interest rate risk factors, risk sensitivities based on the QR approach exhibit varying dependence on return distribution. For the former, the impact is positive and stronger in the upper tail of the distribution. The impact of interest rate risk on stock returns is significantly negative in the lower tail for the dry bulk sector and positive and significant for the tanker and

container portfolio in the intermediate and upper quantiles. In the event of extreme values in the risk factors, the container and tanker sectors experience higher levels of tail loss than does the dry bulk portfolio.

We acknowledge that there are further tests of robustness occasionally used in the literature. For instance, [Drobetz et al. \(2016\)](#) propose to construct a matched sample of manufacturing firms based on the closest matches of shipping company size and market-to-book ratios. However, in constructing a control sample by matching the average of these financial ratios only, researchers risk creating a group that bear no resemblance with regards to the volatility, cyclical, and correlation of earnings, and so this says very little about the robustness of the empirical findings in our context. We also acknowledge that factor models, such as the one considered here, are subject to the general criticism that relationships are not stable over time. For instance, the crude oil price can be increasing because of supply constraints or because of increasing demand and a stronger global economy. Similarly, shipping company earnings can be driven primarily by broader economic trends or oversupply specific to a particular fleet segment.

A natural extension for further research is to include additional macroeconomic risk variables and to extend this study to examine the impact of book-to-market, leverage, and size on shipping stock returns using firm-level data. Follow-up research in this area should back-test the Value-at-Risk (VaR) estimates with duration test and investigate the impact of the QR model on VaR measures compared with other estimation techniques. According to [Firpo et al. \(2009\)](#), conditional results cannot be generalized to the population, unlike OLS. In OLS we can always go from conditional to unconditional via the law of iterated expectations, but this is not available for quantiles. Hence, the unconditional quantile might not be the same as conditional quantile. It could also be interesting to understand how the risk factors map to the unconditional quantiles of the portfolio returns. For instance, if the VIX has a negative relationship to lower quantiles and positive relationship to higher quantiles, then higher VIX stretches the unconditional return distribution, i.e., increases volatility. More investigation into this relationship between stock returns and volatility would be a fruitful path to follow.

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Appendix A. Definition of Variables

| Variable | Definition |
|-------------|---|
| RetBulk | Return of each shipping company selected to be in the bulk segment is market weighted using market weight of each bulk company into an index of returns. Market weight is defined as market value of company divided by total market value of the companies in the segment. |
| RetChem | Similar to RetBulk for the Chemical/gas segment. |
| RetCont | Similar to RetBulk for the Container segment. |
| RetTank | Similar to RetBulk for the Tank segment. |
| RetDiverse | Similar to RetBulk for the Diverse segment. |
| OIL | The log of WTI Oil Spot price changes from $t - 1$ to t . |
| VIX | Volatility Index of S&P 500. |
| $R_m - R_f$ | Excess return on value-weight return of all firms as calculated by Fama and French for their Global portfolio. |
| UST | Change in 10-Year US Treasury yield from $t - 1$ to t . |
| FX | Change in the levels of the Trade Weighted US Dollar Index from $t - 1$ to t . |
| SMB | Return Differential of small minus big companies based on Fama–French factor. |
| HML | Return differential of high-book-to-market minus low-book-to-market companies based on Fama–French factor. |
| RMW | Return differential of robust operating profit minus weak operating profit firms based on Fama–French factor. |
| CMA | Return differential of conservative minus aggressive firms based on Fama–French factor. |
| WML | Return differential of winners minus losers based on momentum factor. |
| BDI | The log of Baltic Exchange Dry Index price changes from $t - 1$ to t . |
| HPX | The log of Harpex Shipping Index price changes from $t - 1$ to t . |
| BFI | The log of Bunker Fuel price changes from $t - 1$ to t . |

Appendix B. Lists of Companies by Segment

Appendix B.1. Bulk Companies

| | |
|--|--------------------------------|
| BULGARIAN RIVER SHIPPING | PACIFIC BASIN SHIP. |
| CHANG JIANG SHIP.GP. PHNX. 'A' | PARAGON SHIPPING CLA |
| CMB DEAD - 22/12/15 | PRECIOUS SHIPPING |
| COMPANIA CHILENA DE NAVIGACION INTEROCEANICA | PREMUDA DEAD - DELIST.16/05/17 |
| DIANA SHIPPING | SAFE BULKERS |
| DRYSHIPS | SEABOARD |
| GENCO SHIP.& TRDG. | SEANERGY MARITIME HDG. |
| GLOBUS MARITIME | SIPSA |
| GOLDEN OCEAN GROUP | STAR BULK CARRIERS |
| JINHUI SHIP.& TRSP. | VIETNAM OCEAN SHIPPING |
| KUANG MING SHIPPING DEAD - DELIST.05/02/16 | WILSON |
| NAVIOS MARITIME HDG. | WINLAND OCEAN SHIPPING |
| NAVIOS MARITIME PTNS. | |

Appendix B.2. Tanker Companies

| |
|--|
| AMERICAN SHIPPING CO. |
| DHT HOLDINGS |
| FRONTLINE |
| KIRBY |
| NORDIC AMER.TANKERS |
| SCORPIO TANKERS |
| STELMAR SHIPPING DEAD - DELIST.20/01/05 |
| VARUN SHIPPING |
| WATERFRONT SHIPPING DEAD - DELIST 24/05/00 |

Appendix B.3. Chemical/gas Companies

| | |
|---|---------------------------|
| ARDMORE SHIPPING | NAVIGATOR HOLDINGS |
| AVANCE GAS | NAVIOS MARITIME ACQ. |
| CHINA MRCH.EN.SHIP. 'A' | SHAHI SHIPPING |
| D'AMICO INTL.SHIP. (OTC) DEAD - DELIST.29/01/18 | SOLVANG |
| DORIAN LPG | STEALTH GAS |
| EURONAV (NYS) | TEEKAY |
| EXMAR | TOP SHIPS |
| GASLOG | TSAKOS ENERGY NAV. |
| GOLAR LNG (NAS) | US SHIPPING PARTNERS UTS. |
| JASON SHIPPING DEAD - 12/08/13 | |

Appendix B.4. Container Companies

| | |
|---|---|
| A P MOLLER - MAERSK 'B' | JORDAN NAT.SHIPPING LIN. |
| A P MOLLER - MAERSK(OTC) 'A' | KAWASAKI KISEN KAISHA |
| ACTINOR SHIPPING DEAD - DELIST 10/12/01 | LORENZO SHIPPING |
| BOX SHIPS | MARINSA |
| CAPITAL PRODUCT PARTNERS | MATSON |
| COSCO SHIP.SPZ.CRRS.'A' | MEIJI SHIPPING |
| COSCO SHIPPING DEV.'A' | NIPPON YUSEN KK |
| COSCO SHIPPING HDG.'A' | NORTH-WSTN.RVR.SHIP. |
| COSTAMARE | PAKISTAN NAT.SHIP. |
| DANAOS | PRIMORSKY SEA SHIPPING DEAD - 28/06/17 |
| DIANA CONTAINERSHIPS | QATAR SHIPPING DEAD - 16/04/10 |
| DMPKBT.NORDEN | REGIONAL CONTAINERS LIN. |
| ERRIA | SAKHALIN SEA SHIP. |
| GLOBAL SHIP LEASE | SAMUDERA SHIP.LINE |
| GREAT EASTERN SHIPPING | SEASPAN |
| HAMMONIA SHIPPING | SHIPPING CORP.OF INDIA |
| HANJIN SHIPPING DEAD - DELIST.07/03/17 | SIEM SHIPPING INC. DEAD - DELIST.15/02/17 |
| HCI HAMMONIA SHIP. (XET) | SINOTRANS SHIPPING |
| HEUNG-A SHIPPING | WAN HAI LINES |
| HYUNDAI MERCHANT MARINE | YANG MING MAR.TRAN. |

Appendix B.5. Diversified Companies

| | |
|--|--------------------------|
| ANTONG HOLDINGS 'A' | NTS ASA |
| COSCO SHIP.EN.TRSP.'A' | ODFJELL 'A' |
| ESSAR SHIPPING | QATAR NAVIGATION |
| EUROSEAS | SEACOR HDG. |
| FAR EASTERN SHIP. | SHIP FINANCE INTL. |
| GRUPO TMM | SHREYAS SHIP.& LOGIST. |
| INTERNATIONAL SHIPHLDG. DEAD - DELIST.05/07/17 | SINO-GLOBAL SHIPPING AM. |
| MITSUI OSK LINES | SITC INTERNATIONAL HDG. |
| NEWLEAD HOLDINGS | TTS GROUP |

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