Norwegian School of Economics
Bergen, Spring 2023

Do Shipping Freight Rates Predict Stock Market Returns?

An Empirical Study of the Relationship between Shipping Freight Rates and Broad Stock Market Returns

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Master thesis, Economics and Business Administration

Major: Financial Economics

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Acknowledgements

We would like to extend our gratitude towards our supervisor Jørgen Haug for his valuable contributions and insights, especially regarding econometric models. Without his contributions, this thesis would not have been possible.

Writing a thesis on a relatively unexplored topic has presented its challenges, however we take pride in the potential value our work brings to an area of limited existing research. Introducing somewhat complex econometric models to our research has been demanding but rewarding.

Finally, we would like to express our humbleness to the challenges of writing an empirical research paper that is reliable and value-adding to academics, policymakers and market participants.

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Abstract

Given the availability and real-time inference of shipping freight rates, they are often regarded as a gauge for the economy. Stock market commentators and participants often stress the importance of falling freight rates as a leading indicator of recession. This thesis investigate the relationship between shipping freight rates and stock market returns, to determine whether the former can predict the latter. Using a time series from 2000-2022, we find that an index for dry bulk freight rates significantly predicts the broad MSCI World, OSEBX, S&P500, and STOXX600 indices, with the most substantial predictability observed at a one-month lag. Our findings suggest that this predictability is not due to time-varying risk premium, thus challenging the efficient market hypothesis. Additionally, we find a feedback relationship between dry bulk freight rates and stock market returns, meaning that they both are helpful in predicting each other at different periods in time. Therefore we suggests complexity in the relationship that warrants further research. Furthermore, increasing dry bulk rates coincides with reduced stock market volatility. Moreover, we conclude that the relationship between dry bulk freight rates and stock market returns is time-varying and correlations becomes stronger during periods of financial uncertainty. The sign of the relationship during crisis periods depends on the behavior of supply and demand curves for shipping capacity before and during a shock. Our research enlightens shipping freight rates ability to predict stock market returns, offering valuable insights for investors, policymakers, and academics alike.

Keywords – Shipping, Stock returns, Predicting, DCC-GARCH, Granger-Causality, OLS, GARCH-In-Mean-X

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1 Introduction

Shipping freight rates reflect the equilibrium between the supply and demand of seaborne transport capacity, with the main driver for aggregate capacity being world economic developments (Stopford, 2009). Periods of high economic activity increase the demand for commodities used for industrial purposes. These input factors require transportation between locations, increasing the demand for seaborne transport. Given the real-time availability of shipping freight rates, the financial press often refers to shipping freight rates as a gauge, reflecting the economy's temperature:

"Shipping rates are still falling, in another sign that a global recession may be coming." – Su-Lin Tan of CNBC (07.09.2022)[1]

"The question is whether the freight recession is foretelling a broader recession, or if it's just a temporary reset. Freight markets are usually a leading indicator of economic activity, but at a high level, it wouldn't be shocking if the market needs a moment to breathe after the supply-chain insanity of the past two years." – Robert Armstrong & Ethan Wu of Financial Times (05.05.2023)[2]

Our observation is that there seems to be a unanimous consensus among stock market commentators and participants that one should watch shipping freight rates when establishing a view of the economy going forward. Based on this "consensus view", this thesis aims to examine whether shipping freight rates can predict broad stock market returns.

Through the dividend discount model by Gordon and Shapiro (1956), we know that stock returns reflect earnings and discount rate, which both are determined by real economic factors. Chen et al. (1986) show how a set of significantly priced real economic factors explain long-term stock market returns. We question whether shipping freight rates could be added to this range of variables or whether they predict stock market returns, constituting a challenge to the efficient market hypothesis (Fama, 1970).

Shipping freight rate's ability to predict stock market returns is to a very small extent investigated in earlier academic research, strengthening our interest, as it yields many

[1] (Financial-Times, 2023)
[2] (CNBC, 2022)

unanswered questions given the properties of shipping freight rates. The only articles we are aware of are Alizadeh and Muradoglu (2014) and Bakshi et al. (2010). Both articles conclude that dry bulk freight rates predict stock market returns. However, the time series they analyzed ended ten years ago, and the relationship may have changed since then. We contribute by further enlightening the relationship using newer time series, introducing a broader range of statistical models, and investigating the complexity of the relationship. Our investigation into shipping freight rate's ability to predict stock market returns is relevant for several stakeholders. Firstly, we contribute to the scarce body of research in this area, thereby opening avenues for further investigation by scholars in both shipping and finance. Secondly, should shipping freight rates demonstrate predictive power over stock markets not explained by time-varying risk premium, investors may generate excess returns by integrating freight rates into their investment strategies and portfolio allocation decisions. Thirdly, policymakers can expand their range of informative variables for decisions affecting the stock market.

The research question for our thesis is simple:

Do shipping freight rates predict broad stock market returns?

2 Background

In this section, we discuss theoretical background and earlier research to motivate our investigation of the relationship between shipping freight rates and stock market returns. The following subsections will present the theory and background essential to our analysis. Firstly, we discuss how the real economy, shipping freight rates, and stock market returns relate. Secondly, we discuss earlier research on commodity-related variables in stock market return predicting. Thirdly, we discuss predictability and market efficiency considering time-varying risk premium by Fama and French (1989) and the Gradual Diffusion Hypothesis by Hong and Stein (1999).

2.1 The real economy and the stock market

The fundamental relationship between firms' long-term earnings and stock market returns has been thoroughly discussed in financial theory. Through the dividend discount model (DDM), Gordon and Shapiro (1956) demonstrate that stock prices can be expressed as the dividend, discounted by the cost of equity minus the dividend growth rate. D represents dividend in year 1, r represent the required rate of return, and g represent the growth rate of dividends. The stock price of a single stock P is shown in equation (2.1). Rearranging the DDM yields the total return of a stock, as shown in equation (2.2).

$$P = \frac{D_1}{r - g} \tag{2.1}$$

$$\frac{D_1}{P_0} + g = r \tag{2.2}$$

Changes in the dividend, growth rate of dividend, or the stock price would change total return of a stock. Developments in the real economy are a major factor explaining companies' ability to generate a profit, and thus the size of the dividend affecting D_1 in equation 2.1 and 2.2. Real economic factors such as inflation and risk-free interest rates alter the discount rate r. Thus, the stock price P changes, and the return of a stock r changes. On a disaggregated level, we know that some firms can outperform others given the same macroeconomic conditions. However, it is well-established that real economic factors influence the variables in equation 2.2. These factors are the predominant driving force behind long-term aggregate stock returns. It is impossible for companies to enhance their dividend growth in the absence of demand for their services or products. And furthermore, elevated interest rates lead to diminished long-term aggregate stock returns due to heightened discount rate following equation 2.2. Long-run correlations between stock indices and real economic factors such as inflation, interest rates, industrial production, and money supply are well established (Fama, 1981; Campbell, 1987; Chen et al., 1986; Geske and Roll, 1983). In the long run, aggregate stock returns will reflect the development of real economic output, opening for the idea that leading indicators for real economic output can predict the development of stock returns. The following two subsections motivate why we suggest shipping freight rates to be such a leading indicator.

2.2 Shipping freight rates and the real economy

The long-run relationship between variables with real economic significance and the stock market leads to an interesting question for both market participants and academics. Which macroeconomic variables are able to predict stock market returns? Chen et al. (1986) find that changes in the bond risk premium[3], the yield curve, and industrial production serves as the most significant variables explaining stock market returns. While bond risk premium, yield curve changes, and industrial production are tightly correlated with business cycles, they report information about the economy with a lag (Bansal et al., 2004; Backus and Kehoe, 1992). In simple terms, this implies that these variables are not leading but lagging economic output, as they consider or reflect data on real economic output. Industrial production records actual economic output. However, it is also reported with a monthly lag, as we cannot observe it in real-time. Thus, the article by Chen et al. (1986) find that these variables are significantly priced in the stock market.

In today's world economy, factors for industrial production require transportation from producer to consumer. This has increased the demand for transport capacity of commodities, and especially seaborne transport. In 2022 approximately 80 percent of global trade was transported by ships. In terms of deadweight tonnage, dry bulk carriers and oil tankers account for approximately 70 percent of the world's total shipping capacity (United-Nations, 2022). Dry bulk carriers transport coal, iron ore, grain, and other metals,

[3] The spread between corporate bonds and government bonds.

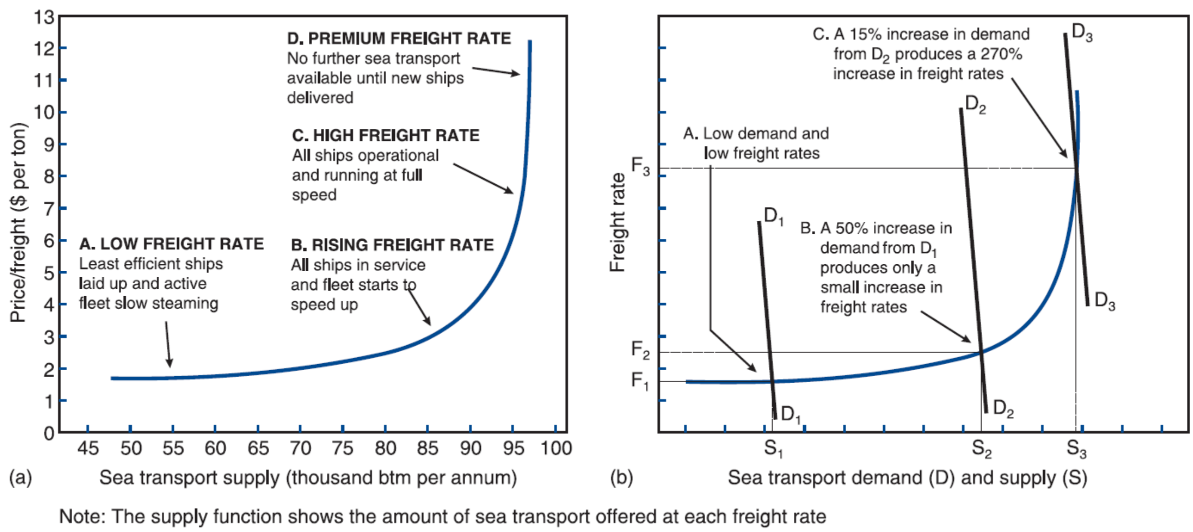
while oil tankers transport oil and oil products. Together, these two shipping segments transport the most essential input factors in industrial production. If shipping freight rates are leading indicators for real economic activity, they may also suit as a proxy for changes in aggregate dividends D_1 and the growth of dividends g, leading to changes in stock returns following equation (2.2).

2.2.0.1 Demand for freight capacity and rate formation

Shipping freight rates are instantly available, and reflect real-time supply and demand of shipping capacity. Freight rates form as shipowners and shippers negotiate a rate that, in the end, reflects the balance of ships and cargo in the market (Stopford, 2009). The real-time formation of freight rates through the spot market is one of the central characteristics of why we suggest shipping freight rates as an interesting variable in terms of stock market predictability. Activity in the world economy is well established as the most important factor for shipping demand (Stopford, 2009; Klovland, 2004). Demand for overall shipping capacity increases in real-time when activity in the world economy is increasing and vice versa, reflecting the demand for commodities.

Figure 2.1: Short-run equilibrium of freight rates (Stopford, 2009)

Figure 2.1 shows the short-run equilibrium of freight rates. The x-axis shows the transport capacity, while the y-axis shows the shipping freight cost.



The supply of shipping capacity is largely different depending on the timeframe. Short-term freight rates depends strongly on the fraction of the world fleet in lay-up. As Figure 2.1 shows, freight costs exhibit a "J" shape, given the availability of capacity in the world fleet. As demand increases, older vessels are drawn out of layup as ship owners can earn a net positive return having them at sea. When all available capacity is drawn out of layup, demand determines the cost entirely. This may result in an exponential growth in freight rate due to lack of capacity. The effect of the inelasticity of demand in the short run can lead to very volatile freight rates, hence lead to an exponential relationship between real economic output and freight rates. However, in the long run, the volatile freight cycles should average out to a more natural equilibrium. This longer-term freight rate equilibrium is theoretically found where ship owners and cargo owners agree on a price that ensures a good return on investment for the former and affordable freight for the latter. Following this reasoning, a long-run relationship between world economic activity and shipping freight rates should prevail in longer time series.

Kilian (2009) noted that there has been a long-standing correlation between shipping freight rates and global business-cycles, citing the work of Isserlis (1938), Tinbergen (1959), Stopford (1997), and Klovland (2004). Given the real-time contemporaneous availability and economic significance of shipping freight rates, we find reason to believe that the freight cost may be able to predict stock market returns.

2.3 Stock market predictability literature

Research has extensively established the ability to predict stock market returns to some extent by utilizing prior information on economic variables. Various factors, including dividend yields, spreads between long and short-term interest rates, stock volatility, and equity issuance, have demonstrated a certain degree of predictability (Fama and French, 1988; Campbell, 1987; French et al., 1987; Baker and Wurgler, 2000). However, the investigation of commodity-linked variables as predictors of stock market returns has received limited attention, except for oil prices. In the subsequent subsections, we will delve into earlier research that explores the relationship between oil prices and shipping freight rates as potential indicators of stock market movements.

2.3.0.1 The oil price

We belive it is important to review the relationship between the oil price and the stock market, due to the real economic similarities between oil price and shipping freight rates. The significance of crude oil in the world economy is undisputedly large. The International Monetary Fund (IMF) estimates that a $5 increase in the per barrel price of oil would result in a 0.3% decrease in global economic growth the following year (Mussa, 2000). The relationship between oil prices and the economy has been proven to exist dating back to the post-World War II era (Hamilton, 1983). Driesprong et al. (2008) extend this relationship to examine the relationship to stock market returns. Furthermore, they find that the price of oil predicts the return of the stock market with a negative sign in several developed and emerging markets between 1988-2003. They find that an increase in one standard deviation (approximately 10%) of the oil price reduces the annual return of the global stock market by 1% and vice versa. Recent studies conducted on recent time series confirm that this relationship still holds. Among them, Chiang and Hughen (2017) found that a 1% change in the curvature factor of the oil futures curve predicts a 0.4% per month decline in the US stock market. The economic reasoning behind the oil price as a predictor of stock market returns is that most stock-listed firms are oil and oil product consumers. Hence, a higher price increases their costs, thus lowering their earnings leading to a decrease in stock prices.

For shipping freight rates, the reasoning is that freight cost acts as a gauge for activity in the world economy. Increasing demand for shipping capacity leads to increasing freight cost following the reasoning in subsection 2.2.0.1. At the same time, increasing freight rates serves as a leading indicator for growth in revenue and earnings of listed companies, due to expanding economic conditions and vice versa.

2.3.0.2 Shipping freight rates

Despite the economic significance of freight rates, few researchers have empirically investigated their statistical significance on stock market returns. A working paper by Bakshi et al. (2010) investigates the relationship between the Baltic Dry Index (BDI), the global economy, stock returns, and commodities in the period 1985-2010. Their results conclude that BDI, an index of dry bulk rates, has predictive power on stock market returns in most of the developed and emerging markets they investigate. In addition, they find that BDI predicts industrial production in 15 of the 20 surveyed countries. These findings indicate that shipping freight predicts stock market returns due to their strong link to the real economy.

Using a time series from 1989-2013, Alizadeh and Muradoglu (2014) investigate the relationship between the international shipping market and the stock market. Using BDI, they examine several broad indices, such as the S&P 500, as well as sector-specific indices. Their results indicate that dry bulk shipping rates predict the stock market with a lag of one month. They also investigate the influence of dry bulk shipping rates on stock market volatility. Their evidence suggests that an increase in shipping freight rates coincide with decreasing stock market volatility in the broader US stock market, as well as several sector-specific indices.

To our knowledge, the papers by Bakshi et al. (2010) and Alizadeh and Muradoglu (2014) are the only ones to properly investigate shipping freight rates as a leading indicator for stock market returns. Our paper contributes by introducing newer time series and utilizing a broader range of econometric models to examine the relationship further. The main goal is to further enlighten the importance of shipping freight as an indicator, as well as adding to the limited amount of research done on the topic.

2.4 Predictability due to time-varying risk premium

Until the 1980s, it was believed that the equity risk premium was constant regardless of movements in the real economy. The capital asset pricing model (CAPM[4]) assumes that the risk premium is constant and is measured as the excess return of the market[5]. Fama and French (1989) however suggest that the risk premium varies due to changes in the business cycle. In periods of weak economic conditions, expected returns increase due to investors seeking higher risk premiums to compensate for their increased risk. Meanwhile, in periods of stronger economic conditions, market risk premiums, and expected returns tend to decrease. Thus, predictability of stock market returns, due to variations in the

[4] The Capital Asset Pricing Model (CAPM) is based on the independent work of Jack Treynor (1961, 1962), William F. Sharpe (1964), John Lintner (1965), and Jan Mossin (1966).

[5] $R_i = R_m - R_f$, where R_i is the market risk premium, R_m the expected market return and R_f the risk-free rate

risk premium, would reflect changes in business conditions. As pointed out by Schwert (2003), the obvious question is therefore to investigate whether return predictability is due to market inefficiencies or simply evidence of time-varying risk premium. In the case of shipping freight rates, Alizadeh and Muradoglu (2014) find that predictability is not due to time-varying risk premium (TVRP), challenging the efficient market hypothesis (EMH). The next subsection discusses a theoretical framework helpful for explaining why and how shipping freight rates could potentially predict stock market returns and constitute a challenge to the EMH.

2.5 The Gradual Diffusion Hypothesis

The idea that markets are efficient, and that prices reflect all known information has existed for a very long time[6]. The Efficient Market Hypothesis, introduced by Fama (1970) states that a market in which prices reflect all available information is said to be "efficient." This implies that predictability is essentially nonexistent if a market is strong form efficient. To what degree, and in which markets one finds efficiency is to this day vigorously debated among both market participants and academics.

The Gradual Diffusion Hypothesis (GDH) introduced by Hong and Stein (1999) is helpful in reasoning why the hypothesis of efficient markets fails to hold for certain assets and markets. The hypothesis states that prices underreact to fundamental value because investors process information differently. Firstly, price-sensitive information is processed by investors at different times, indicating that the information is not reflected in prices immediately, hence forming a structural underreaction. Secondly, investors have difficulty evaluating and pricing information that they view as price relevant. This enhances the underreaction of asset prices, leading to the valuation not reflecting fundamental value.

GDH can further be drawn to the cognitive biases of equity investors. Tversky and Kahneman (1973) suggest that a decision-maker takes cognitive shortcuts, where they use the knowledge that is already available in the decision-making process. Investors in global stock markets might have a hard time recognizing the relation of shipping freight rates to the stock market. Inference of said information might not be in their decision-making

[6]The idea of efficient markets was introduced in 1900 when the French mathematician Louis Bachelier wrote his doctoral thesis "The Theory of Speculation" (Bachelier, 1900)

set when making portfolio investment decisions. This reasoning opens for the idea that shipping freight rates could in fact lead stock market returns, and thus challenge the EMH. Hong et al. (2007) investigates the predictability of stock market returns given the assumptions in GDH. They find that the returns of industry portfolios are in fact capable of predicting the US stock market and the eight largest stock markets outside the US, indicating that predictability does in fact exist following the reasoning in the GDH (Hong et al., 2007).

3 Methodology

This section will thoroughly explore our motivation, methodology, and models used to test our hypotheses. Additionally, we will discuss how we determine our model specifications and compare them to prior research. Subsection 3.1 presents our hypotheses and the motivation behind them. Subsection 3.2 focuses on methodology for examining the predictability of stock market returns based on freight rates. In subsection 3.3, we introduce the methodology for the hypotheses of predictability linked to time-varying risk premiums and volatility prediction. Finally, subsection 3.4 investigates the methodology for determining the time-varying nature of the relationship between freight rates and stock market returns.

3.1 Hypotheses

Our hypotheses are primarily based on our own reasoning and motivation, however rooted in previous research and literature. Some of the hypotheses are conditional on others, while some are stand-alone. This subsection provides explanation and motivation behind each hypothesis, while the following three subsections will discuss the methodology used to test them.

"H1: Shipping freight rates have explanatory power on stock market returns."

To begin our debate regarding the shipping freight rate's ability to predict stock market returns, we need to establish whether shipping freight rates have explanatory power on stock market returns. We expect to confirm this hypothesis based on the literature review in section 2 and previous research by Bakshi et al. (2010) and Alizadeh and Muradoglu (2014).

"H2: Shipping freight rates predict stock market returns."

Hypothesis two is conditional on confirming hypothesis one. This hypothesis might seem like a clear-cut answer to our research question presented in the introduction. However, we expect it to entice discussion as the econometric models of choice discuss and estimate predictability differently. "Predictability" in this paper suggests that the movement of one variable in $t-1$ is helpful in predicting the movement of another variable in $t=0$.

"H3: Shipping freight rates predictability of stock market returns is not due to time-varying risk premium."

The third hypothesis is conditional on the second. As discussed in subsection 2.4, we want to infer whether a potential predictability of stock market returns constitutes a challenge to the efficient market hypothesis. Alizadeh and Muradoglu (2014) conclude that dry bulk freight rates predict stock market returns regardless of the time-varying risk premium. However, our paper is the first time such a relationship has been tested on newer data. Thus, we are unsure what outcome to expect for this hypothesis.

"H4: Shipping freight rates predict stock market volatility."

Hypothesis four focuses on volatility rather than mean returns and is thus not dependent on the two previous hypotheses. Stock market volatility is dependent on a broad range of factors and is to a large extent challenging to explain. Shipping freight rate's connection to the real economy might suggest that they would influence the volatility of stock market returns. Thus, we expect there might be a possibility that we accept the hypothesis that shipping freight rates predict volatility of the stock market.

"H5: The relationship between shipping freight rates and stock market returns is time-varying."

The fifth hypothesis invites insight into the complexity of the relationship between shipping freight rates and stock market returns. The relationship dynamics have to our knowledge never been investigated, which evokes our curiosity to a large extent. We have no clear expectations for the outcome of this hypothesis.

3.2 Investigating return predictability

We perform multiple regression analyses and Granger-Causality analyses to investigate the return predictability of shipping freight rates on stock market returns. The aim is to examine whether there is a significant relationship between shipping freight rates and stock market returns, and whether the former can predict the latter. The specifications for our regression models are based on the works of several stock market predictability articles, where the log returns of the stock market is presented as the dependent variable and the contemporaneous and lagged log return of the predictor variable as the independent variable (Alizadeh and Muradoglu, 2014; Driesprong et al., 2008; Hodrick, 1992).

$$\ln\left(r_{i,t=0}\right) = \alpha + \beta \ln\left(r_{fr_{t=0}}\right) + \beta \ln\left(r_{fr_{t-1}}\right) + \cdots \beta \ln\left(r_{fr_{t-4}}\right) + u_t, \quad u_t \sim iid\left(0, \sigma_i^2\right) \tag{3.1}$$

Our regression equation 3.1 shows the stock market returns for time zero as $ln(r_{it=0})$, the constant as α, the logarithmic growth rate of shipping freight rate on time one to four as $ln(r_{fr=x})$ and the error term as u_t. The error term is assumed to be independent and identically distributed with constant variance and zero mean, implying that the error term is absent of both heteroskedasticity and autocorrelation.

In addition to the OLS model, Hodrick (1992) suggests that a Vector Autoregressive (VAR) approach is useful when investigating long-term relationships between dividend yields and stock market returns. To investigate return predictability, we extend such a VAR framework into a Granger-Causality test (Granger, 1969). The Granger-Causality test is more suitable for measuring the predictability of one variable on another, considering lagged values of the variables. The model is estimated in two steps. Firstly, it estimates a prediction of a variable based on its own lags. Secondly, it assesses whether the accuracy of the prediction improves by adding lagged values of another variable. If such improvement occurs, we infer a "Granger-causal" relationship between the variables.

$$P_t\left(r_{i,t} \mid \overline{r_{i,t}}, \overline{r_{fr,t}}\right) = \sum_{j=1}^{\infty} a_j r_{i,t-j} + \sum_{j=1}^{\infty} b_j r_{fr,t-j} \tag{3.2}$$

Equation 3.2 shows the Granger-Causality equation, where $P_t\left(r_{i,t} \mid \overline{r_{i,t}}, \overline{r_{fr,t}}\right)$ refers to the conditional probability distribution of the current value of stock index return given $\overline{r_{i,t}}, \overline{r_{fr,t}}$ which is vectors subtracted from the observed values of stock index returns and freight rate changes before fitting the VAR model. a_j and b_j are chosen to minimize $\sigma^2\left(r_{i,t} \mid \overline{r_{i,t}}, \overline{r_{fr,t}}\right)$. The past values of stock index returns and freight rate changes are shown as $r_{i,t-j}$ and $r_{fr,t-j}$. In the event that $b_j \neq 0$, it is implied that freight rates are causing stock returns.

$$P_t\left(r_{fr,t} \mid \overline{r_{fr,t}}, \overline{r_{i,t}}\right) = \sum_{j=1}^{\infty} a_j r_{fr,t-j} + \sum_{j=1}^{\infty} b_j r_{i,t-j} \tag{3.3}$$

In equation 3.3 the test is reversed, and we can test wheter it is implied that stock market returns are causing freight rates if $b_j \neq 0$. If both variables are helpful in predicting eachother, there is said to be "feedback relationship" between the variables (Granger, 1969).

The Granger-Causality framework is previously not used in the literature of shipping freight rate's ability to predict the stock market (Alizadeh and Muradoglu, 2014; Bakshi et al., 2010). However, we belive it is strongly value-adding to perform such a model since it is widely used in other parts of stock market predictability literature such as Bollen et al. (2011) and Mahdavi and Sohrabian (1991).

3.3 Predictability due to time-varying risk premium

Motivated by the research of Fama and French (1989), we investigate whether predictability is unrelated to the time-varying risk premium. If freight rates predict stock market returns unrelated to time-varying risk premium, it challenges the efficient market hypothesis following the discussions in section 2.4. We perform two separate analyses to test for the effect of time-varying risk premium. Firstly, we introduce a simple correlation matrix using Pearson's correlation coefficients between shipping freight rates and factors explaining time-varying risk premium. Chen et al. (1986) introduced a set of variables that explain stock market returns significantly priced by the market. These variables should thus proxy changes in time-varying risk premium. In our analysis a high correlation to these factors is conclusive with the fact that freight rates also proxy time-varying risk premium, thus not challenging the efficient market hypothesis in terms of stock return predictability.

Secondly, we use a GARCH-In-Mean model with freight rates as explanatory variable following Driesprong et al. (2008) and Alizadeh and Muradoglu (2014). The Generalized Autoregressive Conditional Heteroscedastic (GARCH) model is used as a framework for testing the hypothesis regarding time-varying risk premium, volatility influence, as well as the hypothesis regarding whether the relationship between freight rates and stock market returns is time-varying.

Introduced by Bollerslev (1986), the GARCH model serves as an extension to the ARCH model by Engle (1982). The model is helpful in analyzing and forecasting data that exhibits behavior of volatility clustering, in other words, the tendency of abnormal variance in a time series to cluster together in specific periods. The following equation show how the framework model the variance of the dependent variable:

$$r_{i,t} = \mu + \sigma_{t-1}^2 + u_t, \quad u_t \sim N\left(0, \sigma_t^2\right) \tag{3.4}$$

$$\sigma_t^2 = \alpha_o + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{3.5}$$

Among several specifications for the model, the most widely used assert that the best predictor of variance in t=1 is a weighted average of the long run variance α_0, the predicted variance for this period σ^2 and the most recent squared residual u^2 (Engle, 2001). It allows for modeling the conditional variance in the residuals, such that it is allowed to depend on all the prior values of the residuals (Brooks, 2019). We present a GARCH (1.1) model where the first number (1) refers to an autoregressive lag of one, and the second number (1) refers to a moving average lag of one. In a working paper by Hansen and Lunde (2005), 330 different ARCH-type models where tested on exchange rates. Their evidence suggest that no other specifications outperform the GARCH (1.1) model in terms of describing conditional variance. Testing the different specifications for lag length on our data yields negligible differences in AIC for the various specifications. Therefore, we stick to the (1.1) specification shown in equation 3.5.

We present a modified GARCH model to test if predictability is due to time-varying risk premium. Based on the work of Engle et al. (1987), we introduce a GARCH-M model where we include the conditional variance in the mean equation. In this specification the observation of a unit increase in variance should lead to a corresponding increase in mean returns, following the economic intuition of risk premiums. Further, we extend our model to incorporate an exogenous variable in the variance equation, resulting in a GARCH-In-Mean-X model. This extension allows us to model the volatility and return of the stock market, given an increase in its own volatility, as well as how it responds to a change in the shipping freight rates.

$$r_{i,t} = \mu + \delta \sigma_{t-1}^2 + u_t, \quad u_t \sim N\left(0, \sigma_t^2\right) \tag{3.6}$$

$$\sigma_{i,t}^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 + \pi r_{\text{frt-1}}^2 \tag{3.7}$$

Equations 3.6 and 3.7 shows the mean and variance equation subsequently, where r_{it} is the return of the stock index, δ coefficient for the variance and π is the coefficient for the changes of shipping freight rates r_{fr}.

The mean-equation now contains a delta sign δ, which is subject to be positive and significant if increased volatility leads to increased returns and vice versa. Given that the variance equation is now modeled with an additional term containing the exogenous regressor r_{fr}, we can measure its impact on the return of the stock market via the conditional variance equation 3.7. If π is significant and negative, we can infer that an increase in shipping freight rate does not increase the conditional volatility of the stock market and vice versa. Such a relationship coincides with the fact that the predictability of stock market returns cannot be attributed to time-varying risk premium.

3.4 Dynamic relationship?

As an extension to the work done by Alizadeh and Muradoglu (2014) and Bakshi et al. (2010), we examine whether the relationship between freight rates and stock market returns is time-varying. Given that a broad range of factors influence stock market returns and freight rates, it seems obvious to investigate whether the correlations between them are subject to change over time. We introduce the Dynamic Conditional Correlation GARCH or DCC-GARCH model by Engle (2002) to investigate the existence of a dynamic relationship between our variables[7]. This multivariate extension to the GARCH framework allow modeling of the dynamic conditional correlation relationship between the variables. The model is useful when investigating both the sign and strength of the conditional correlation and identifying if and how periods of high or low volatility influence the conditional correlation (Jones and Olson, 2013; Niyitegeka and Tewari, 2020).

Following Engle (2002), our DCC-GARCH model calculates a variance-covariance matrix H_t between shipping freight rates and stock market returns. Where D_t is the diagonal matrix containing the standard deviations from two separate univariate GARCH models for each variable, as shown in equation 3.5. R_t is the conditional correlation matrix of a vector of shipping freight rates and stock market returns.

[7]"H5: The relationship between Shipping freight rates and stock market returns is time-varying."

We ensure that two important requirements are met for the DCC-GARCH, following Orskaug (2009):

1. H_t needs to be positive since it is a covariance matrix, requiring R_t to be positive. D_t is positive since all diagonal elements are positive.
2. For R_t, all elements in the correlation matrix have to be equal or less than one.

$$H_t = D_t R_t D_t \tag{3.8}$$

Equation 3.8 shows the calculation of the variance-covariance matrix H_t. Where the correlation matrix of the conditional standard deviations from two separate GARCH models are:

$$D_t = \begin{pmatrix} \sqrt{H_{1,t}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sqrt{H_{n,t}} \end{pmatrix} \tag{3.9}$$

The conditional correlation matrix of a vector of shipping freight rates and stock market returns is:

$$R_t = \begin{pmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \cdots & \rho_{1n,t} \\ \rho_{21,t} & 1 & \rho_{23,t} & \cdots & \rho_{2n,t} \\ \rho_{3,t} & \rho_{32,t} & 1 & \cdots & \rho_{3n,t} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho_{n1,t} & \rho_{n2,t} & \cdots & \rho_{n,n-1,t} & 1 \end{pmatrix} \tag{3.10}$$

Further we break the matrix of the conditional correlations into:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{3.11}$$

Where:

$$Q_t = \begin{pmatrix} q_{11,t} & \sqrt{q_{11,t}q_{22,t}} & \cdots & \sqrt{q_{11,t}q_{nn,t}} \\ \sqrt{q_{11,t}q_{22,t}} & q_{22,t} & \cdots & \sqrt{q_{22,t}q_{nn,t}} \\ \vdots & \vdots & \ddots & \vdots \\ \sqrt{q_{11,t}q_{nn,t}} & \sqrt{q_{22,t}q_{nn,t}} & \cdots & q_{nn,t} \end{pmatrix} \tag{3.12}$$

Q_t^* is the diagonal matrix of the square root of the diagonal elements of Q_t at the diagonal. Q_t^* rescales the elements in Q_t to ensure that all elements in the correlation matrix are equal to or less than one (Orskaug, 2009).

$$Q_t^* = \begin{pmatrix} \sqrt{q_{11,t}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sqrt{q_{nn,t}} \end{pmatrix} \tag{3.13}$$

The DCC-GARCH (1.1) model is thus the diagonal matrix of the squared root of the diagonal elements in Q_t:

$$Q_t = (1 - \alpha_{DCC} - \beta_{DCC})\,\bar{Q} + \alpha_{DCC}\varepsilon_{t-1}\varepsilon'_{t-1} + \beta_{DCC}Q_{t-1} \tag{3.14}$$

To ensure that the estimation meets requirement 1, the satisfaction of the following conditions α_{DCC} and β_{DCC} parameters is required:

$$\alpha_{DCC} \geq 0, \beta_{DCC} \geq 0, \alpha + \beta < 1 \tag{3.15}$$

The DCC-GARCH parameters are estimated using the maximum likelihood function, see Engle (2002) for the estimation. The α_{DCC} parameter reflects the sensitivity of a shock of one variable on another, while the β_{DCC} parameter reflects persistence of such a shock. Output coefficients for the DCC-GARCH models will allow us to statistically determine whether there is a dynamic conditional correlation between shipping freight rates and stock market returns. Several research papers covering shipping freight rates use the DCC approach, e.g., Tsouknidis (2016) and Raju et al. (2021). However, to our knowledge, we are the first to apply this approach in investigating the relationship to the stock market using such a model.

4 Data

Having established the methodology framework for testing our hypotheses, this section present the data for our analyses. We use time series of stock market indices and freight rates from 1999-2022 to investigate the relationship between shipping freight rates and the stock market. Monthly frequency data from April 2000 - December 2022 is utilized for hypotheses 1[8] and 2[9], while data on weekly frequency from 12/03/1999 - 30/12/2022 is utilized for hypotheses 3[10], 4[11] and 5[12]. In this section we explain choice of time series frequency, provide descriptive statistics as well as discuss time series implications for our analysis.

4.1 Variables

As a proxy for stock market returns, we use four broad stock indices, eliminating any industry or sector-specific influence on the relationship between freight rates and stock market returns. Price data for shipping freight rates are collected from the Clarksons Shipping Intelligence Network (Clarksons, 2023). The network is a research portal created by Clarksons Group, "the world's leading provider of integrated shipping services" (Maritime-London, 2023). This ensures we can trust the shipping indices to reflect actual market rates. Contrary to Alizadeh and Muradoglu (2014) and Bakshi et al. (2010), we also investigate tanker rates and a general index for all shipping segments.

Data for stock indices are obtained and converted into dollar currency from a Bloomberg Terminal. The stock indices chosen are selected based on markets which we as researchers know well, reducing the risk of observing results we do not understand due to country or market-specific factors.

[8]H1: Shipping freight rates have explanatory power on stock market returns.

[9]H2: Shipping freight rates predict stock market returns.

[10]H3: Shipping freight rates predictability of stock market returns is not due to time-varying risk premium.

[11]H4: Shipping freight rates predict stock market volatility.

[12]H5: The relationship between shipping freight rates and stock market returns is time-varying.

Table 4.1: Variable overview

Table 4.1 shows an overview and description of variables.

Variable	Description
ClarkSea Index	Index of average dollar earnings for oil tankers, dry bulk carriers, gas carriers, and cellular container vessels.
Clarksons Average Tanker Earnings	Index of average dollar earnings for oil tankers.
Clarksons Average Bulker Earnings	Index of average dollar earnings for dry bulk carriers.
MSCI World (MXWO)	Global index of 1508 companies distributed across 23 countries. The index covers approximately 85 percent of the total market value in the countries it measures.
STOXX 600 (SXXP)	Broad European index that includes 600 companies.
S&P 500 (SPX)	Broad US index that includes 500 companies.
Oslo Stock Exchange (OSEBX)	Broad Norwegian index that includes 69 companies.

4.2 Monthly data

Similar to the articles by Driesprong et al. (2008) and Alizadeh and Muradoglu (2014), we have chosen monthly data for testing our hypothesis of freight rate's ability to predict stock market returns. We aim to capture a possible long-term relationship between the two variables using monthly frequency. Long-term correlations between variables of real economic significance are usually captured in data with monthly frequency, such as Chen et al. (1986). Furthermore, higher frequency data tend to contain more information influenced by other factors, which in this setting can be seen as noise when investigating the long-term relationship between fright rates and stock markets.

In time series analysis, stationarity in series is a necessary requirement to avoid spurious results for several statistical models. For the models we outlined in section 3, weak-form stationarity is sufficient to infer correct results. Weak-form stationarity in time series require a constant mean, variance, and autocovariance (Brooks, 2019). A time series is thus stationary in the absence of unit root presence. Financial time series often contain an underlying drift as the series' mean gradually moves upwards. Stock markets for example tend to increase over time, violating the assumption of stationarity gradually.

$$R_t = \log\left(\frac{P_t}{P_{t-1}}\right) \tag{4.1}$$

We transform our data into logarithmic returns, as demonstrated in equation 4.1. R_t is the logarithmic growth rate of the variable, where P_t is the price at time t, P_{t-1} is the price at t-1. The transformation to logarithmic returns often result in stationary financial data and beneficial statistical properties such as additivity and symmetricity (Louca, 2021). Empirical research articles on stock market predictability often transform returns into logarithmic returns, as discussed by Hodrick (1992). In our thesis, all variables are thus transformed into log-returns following equation 4.1

Figure 4.1: Logarithmic monthly growth rates

Figure 4.1 shows time series graphs of variables on monthly frequency. The x-axis show years and the y-axis shows the logarithmic growth rate.

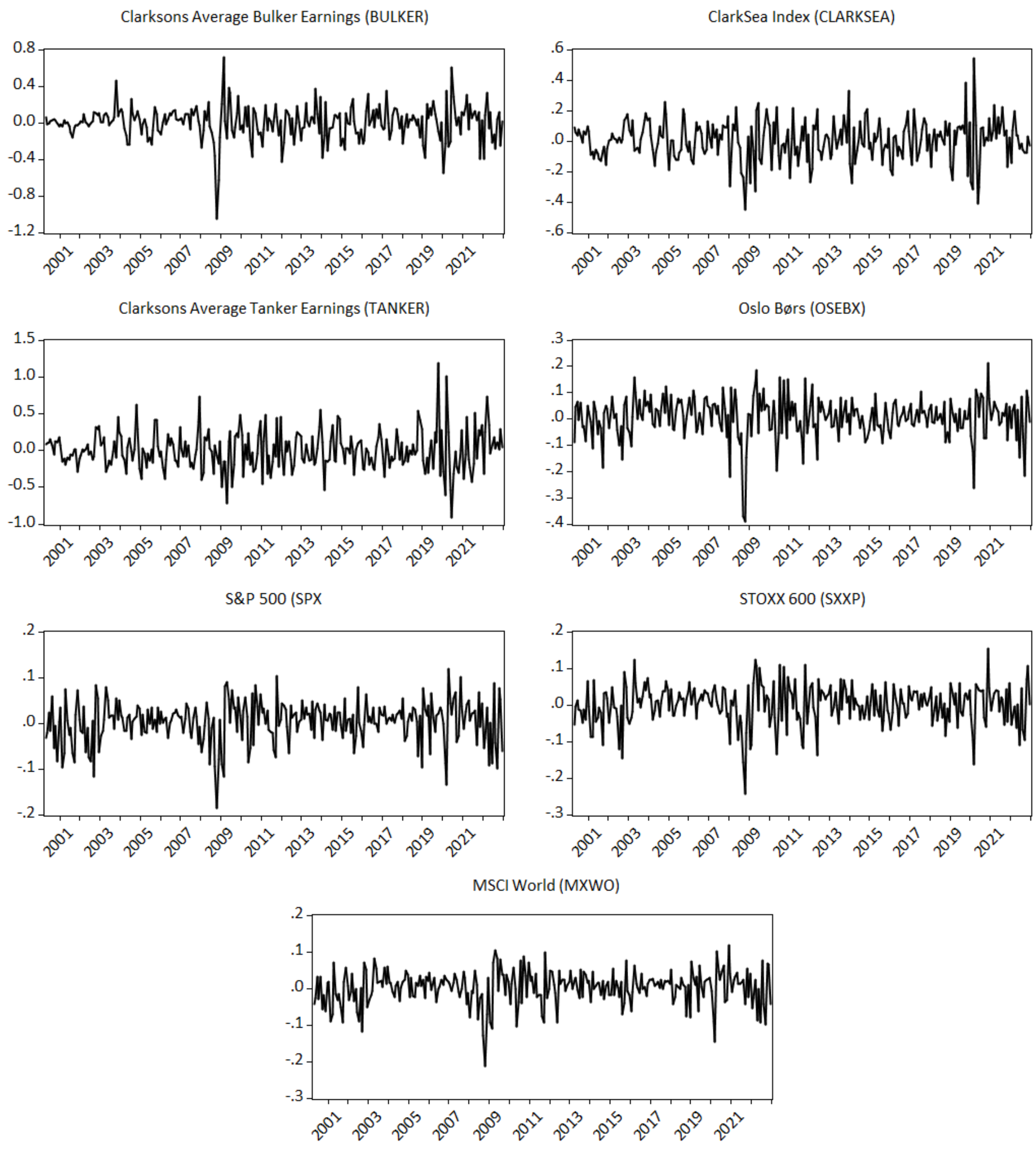


Figure 4.1 shows logarithmic growth rates of the four stock indices and freight rates chosen for our analysis. We observe that all stock indices behave quite similarly due to the interdependencies of global stock markets. However, some local differences are observable between them. An example is that during the financial crisis and covid-19 pandemic, OSEBX experienced more significant drawdowns. The main reasoning being that we

convert the stock market indices from local currencies to USD in order to match shipping freight rates quoted i USD from Clarksons (2023). Larger drawdowns for OSEBX in USD during the financial crisis and covid-19 pandemic can be attributed to the fact that investors seek safe havens, and avoid peripheral currencies, such as the Norwegian krone during times of distress. Our thesis investigates stock predictability in an international perspective, thus we filter out local currency effects by converting all indices to USD.

Monthly transformed data for shipping freights displays more significant deviations among the different shipping segments. Contrary to the global inter-dependencies of stock markets, different shipping segments are to a greater degree influenced by their own supply-demand curves (Kenett et al., 2012). However, similar to the stock indices, we observe large movements for freight rates during the financial crisis and the covid-19 pandemic. Periods of economic uncertainty influence the demand for both stocks and shipping freight, hence leading to significant drops in prices for the mentioned markets.

4.2.0.1 Statistic properties for monthly data

The logarithmic differenced returns for all four monthly stock market indices and freight rates look stationary following figure 4.1. To confirm or reject the suspicion of no unit root, we use Augmented Dickey Fuller (ADF) test (Dickey and Fuller, 1979). The test rejects the null hypothesis of a unit root at a p-value below 1% for all variables, suggesting the series are stationary (see Appendix A1.1 for ADF result).

Table 4.2: Descriptive statistics of monthly variables

Table 4.2 shows descriptive table of monthly variables for the period April 2000 - December 2022. BULKER is the Clarksea average earnings index for dry bulk freight rates, CLARKSEA is the general ClarkSea Index, TANKER is the Clarksea average earnings index for tanker freight rates, OSEBX is Oslo Stock Exchange index, SPX is S&P 500 index, SXXP is STOXX 600 index, MXWO is MSCI World index.

	BULKER	CLARKSEA	TANKER	OSEBX	SPX	SXXP	MXWO
Mean	0.002	0.003	0.005	0.006	0.003	0.001	0.002
Median	0.017	0.012	-0.011	0.015	0.01	0.003	0.01
Maximum	0.72	0.541	1.193	0.211	0.119	0.155	0.119
Minimum	-1.054	-0.447	-0.915	-0.392	-0.186	-0.243	-0.211
Std. Dev.	0.181	0.131	0.262	0.078	0.045	0.054	0.046
Skewness	-0.704	-0.163	0.52	-1.194	-0.693	-0.663	-0.789
Kurtosis	8.256	4.274	5.142	7.321	4.131	4.625	4.714
Jarque-Bera	336.72	19.67	61.74	277.23	50.02	36.40	64.46
P-value	0.0	0.0	0.0	0.0	0.0	0.0	0.0
n	273	273	273	273	273	273	273

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4.2 displays descriptive statistics for monthly variables. We observe that freight rates exhibit approximately three times higher volatility than stock indices, as measured by the standard deviation. Large standard deviations for freight rates may be due to the mechanics of freight rate formation discussed in subsection 2.2.0.1. As anticipated, all stock indices demonstrate negative skewness[13]. Stock markets tend to follow a consistent upward trend with small returns while experiencing more significant drawdowns during economic downturns. Furthermore, ClarkSea and Bulker also exhibit negative skewness. Negative skewness is expected given that shipping follow the same economic cycles as stock markets, which we know have long and stable movements upwards with more rapid and shorter downturns. Given this relationship, the demand for shipping will increase slowly but steadily, followed by a larger demand disruption. Conversely, tanker rates show positive skewness indicating several small changes downwards, with more intense price changes upwards as the fleet reaches its maximum capacity constraint, consistent with the working paper of Abouarghoub (2010). An example of such intense price change upwards when the capacity constraint is reached is the event during the covid-19 pandemic when demand for tankers as floating storage increased during a historic fall in oil prices. Also, a smaller drop in tanker freight rates compared to other shipping segments during the

[13]Indicating a left-side asymmetric distribution, where the median is to the right, and several significant negative values result in a long left-tail.

financial crisis can partly explain the difference to other shipping markets in terms of skewness.

In addition to skewness, kurtosis measures tail thickness, and data with high kurtosis has a high peak at the median with flattened tails. All variables demonstrate positive excess kurtosis[14], where most observations cluster around the median with some significant outliers. Positive skewness and excess kurtosis indicate non-normality in our data.

$$JB = \frac{n}{6}\left(S^2 + \frac{1}{4}(K-3)^2\right) \tag{4.2}$$

This is confirmed by a Jarque-Bera test (Jarque and Bera, 1987) as shown by equation 4.2, where JB is the test-statistic, n the number of observations, S sample skewness, and K sample kurtosis. Table 4.2 show that JB-values are high and that p-values are below 1%, indicating that our variables exhibit a non-normal distribution. Non-normality in our data tells us something about the distribution of observations. Even though none of the statistical models used in our report assumes normality of the underlying data, we believe it is important to understand the behavior of the data used in our analyses.

4.3 Weekly data

We use weekly data for investigating hypotheses 3-5. When examining the volatility in time series, we aim to increase the data frequency for two primary reasons, the first being linked to the properties of the GARCH model. Hwang and Pereira (2006) investigated the characteristics of small samples in GARCH modeling. They found that modeling the logarithmic return of the S&P 500 on daily frequency with small samples could result in incorrect estimates. They suggest that GARCH models require a minimum of 500 observations. Our monthly frequency data only contains 273 observations, far to few to model volatility in our view. The second reason for utilizing weekly data in volatility modeling is the problem of temporal aggregation (Rossana and Seater, 1995). Aggregated time series may lose important movements and information. In our case, we wish to investigate whether freight rates predict stock market volatility. Monthly aggregated data may lose important information about the relationship and is rarely used in volatility

[14] Excess Kurtosis = Kurtosis-3

modeling. Thus we perform our GARCH analyses with weeekly data as it is the lowest frequency available for our freight rate indices. Weekly price observations for all variables are logarithmic transformed following the same equation as monthly data (see equation 4.1).

Figure 4.2: Logarithmic weekly growth rates

Figure 4.2 shows time series graphs of variables on monthly frequency. The x-axis show years and the y-axis shows the logarithmic growth rate.

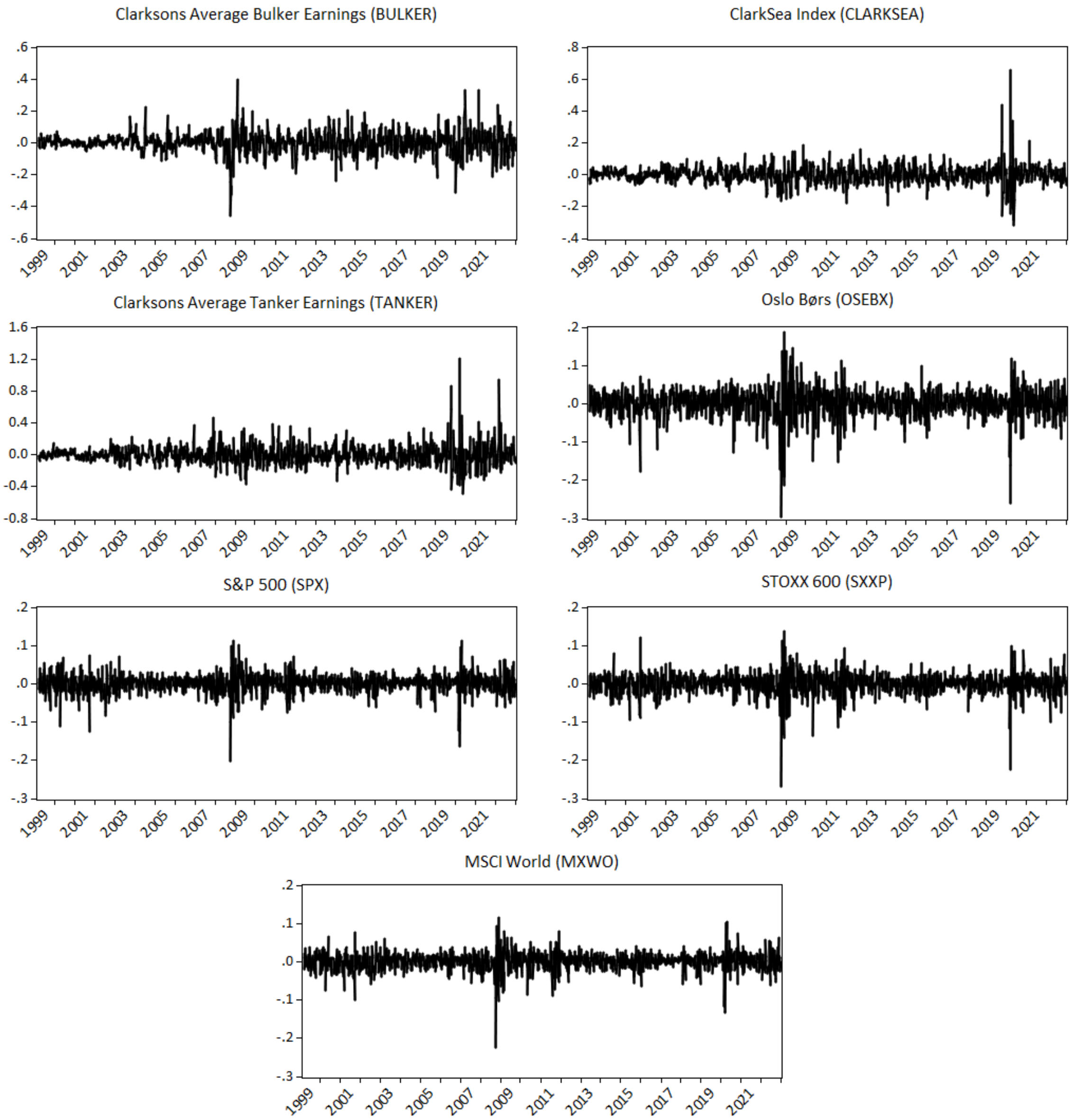


Figure 4.2 shows the logarithmic growth rate for stock indices and freight rates on a weekly frequency. Weekly data provides more data points, which reveals the presence of volatility

clustering in our data. First observed by Mandelbrot (1963), volatility clustering is the tendency of abnormal changes in the value of a variable to be followed by an abnormal change and vice versa. This results in the tendency of volatility to cluster together in specific timeframes. Volatility clustering seems to appear in periods with increased uncertainty in the world economy for shipping freight rates and stock markets. Such clustering is tightly related to the concept of conditional heteroskedasticity. ARCH-models aim to model the volatility of an asset given the previous values of the asset. Volatility clustering reveals asset's tendency of volatility in $t = 0$ to be strongly dependent on the volatility in $t - 1$. Performing an Engle's ARCH-test by Engle (1982) confirms that there are ARCH-effects or periods of volatility clustering in all variables (see appendix A1.3) motivating the use of GARCH model in our analysis. Stationarity is assumed to obtain the correct inference of the model (Bollerslev, 1986). ADF-tests for weekly frequency reject the null hypothesis of unit root for all variables at the 1% level (see appendix A1.2).

5 Analysis

In this section, we present and discuss our results from our analysis. Table 5.0 shows the different models presented in this section and which hypothesis they aim to answer. Results are interpreted and discussed in section 5, before we conclude the entirety of our paper in section 6. Subsection 5.1 covers the regression analysis. Subsection 5.2 covers the Granger-Causality analysis. Subsection 5.3 covers the Time-varying risk premium analyses. And finally subsection 5.4 covers the DCC-Garch analysis.

Table 5.1: Table overview – Models and hypotheses

Table 5.1 gives an overview of the hypotheses and models performed to test them.

Model	Hypothesis
Regression (OLS) and Granger-Causality	*H1: Shipping freight rates have explanatory power on stock market returns.*
Regression (OLS) and Granger-Causality	*H2: Shipping freight rates predict stock market returns.*
Correlation Matrix and GARCH-In Mean-X	*H3: Shipping freight rates predictability of stock market returns is not due to time-varying risk premium.*
GARCH-In Mean-X	*H4: Shipping freight rates predict stock market volatility.*
DCC-GARCH	*H5: The relationship between Shipping freight rates and stock market returns is time-varying.*

5.1 Regression analysis

The aim of the regression analysis is to answer the following hypotheses: *H1: Shipping freight rates have explanatory power on stock market returns.* As well as: *H2: Shipping freight rates predict stock market returns.* In the literature of stock market return predictability, regression equations are often specified as regressing the predicting variable onto stock market returns at different lags. Our regression specification differs from Driesprong et al. (2008) and Alizadeh and Muradoglu (2014) by the fact that we regress upon several lags, instead of just the first. We include several lags to infer wheter explanatory power can be proven at previous periods, given that the economic significance of such effect is theoretically not limited to only prevail at the first lag. As introduced in the methodology section, equation 3.1 shows our regression specification. Significant β coefficients at each lag will indicate that this lag of shipping freight rate would have an explanatory power on the stock market index. However, before we begin to interpret our regression results, we investigate the validity of the OLS assumptions in our regression models.

Firstly, we perform a variance inflation factor (VIF) test to investigate the presence of multicollinearity between our independent variables. Lagged freight rates from period 1-4 result in values slightly above 1 (see appendix A1.4). According to (Johnston et al., 2018), a value below 2.5 is unproblematic in terms of multicollinearity. Therefore, we can conclude that there is no linear relationship between freight rates on different lags.

Secondly, we conduct tests for autocorrelation of the residuals for all regression models between the stock market returns and shipping freight rates. We perform a Breusch-Godfrey test[15] for autocorrelation up to lag 12. The tests conclude that we accept the null hypothesis of zero autocorrelation in the residuals up to 12 lags (see appendix A1.5).

Lastly, we test for heteroskedasticity in the residuals for all regression models. A Breusch-pagan test[16] reveal that heteroskedasticity is present in all regression models. To treat the presence of heteroskedasticity in our regressions, we use HAC robust standard errors introduced by Newey and West (1987) when performing our regressions. HAC standard errors adjust the standard error by weighting the residuals by a matrix that reflects the degree of heteroskedasticity and autocorrelation in the data.

Regression results for stock indices on lagged values of the ClarkSea Index and tanker freight rate index demonstrate a weak or non-existent statistical significance (See appendix A2.2 and A2.1). We are surprised to observe that tanker freight rate has no statistically significant explanatory power on the four stock indices. Following our discussion of

[15](Breusch, 1978);(Godfrey, 1978)
[16]Breusch and Pagan (1979)

seaborne commodity trade in section 2, we expected to find a relationship in the regression. Furthermore, the central role of oil in the world economy and its influence on stock markets led us to expect that the relationship would extend to tanker freight rates and the stock market. However, since the regression results for theese two indices yield weak or no significance, we continue the analysis in our thesis by focusing on dry bulk freight rates.

Table 5.2: Regression table of stock returns and dry bulk rates

Table 5.2 shows regression models between stock indices and dry bulk freight rates contemporaneous and lagged 1-4. The regressions are performed on monthly data in the period April 2000 – December 2022. The numbers given in parenthesis are t-statistics for the coefficients. All regressions are run with HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 6.0000). All models are estimated using the statistical software R.

	STOXX 600	S&P 500	OSEBX	MSCI World
	(1)	(2)	(3)	(4)
β $Bulker_{t=0}$	0.030	0.016	0.070	0.022
	(0.928)	(0.605)	(1.260)	(0.761)
β $Bulker_{t-1}$	0.032**	0.042**	0.038	0.035**
	(1.953)	(2.396)	(1.410)	(2.077)
β $Bulker_{t-2}$	0.036*	0.026	0.052**	0.028
	(1.704)	(1.615)	(1.983)	(1.617)
β $Bulker_{t-3}$	0.009	0.009	−0.031	0.010
	(0.374)	(0.443)	(−1.033)	(0.481)
β $Bulker_{t-4}$	0.035**	0.022*	0.044*	0.026**
	(2.181)	(1.711)	(1.934)	(2.008)
Constant	0.0003	0.003	0.006	0.002
	(0.099)	(1.242)	(1.237)	(0.691)
Observations	273	273	273	273
R^2	0.061	0.068	0.063	0.065
Adjusted R^2	0.044	0.050	0.045	0.047
Residual Std. Error (df = 267)	0.053	0.044	0.076	0.045
F Statistic (df = 5; 267)	3.490***	3.887***	3.566***	3.682***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5.2 reveals a significant and positive relationship between bulk rates and stock index returns at certain lags. Dry bulk freight rates are significant and positive on the first and fourth lag on most stock indices. Our significant coefficients range between 0.022-0.052, meaning that a 1% increase in dry bulk freight rates leads to a 0.022%-

0.052% increase in the stock market in the month following the lagged freight rate. For example, a 10% increase in dry bulk rates at period $t-1$, leads to a 0.32% increase in STOXX 600 the following month. For S&P 500, our coefficients are larger at the first lag, compared to that of Alizadeh and Muradoglu (2014), indicating that the relationship has strengthened between dry bulk freight rates and the US stock market the last years. It is worth mentioning that using HAC standard errors results in prudent t-statistics and coefficients. For our sample, none of the coefficients passes the confidence level of 99%. However, several of them do pass the 95% level, leading us to believe that there is in fact a relationship worth investigating further between dry bulk freight rates and stock market returns.

Adjusted R-squared range from 0.044-0.050 for our four models. This number is roughly the size that we expected. There are a broad range of factors explaining aggregate stock market returns, using only one variable to explain stock market returns is expected to yield relatively low R-squared. Compared to other research papers on predictability using only one variable, our Adjusted R-squared values seems acceptable (Alizadeh and Muradoglu, 2014; Guo, 2006; Chiang and Hughen, 2017; Driesprong et al., 2008).

Significant and positive coefficients of lagged dry bulk freight rates are consistent with the hypothesis of gradual diffusion of information (Hong and Stein, 1999). The lagged significance on stock indices might be explained by investors processing the information at different times and that the informations relevance to price is considered differently. The regression analysis favors accepting our hypothesis that shipping freight rates have explanatory power on stock market returns, as well as our hypothesis that shipping freight rates predict stock market returns. This is due to the lagged nature of the relationship, giving market participants the possibility to achieve excess returns by scaling in and out of the market. We believe, however, that further investigation is needed. The next section introduce a Granger-Causality to further investigate predictability.

5.2 Granger Causality analysis

In this section, we extend our analyses of the relationship and predictive power of dry bulk freight rates on aggregate stock returns. We perform Granger Causality analysis with the specifications shown in equations 3.2 and 3.3 in subsection 3.2.

Each test comprises of two models: the first model predicts a variable based solely on its own lags, while the second model incorporates both its own lags and the lags of the explanatory variable. If the tests are statistically significant, we can reject the null hypothesis that dry bulk freight rates lack explanatory power over the stock market. The inclusion of the explanatory variable enhances the predictive accuracy of the estimates in comparison to those obtained by considering only the variable's own lags. The number of lags used in the tests is selected based on the criterion of the highest Akaike Information Criterion (AIC) (See appendix A4.1).

Table 5.3: Granger Causality between dry bulk rates and stock indices

Table 5.3 shows Granger-Causality models with four lags on data with monthly frequency ranging from April 2000 – December 2022. Referring to section 3.2, the following equation shows how X granger cause Y taking into account 4 lags: $Y \sim \cdots + X_{=1-4}$. Note from the table that we run the model with stock market returns and dry bulk freight rates as both X and Y to check for a reverse causality. All models are estimated using the statistical software R.

$H_0 = X$ do not granger cause Y $H_a = X$ granger causes Y			
	Model	P-Value	F-stat
$SPX \sim \cdots + BULKER_{t=1-4}$	(1)	0.001609***	4.4837***
$BULKER \sim \cdots + SPX_{t=1-4}$	(2)	0.000176***	5.7935***
$MXWO \sim \cdots + BULKER_{t=1-4}$	(3)	0.0108**	3.3459**
$BULKER \sim \cdots + MXWO_{t=1-4}$	(4)	3.929e-06***	8.0489***
$SXXP \sim \cdots + BULKER_{t=1-4}$	(5)	0.0254**	2.8252**
$BULKER \sim \cdots + SXXP_{t=1-4}$	(6)	2.781e-06***	8.2552***
$OSEBX \sim \cdots + BULKER_{t=1-4}$	(7)	0.0714*	2.1815*
$BULKER \sim \cdots + OSEBX_{t=1-4}$	(8)	7.117e-09***	11.873***
Observations		264	264
Note:		*p<0.1; **p<0.05; ***p<0.01	

Table 5.3 shows that models (1-8) are significant at a 90-99% level. Models (1,3,5,7) confirms that dry bulk freight rates are said to be helpful in predicting stock market returns on lag one through four. This is compelling evidence that dry bulk freight rates predict stock market returns. However, we observe a reverse relationship where stock market returns are helpful in predicting dry bulk freight rates. Following the interpretation of the Granger-causality model we observe a "feedback relationship" (Granger, 1969).

Dry bulk freight rates are said to be helpful in predicting stock market returns and vice versa. The Granger-Causality model implies that at specific points, stock market returns are helpful in predicting dry bulk freight rates, and at specific points, dry bulk freight rates are helpful in predicting stock market returns. The result is significant in the linear relationship throughout the time series. We know that stock markets react quickly to information about economic uncertainty. In periods of real economic shocks, stock market returns could potentially front-run a possible demand destruction response in the formation of shipping freight rates.

Earlier, we discussed how predictability could be due to time-varying risk premium. Business cycles and investors observed risk aversion determines the risk premium on stocks. If dry bulk freight rates significantly predict stock market returns, this could still be due to varying risk premium rather than "true predictability"[17]. This discussion raises questions as to whether we can confirm dry bulk freight rate's ability to predict stock market returns[18]. In the next section, we investigate whether this feedback relationship can be explained by time-varying risk premium.

5.3 Time-varying risk premium analyses

Our regression and Granger-causality analyses suggest that dry bulk freight rates do in fact predict stock market returns. However, the latter analysis also suggested a reverse or so-called feedback relationship. This raises concern whether the relationship is due to time-varying risk premium. If this is the case, predictability does not challenge the efficient market hypothesis, but rather reflects investors' risk aversion due to a changing economic environment. The two following subsections aim to answer hypothesis 3: *Shipping freight rates predictability of stock market returns is not due to time-varying risk premium.* Firstly, we introduce a correlation matrix between shipping freight rates and factors explaining time-varying risk premium. Secondly, we introduce a GARCH-In-Mean model with freight rates as an explanatory variable.

[17]We use «true predictability» when describing predictability that could lead to excess returns and constitute a challenge to the EMH.

[18]H2: Shipping freight rates predict stock market returns.

5.3.0.1 Correlation to risk premium variables

To investigate predictability due to TVRP, we begin by showing a correlation matrix between dry bulk freight rates and factors that systematically explain stock market returns. Even though the factors introduced by Chen et al. (1986) do not directly influence cash flows and dividends of companies, it changes the opportunity set for the investor. Hence, they reflect investors required risk premium to hold equity. For Industrial Production, we have chosen numbers for Norway, the US, and the EU, reflecting the stock indices we investigate. The inflation, bond spreads, and yield curve variables are US-related variables. However, the interdependency of stock markets and the importance of the US economy in financial markets should justify this.

Table 5.4: Pearsons correlation matrix of dry bulk freight rates and TVRP factors.

Table 5.4 shows a Pearson's correlation matrix of dry bulk freight rates and TVRP factors with p-values shown in the second table. Bulker = Clarksons Average Bulker earnings, Brent = Spot price for Brent Crude Oil, IP NO= Industrial Production for Norway, IP US = Industrial Production the US, IP EU = Industrial Production for EU, YC = US AAA Corporate Bond Yields – Treasury Bond Yields US, 10-3 = 10 Year US Treasury – 3 Month US Treasury, CPI = US Consumer Price Index. All variables are transformed into logarithmic returns. The data is retrieved from: Brent: Bloomberg Terminal, Industrial Production: (OECD, 2023), Yield Curve: (FRED, 2023c), 10 year – 3 months bond spread: (FRED, 2023a), Consumer price index: (FRED, 2023b).

Correlations	Bulk	Brent	IP NO	IP US	IP EU	RP	10-3	CPI
Bulker	1.000							
Brent	0.132**	1.000						
IP NO	-0.010	0.040	1.000					
IP US	0.1930***	-0.050	0.140**	1.000				
IP EU	0.074	-0.065	0.118*	0.775***	1.000			
YC	-0.121**	-0.227***	-0.067	0.009	-0.003	1.000		
10-3	-0.031	-0.031	0.006	-0.025	0.014	-0.036	1.000	
CPI	-0.006	0.033	0.065	0.070	0.053	0.045	-0.045	1.000

Note: *p<0.1; **p<0.05; ***p<0.01

P-Values	Bulk	Brent	IP NO	IP US	IP EU	RP	10-3	CPI
Bulker								
Brent	0.029							
IP NO	0.869	0.510						
IP US	0.001	0.411	0.021					
IP EU	0.223	0.285	0.051	0.000				
YC	0.046	0.000	0.270	0.882	0.961			
10-3	0.610	0.610	0.921	0.681	0.818	0.554		
CPI	0.921	0.587	0.285	0.249	0.383	0.459	0.459	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5.3 shows relatively low correlations between dry bulk freight rates and the TVRP-explaining factors. The highest correlation is found with industrial production in the US, oil price, and the yield spread between US corporate and treasury bonds. The correlations for these factors are positive and significant at a 95-99% confidence interval, indicating that an increase in these variables coincides with an increase in dry bulk freight rates. Both the positive and significant correlation of 0.193 towards industrial production in the US, and 0.132 toward the oil price can be explained by commodity demand in business cycles. Strong economic activity drives demand for both oil and dry bulk commodities yielding a significant positive correlation to demand for seaborne trade of dry bulk. Dry bulk freight rates have a negative significant correlation of 0.121 on a 95% confidence level to the spread between US corporate bond yields and treasury yields. In periods where the economy is strong, default spreads are low. In periods when the economy is weak, investors demand higher risk premium, and hence the spread widens. As the spread widens due to weaker economic conditions, dry bulk freight rates fall due to weaker demand for commodity shipping capacity. The negative correlation seems to have strengthened in recent years in comparison to Alizadeh Muradoglu (2014), which observes a negative correlation of 0.046 in their time series from 1989-2013.

The entirety of our results from the TVRP-correlation analysis coincides with the results by Alizadeh and Muradoglu (2014). They conclude that the correlations are low enough to support that there is no relationship between dry bulk freight rates and time-varying risk premium (TVRP). Schober, Boer, and Schwarte (2018) note that Pearson's correlations between 0.1 and 0.39 are considered weak correlations. We consider the correlations between dry bulk freight rates and TVRP to be relatively weak, taking these factors into account. This strengthens the hypothesis that the predictability dry bulk freight rates have on the stock market is not due to time-varying risk premium. However, the correlations are not negligible in our view, and further investigation is due in the next subsection.

5.3.0.2 GARCH-In-Mean-X

A GARCH model with conditional variance inserted into the mean-equation (see equations 3.6 and 3.7) allows us to test whether an increase in variance leads to an increase in return. If this relationship holds, it suggests that investors are demanding higher returns as economic uncertainty increases, also known as a risk-premium. In economic uncertainty or downturns, volatility increases. The risk premium should therefore increase due to weaker economic conditions and decrease in periods of stronger economic conditions (Fama and French, 1989). Similar to Driesprong et al. (2008) and Alizadeh and Muradoglu (2014), we suggest a specification to the model where dry bulk freight rates are introduced as an exogenous variable in the variance equation. This allows us to observe how stock market volatility is influenced by changes in dry bulk freight rates, as well as how the return equation responds to changes in dry bulk freight rate volatility. Equation 3.4 and 3.5 shows the return and variance equations for the stock indices used in our GARCH-In-Mean-X analysis.

Table 5.5: GARCH-In-Mean model for stock indices

Table 5.5 shows GARCH-In-Mean-X models for stock market returns, where dry bulk freight rates are introduced as an exogenous variable. Time series period: 12/03/1999 - 30/12/2022, Z-scores in parentheses. All models follow a GARCH(1,1) specification. Results are estimated using the Broyden–Fletcher–Goldfarb–Shanno algorithm. Error Distribution: Normal (Gaussian). All models are estimated using the statistical software Eviews 13.

	STOXX 600	S&P 500	OSEBX	MSCI World
X-Regressor	BULKER	BULKER	BULKER	BULKER
δ *Delta*	2.197**	4.290***	2.005**	3.796***
	(2.106)	(4.251)	(2.548)	(3.325)
μ *Mean*	3.90e-05***	3.85e-05***	5.53e-05***	3.68e-05***
	(4.53)	(5.32)	(4.538)	(4.542)
α *Alpha*	0.131***	0.231***	0.087***	0.198***
	(11.95)	(8.996)	(10.45)	(9.95)
β *Beta*	0.819***	0.722***	0.871***	0.746***
	(39.64)	(27.38)	(57.27)	(26.03)
π $Bulker_{t-1}$	−0.00065***	−0.00032***	−0.00085***	−0.00015**
	(−6.89)	(−2.898)	(−4.962)	(−1.92)
Observations	1243	1243	1243	1243
Log-Likelihood	2806.49	2998.45	2463.77	3034.84
Model	GARCH(1.1)	GARCH(1.1)	GARCH(1.1)	GARCH(1.1)
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table 5.5 shows that delta δ is positive and significant for all stock indices at a 95% and 99% confidence level. Delta can be interpreted as the risk premium, indicating that a change in the variance of stock market returns corresponds to a positive change in returns. Therefore, we can conclude that the risk premium is time-varying for all stock indices. α *Alpha* and β *Beta* are coefficients that reflect short and long-term volatility persistence

for the stock indices. They provide limited valuable insight to this analysis and will therefore not be further discussed. For π $Bulker_{t-1}$, we observe significant and negative coefficients for all stock indices at a 95% and 99% confidence level. The low and significant coefficients of π indicate that an increase in dry bulk rates leads to a slight reduction of volatility of the conditional variance equation 3.7. Since the exogenous regressor in our model is dry bulk freight rates lagged by one week, we can infer that dry bulk freight rates slightly predicts stock market volatility negatively. However, comparing the size of the π coefficients for all models to α *Alpha* and β *Beta* we observe that the influence is quite small. We confirm hypothesis 4[19], however we stress that the effect is quite small.

Our main question for the model in table 5.5 is inferring whether dry bulk freight rates predictability of stock market returns is due to time-varying risk premium or not. As π is negative and significant, it constitutes a negative effect on σ^2_{t-1} in the return equation 3.6. This is consistent with the findings by Alizadeh and Muradoglu (2014), and suggests that dry bulk freight rate's ability to predict the stock market is not due to time-varying risk premium.

Taking the correlation matrix as well as the GARCH-In-Mean-X model into account, we find convincing evidence suggesting that predictability is not due to time-varying risk premium[20]. This challenges the efficient market hypothesis by Fama (1970), because it indicates that an investor can buy or sell his or her portfolio of stocks and achieve excess returns based on information that all investors have access to.

Challenging the EMH leads us to the discussion of the Gradual Diffusion Hypothesis (GDH) by Hong and Stein (1999). As introduced in subsection 2.4, the hypothesis explains key reasons why the efficient market hypothesis (EMH) fails to hold in particular assets. In the case of shipping freight rates and the stock market, informational bias could explain the deviation from EMH. As information on dry bulk freight rates does not directly influence the cash flow of the broader stock market, market participants might find the information not relevant to influence their portfolio decisions. The disability to recognize the importance of shipping freight rates as a leading indicator of economic activity lead to predictability of broad stock market returns.

[19] H4: Shipping freight rates predict stock market volatility.

[20] H3: Shipping freight rates predictability of stock market returns is not due to time-varying risk premium.

5.4 DCC-GARCH analysis

In the previous sections, we have established that dry bulk freight rates have explanatory and predictive power on stock market returns. We have also concluded that the relationship is not due to time-varying risk premium. However, the result of the Granger-Causality analysis suggested a feedback relationship between the two variables. This raises questions about the dynamics and complexity of this relationship. This subsection examines these dynamics, with the goal of enlightening the time-varying nature of the relationship. Section 5.4 aims to answer hypothesis 5: *The relationship between Shipping freight rates and stock market returns is time-varying.*

To infer the strength and direction of the relationship in different market conditions, we introduce a Dynamic Conditional Correlation GARCH (DCC-GARCH). As previously discussed in subsection 3.3, this multivariate extention to the GARCH model allows us to observe whether there is a dynamic relationship, the strength of such a relationship, and the observed correlation at different points of time in our time series. Similar to the GARCH-In-Mean model we perform the DCC-GARCH on weekly frequency time series in order to capture any shorter-term complexity of the relationship, as well as ensuring that the GARCH model provides the best possible estimates following the discussion of data frequency in subsection 4.3.

Table 5.6: Dynamic Conditional Correlation - GARCH

Table 5.6 shows DCC-GARCH models where dry bulk freight rates and the different stock indices are both dependent variables. Numbers (1) and (2) corresponds to which of the dependent variables the coefficients belong to. Time series period: 12/03/1999 - 30/12/2022, T-values in parentheses. All models follow a DCC-GARCH(1.1) specification. Results are estimated using the Broyden–Fletcher–Goldfarb–Shanno algorithm. Error Distribution: Normal (Gaussian). All models are estimated using the statistical software RATS Econometrics from Estima.

Dependent Variable (1)	STOXX 600	S&P 500	OSEBX	MSCI World
Dependent Variable (2)	BULKER	BULKER	BULKER	BULKER
Model ID.	(I)	(II)	(III)	(IV)
μ $Mean(1)$	0.001**	0.002***	0.002***	0.002***
	(2.407)	(4.405)	(2.669)	(4.021)
μ $Mean(2)$	0.003***	0.003***	0.003***	0.003***
	(2.979)	(2.986)	(2.859)	(3.110)
ω $Omega(1)$	0.000***	0.000***	0.000***	0.000***
	(3.812)	(4.624)	(3.561)	(3.814)
ω $Omega(2)$	0.000*	0.000	0.000*	0.000*
	(1.658)	(1.600)	(1.752)	(1.691)
α $Alpha(1)$	0.207***	0.259***	0.120***	0.222***
	(6.142)	(7.527)	(5.813)	(7.311)
α $Alpha(2)$	0.117***	0.120***	0.120***	0.120***
	(6.220)	(6.324)	(6.337)	(6.281)
β $Beta(1)$	0.715***	0.708***	0.824***	0.727***
	(15.31)	(22.37)	(27.55)	(21.25)
β $Beta(2)$	0.894***	0.892***	0.892***	0.892***
	(60.23)	(58.30)	(61.18)	(60.40)
α $DCCAlpha$	0.035*	0.018	0.027***	0.021**
	(1.810)	(1.311)	(2.848)	(2.028)
β $DCCBeta$	0.845***	0.576	0.951***	0.958***
	(4.794)	(1.422)	(54.71)	(47.69)
Observations	1243	1243	1243	1243
Log Likelihood	4648.3	4840.4	4305.6	4883.6
Model	DCC(1.1)	DCC(1.1)	DCC(1.1)	DCC(1.1)
Estimation Algorithm	BFGS	BFGS	BFGS	BFGS
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 5.6 presents the results of the various DCC-GARCH (1.1) models between stock market indices and dry bulk freight rates. μ $Mean(1)$ and (2) is the constant term in the return equation of the separately estimated GARCH models from equation 3.4. ω $Omega(1)$ and (2) is the constant term in the variance equation from equation 3.5. Interpretation of these variables give no valuable insight to our analysis regarding dynamic

relationships and will not be further discussed.

α $Alpha(1)$ indicates the sensitivity of stock market volatility followed by a volatility shock to itself. Across all stock indices, we observe that a volatility shock in $t-1$ lead to increased volatility in $t=0$. This is significant at the 99% level. Similarly, α $Alpha(2)$ indicates the sensitivity of dry bulk rate volatility followed by a volatility shock on itself. This is significant at the 99% level, which means that a volatility shock in $t-1$ leads to increased volatility in $t=0$. α $Alpha(2)$ should return the same coefficient for all models since the dry bulk freight rate is identical for all models. However, a slight insignificant deviation occurs due to the calculation precision of the matrices in the statistical software.

β $Beta(1)$ and (2) are positive and significant at a 99% level for all stock indices and dry bulk rates. This implies that the variables have a strong tendency to follow their momentum in terms of volatility. Increasing volatility in $t-1$ often leads to increased volatility in $t=0$ and vice versa. The coefficients are slightly higher for dry bulk freight rates than for the stock indices, indicating that volatility momentum is slightly stronger for the former. If Alpha and Beta sum to above one, the conditional likelihood can increase indefinitely, and the non-conditional volatility will become negative. As mentioned in subsection 3.4, this violates the condition of positivity for DCC-GARCH resulting in coefficients that we cannot infer correctly. For our estimated models, we note that Alpha and Beta coefficients sum to less than one for both stock indices and dry bulk freight rates. This suggests that the model is estimated correctly, and can trust that results are not spurious.

α $DCCAlpha$ and β $DCCBeta$ are the most important coefficients in table 5.6. They provide answer to whether a dynamic conditional correlation exists between freight rates and the stock market. For all models (I-IV), α $DCCAlpha$ and β $DCCBeta$ sum to less than one satisfying the condition of equation 3.15. Significant and positive α $DCCAlpha$ indicates the existence of a short-term volatility effect between dry bulk rates and the stock market. The coefficient is estimated by measuring the persistence of the standardized residuals from $t-1$. Positive coefficients indicate that a short-term increase in volatility for dry bulk rates leads to a short-term increase in volatility in the stock markets and vice versa. α $DCCAlpha$ are significant and positive for STOXX 600 at a 90% confidence level, OSEBX at a 99% level, and MSCI World at a 95% level. Thus indicating that the volatility of these markets increases when volatility in dry bulk freight rates increase and vice versa. Results for S&P 500, however show no significance and we cannot establish a dynamic correlation between this market and dry bulk freight rates.

β $DCCBeta$ measures the long-term volatility effects following a shock in the conditional correlation. While α $DCCAlpha$ provides the contribution of realized correlation from the last period, β $DCCBeta$ measures the contribution based on the correlation matrix of all previous periods. Positive coefficients indicate that a long-term increase in volatility for dry bulk rates leads to a long-term increase in volatility in the stock markets and vice versa. β $DCCBeta$ is significant and positive for STOXX 600, OSEBX, and MSCI World at a 99% confidence level. The effect seems to be largest for OSEBX and MSCI World. For the model between dry bulk freight rates and S&P 500, however, the coefficient is not significant. As both α $DCCAlpha$ and β $DCCBeta$ are insignificant, we conclude that there is no statistical evidence to suggest that S&P 500 and dry bulk freight rates have a dynamic conditional correlation.

The results from models (I), (III), and (IV) indicate that there is a positive dynamic conditional correlation, both short and long-term, between dry bulk freight rates and STOXX 600, OSEBX, and MSCI World. This suggests that periods of increased volatility in dry bulk shipping freight rates coincide with periods of increased volatility in stock markets. In periods with increased real economic uncertainty, stock markets experience higher volatility (Bekaert and Hoerova, 2014). The same reasoning can be applied to freight rates. Real economic uncertainty increases uncertainty for shipping demand and hence induces higher volatility (Lim et al., 2019). Results from table 5.6 confirms the hypothesis that the relationship is time-varying[21]. However, it leaves us with the question of how the dynamics behave through time. To further investigate this, we extract the models dynamic correlation coefficients from equation 3.10.

[21] *H5: The relationship between Shipping freight rates and stock market returns is time-varying.*

Figure 5.1: Conditional Correlations

Figure 5.1 displays a time series graph for the extracted conditional correlations from our DCC-GARCH models on weekly frequency. Model (II) is excluded due to low significance. Correlations are extracted from our DCC-GARCH models estimated in RATS Econometrics by Estima. The y-axis shows conditional correlations with scales from 1.0 to -1.0.

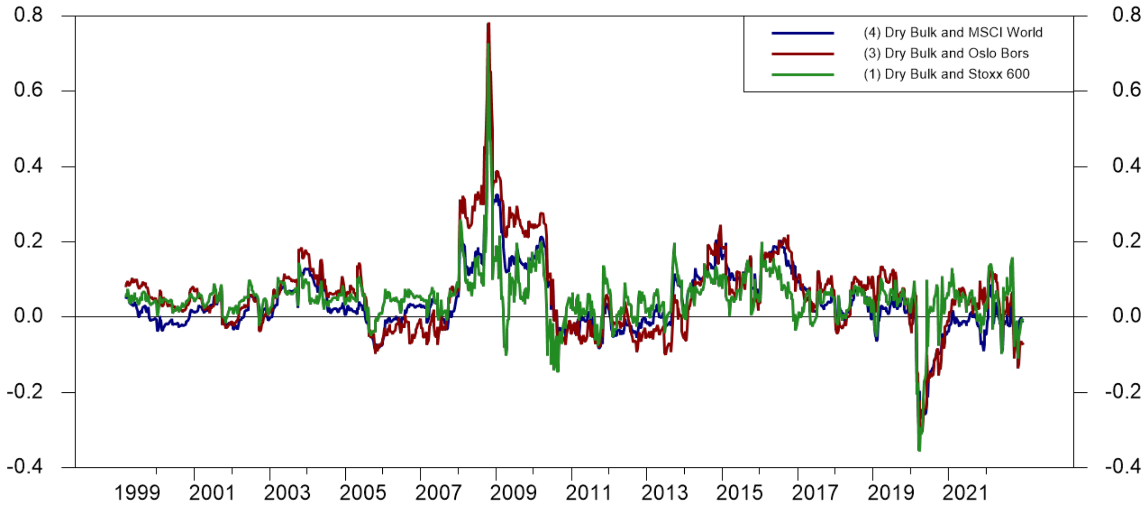


Figure 5.1 displays extracted dynamic conditional correlations as shown in equation 3.10 between dry bulk freight rates and stock indices over the time series for models (I), (III), and (IV). Model (II) is excluded due to its lack of significance for S&P 500. Model (I) has a low significance for α $DCCAlpha$, which might explain the volatile behavior in figure 5.1 compared to the other two models. Our general observation is that most correlations range between 0 and 0.2, suggesting a positive dynamic correlation. We also observe that the correlations are to a large degree similar for all stock markets. This is no surprise given the interdependency among stock market returns.

In periods of known economic uncertainty, we observe that the relationship increases in strength. During the period of the financial crisis in 2008-2010, the correlations between dry bulk freight rates and stock indices became rather large, reaching a peak of almost 0.8 in the fall of 2008. The rapid decrease in shipping capacity demand due to the financial crisis, combined with capacity oversupply, caused dry bulk freight rates to tumble at the end of 2008. At the same time stock indices worldwide collapsed due to fear of recession and increasing risk aversion among investors. This resulted in a strong positive relationship between freight rates and stock indices.

As observed in figure 5.1, the correlation turned negative during the Covid-19 pandemic of 2020. In the case of dry bulk freight rates, the shock was to a high degree freight rate specific. Rather than being influenced directly by longer-term supply or demand for capacity, freight rates fell due to the uncertainty of how a global pandemic would affect the freight market (Park et al., 2023). This resulted in dry bulk freight rates quickly reverting to a positive growth rate, since the demand for capacity of dry bulk transport did not disappear. At the same time stock market returns fell sharply due to the uncertainty of how large the economic impact of the pandemic would be. Risk aversion among investors in stock markets was large, and stock markets continued to tumble while freight rates did not. This resulted in a negative correlation at the beginning of the Covid-19 pandemic before turning positive again in late 2020. The events of the financial crisis and Covid-19 pandemic shows the sensitivity and complexity of the relationship between dry bulk freight rates and stock markets.

From our DCC-Analysis, we confirm the fact that there is a dynamic relationship between dry bulk freight rates and stock market returns. We also observe that the correlation tends to be positive. However, periods of economic uncertainty result in stronger correlations, both negative and positive. This raises interesting questions about the complexity of the relationship, which warrants further research.

6 Conclusion

This thesis aims to enlighten the relationship between shipping freight rates and stock market returns, establishing whether the former predicts the latter. Using a time series from 2000-2022, results from OLS regression on monthly frequency suggests that dry bulk freight rates predict stock market returns with a lag for indices tracking the broad Norwegian, European, US, and World stock markets. We find low or no significant predictive power for tanker freight rates and a general freight rate index tracking multiple shipping segments. These freight rate indices are thus excluded from further analyses.

Our Granger-Causality analysis further suggest that dry bulk freight rates are helpful in predicting stock market returns for all stock markets investigated in this paper. However, we infer a feedback relationship indicating that stock market returns are also helpful in predicting dry bulk freight rates at certain points in our time series.

A Pearson correlation matrix including real economic variables and a GARCH-In-Mean model reveal that dry bulk shipping freight rate's ability to predict stock market returns is not due to time-varying risk premium. Thus, dry bulk freight rates ability to predict stock market returns constitute a challenge to the efficient market hypothesis. Further more, the latter model suggests that an increase in dry bulk freight rates influences stock market volatility negatively. Increasing economic activity coincides with steadily increasing stock market returns, while economic uncertainty and recession coincide with falling dry bulk freight rates and increasing stock market volatility. However, we note that the influence is relatively small, which is no surprise given the vast array of factors explaining stock market volatility.

We reveal the existance of a time-varying relationship between dry bulk freight rates and the MSCI World Index, the Norwegian Oslo Stock Exchange Index, and the European Stoxx 600 Index. However, we find no significant evidence for such a relationship between dry bulk freight rates and the US S&P 500 Index. The DCC-GARCH model reveals the existence of a positive and significant relationship in both the short and long-term volatility dynamics between dry bulk rates and stock indices. Throughout the series, the mean correlation is moderately positive. However, during the financial crisis, the correlation became very strong as the growth rate of both variables fell sharply. During the Covid-19 pandemic, the relationship measured by correlation turned negative. This highlights the need for further research regarding the complexity of the relationship, particularly in light of the complex nature of supply and demand in shipping capacity.

We conclude that dry bulk freight rates predict stock market returns. However, we nuance the conclusion with the fact that only one of the shipping freight indices where significant, and we urge caution to the fact that the OLS model only show moderate significance. The inference of a feedback relationship within the Granger-Causality model not due to time-varying risk premium is also a factor to consider. Despite this, our conclusion for the research question is that dry bulk freight rates do predict stock market returns.

Lastly we would like to address some weaknesses and areas that we suggest for further research. Our thesis performed empirical analysis on the linear relationship between shipping freight rates and stock market returns. This prohibits the inference of non-linear relations which could exists between these two variables. Further research should aim do dive deeper into the non-linear relationship in light of periods where financial uncertainty affects both dry bulk freight rates and stock market returns. Further research should also aim to investigate in which situations stock market returns could lead dry bulk freight rates.

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Appendix

A1 Stationarity, ARCH-Effects, Multicollinearity, Autocorrelation and Heteroskedasticity

A1.0.1 Stationarity

Table A1.1: Augmented Dickey Fuller Test (ADF) – Monthly data

Table A1.1 shows Augmented Dickey Fuller tests (Dickey and Fuller, 1979) of variables on monthly log transformed growth rates for stock indices and shipping freight rates to check for stationarity.

H_0: *Unit Root (non stationarity),* H_a: *No unit Root (Stationarity)*	P-Value	F-Stat
BULKER	$<0.01^{***}$	-7.2332
TANKER	$<0.01^{***}$	-6.5181
CLARKSEA	$<0.01^{***}$	-6.0165
SXXP	$<0.01^{***}$	-5.6308
SPX	$<0.01^{***}$	-5.5313
OSEBX	$<0.01^{***}$	-6.3588
MXWO	$<0.01^{***}$	-5.4714

Note: *p<0.1; **p<0.05; ***p<0.01

Table A1.2: Augmented Dickey Fuller Test (ADF) – Weekly data

Table A1.2 shows Augmented Dickey Fuller tests (Dickey and Fuller, 1979) of variables on weekly log transformed growth rates for stock indices and shipping freight rates to check for stationarity.

H_0: *Unit Root (non stationarity),* H_a: *No unit Root (Stationarity)*	P-Value	F-Stat
BULKER	$<0.01^{***}$	-10.036
TANKER	$<0.01^{***}$	-11.96
CLARKSEA	$<0.01^{***}$	-10.996
SXXP	$<0.01^{***}$	-11.178
SPX	$<0.01^{***}$	-11.43
OSEBX	$<0.01^{***}$	-10.377
MXWO	$<0.01^{***}$	-11.212

Note: *p<0.1; **p<0.05; ***p<0.01

A1.0.2 ARCH-Effects

Table A1.3: ARCH-effects test for weekly variables

Table A1.3 shows a Lagrange Multiplier-Test for conditional heteroskedasticity, based on Engle (1982) to check for ARCH-effects. Performed on the first lag of each variable.

H_0: No ARCH Effects present, H_a: ARCH Effects present	P-Value	LM-Stat
BULKER	$<0.01^{***}$	151.03
TANKER	$<0.01^{***}$	45.35
CLARKSEA	$<0.01^{***}$	73.31
SXXP	$<0.01^{***}$	29.85
SPX	$<0.01^{***}$	112.13
OSEBX	$<0.01^{***}$	123.97
MXWO	$<0.01^{***}$	101.41

Note: *p<0.1; **p<0.05; ***p<0.01

A1.0.3 Multicollinearity

Table A1.4: Variance Inflation Factors (VIF) for all independent variables

Table A1.4 shows a Variance Inflation Factor test for Multicollinearity for all independent variables used in our regression models.

Threshold Value = 2.5	VIF-Value
BULKER_t	1.108
BULKER_{t-1}	1.157
BULKER_{t-2}	1.166
BULKER_{t-3}	1.163
BULKER_{t-4}	1.112
TANKER_t	1.047
TANKER_{t-1}	1.065
TANKER_{t-2}	1.090
TANKER_{t-3}	1.066
TANKER_{t-4}	1.048
CLARKSEA_t	1.052
CLARKSEA_{t-1}	1.081
CLARKSEA_{t-2}	1.098
CLARKSEA_{t-3}	1.082
CLARKSEA_{t-4}	1.053
$p = 12$ Lags	

Note: *p<0.1; **p<0.05; ***p<0.01

A1.0.4 Autocorrelation

Table A1.5: Autocorrelation test for all regression models

Table A1.5 shows a test for Autocorrelation in residuals for all regression models without HAC standard errors up to lag 12. The test performed is a Breusch-Godfrey test (Breusch, 1978; Godfrey, 1978).

H_0: There is no serial correlation up to p, H_a: There is serial correlation up to p	P-Value
$SXXP_t \sim BULKER_t \cdots + BULKER_{t-4}$	0.7558
$SPX_t \sim BULKER_t \cdots + BULKER_{t-4}$	0.1309
$OSEBX_t \sim BULKER_t \cdots + BULKER_{t-4}$	0.6956
$MXWO_t \sim BULKER_t \cdots + BULKER_{t-4}$	0.3923
$SXXP_t \sim TANKER_t \cdots + BULKER_{t-4}$	0.5074
$SPX_t \sim TANKER_t \cdots + BULKER_{t-4}$	0.4390
$OSEBX_t \sim TANKER_t \cdots + BULKER_{t-4}$	0.5260
$MXWO_t \sim TANKER_t \cdots + BULKER_{t-4}$	0.5001
$SXXP_t \sim CLARKSEA_t \cdots + BULKER_{t-4}$	0.4029
$SPX_t \sim CLARKSEA_t \cdots + BULKER_{t-4}$	0.2822
$OSEBX_t \sim CLARKSEA_t \cdots + BULKER_{t-4}$	0.3301
$MXWO_t \sim CLARKSEA_t \cdots + BULKER_{t-4}$	0.3256
$p = 12$ Lags	

Note: *p<0.1; **p<0.05; ***p<0.01

A1.0.5 Heteroskedasticity

Table A1.6: Heteroskedasticity test for all regression models

Table A1.6 shows a test for Heteroskedasticity in residuals for all regression models run without HAC standard errors. The test performed is a Breusch-Pagan test (Breusch and Pagan, 1979).

H_0 = Homoskedasticity in the error term, H_a = Heteroskedasticity in the error term	BP-Stat	P-Value
$SXXP_t \sim BULKER_t \cdots + BULKER_{t-4}$	19.639	0.001***
$SPX_t \sim BULKER_t \cdots + BULKER_{t-4}$	21.489	0.001***
$OSEBX_t \sim BULKER_t \cdots + BULKER_{t-4}$	19.273	0.001***
$MXWO_t \sim BULKER_t \cdots + BULKER_{t-4}$	24.439	0.000***
$SXXP_t \sim TANKER_t \cdots + BULKER_{t-4}$	3.8596	0.570
$SPX_t \sim TANKER_t \cdots + BULKER_{t-4}$	1.8041	0.876
$OSEBX_t \sim TANKER_t \cdots + BULKER_{t-4}$	3.2873	0.656
$MXWO_t \sim TANKER_t \cdots + BULKER_{t-4}$	2.374	0.795
$SXXP_t \sim CLARKSEA_t \cdots + BULKER_{t-4}$	15.203	0.009***
$SPX_t \sim CLARKSEA_t \cdots + BULKER_{t-4}$	11.609	0.04**
$OSEBX_t \sim CLARKSEA_t \cdots + BULKER_{t-4}$	17.446	0.004***
$MXWO_t \sim CLARKSEA_t \cdots + BULKER_{t-4}$	15.041	0.01***
$p = 12$ Lags		

Note: *p<0.1; **p<0.05; ***p<0.01

A2 Additional Regressions

Table A2.1: Regression table of stock returns and tanker rates

Table A2.1 shows regression models between stock indices and tanker freight rates contemporaneous and lagged 1-4. The regressions are performed on monthly data in the period April 2000 – December 2022. The numbers given in parenthesis are t-statistics for the coefficients. The tests are run with HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 6.0000). All models are estimated using the statistical software R.

	STOXX 600	S&P 500	Oslo Stock Exchange	MSCI World
	(1)	(2)	(3)	(4)
β $Tanker_{t=0}$	−0.006	−0.003	−0.015	−0.005
	(−0.396)	(−0.289)	(−0.779)	(−0.441)
β $Tanker_{t-1}$	−0.003	0.003	−0.018	0.000
	(−0.232)	(0.284)	(−0.763)	(0.030)
β $Tanker_{t-2}$	−0.004	−0.015	−0.006	−0.012
	(−0.403)	(−1.529)	(−0.485)	(−1.223)
β $Tanker_{t-3}$	−0.002	0.002	−0.014	0.000
	(−0.184)	(0.331)	(−1.001)	(0.000)
β $Tanker_{t-4}$	0.001	0.005	0.007	0.002
	(0.112)	(0.663)	(0.493)	(0.322)
Constant	0.007	0.003	0.006	0.002
	(0.200)	(1.242)	(1.192)	(0.741)
Observations	273	273	273	273
R^2	0.001	0.009	0.010	0.005
Adjusted R^2	−0.016	−0.008	−0.008	−0.012
Residual Std. Error (df = 267)	0.054	0.045	0.078	0.046
F Statistic (df = 5; 267)	0.095	0.535	0.566	0.316

Note: *p<0.1; **p<0.05; ***p<0.01

Table A2.2: Regression table of stock returns and ClarkSea rates

Table A2.2 shows regression models between stock indices and ClarkSea freight rates contemporaneous and lagged 1-4. lag 1-4. The regressions are performed on monthly data in the period April 2000 – December 2022. The numbers given in parenthesis are t-statistics for the coefficients. The tests are run with HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 6.0000). All models are estimated using the statistical software R.

	STOXX 600	S&P 500	Oslo Stock Exchange	MSCI World
	(1)	(2)	(3)	(4)
$\beta\ ClarkSea_{t=0}$	0.024	0.017	0.044	0.020
	(0.522)	(0.509)	(0.596)	(0.506)
$\beta\ ClarkSea_{t-1}$	0.029	0.046	0.020	0.038
	(0.988)	(1.546)	(0.352)	(1.262)
$\beta\ ClarkSea_{t-2}$	0.019	−0.002	0.025	0.004
	(0.858)	(−0.079)	(0.792)	(0.209)
$\beta\ ClarkSea_{t-3}$	0.011	0.020	−0.027	0.015
	(0.490)	(1.018)	(−0.963)	(0.766)
$\beta\ ClarkSea_{t-4}$	0.045^{**}	0.037^{**}	0.056	0.036^{**}
	(2.120)	(2.078)	(1.577)	(2.036)
Constant	0.000	0.003	0.006	0.002
	(0.044)	(1.013)	(0.300)	(0.547)
Observations	273	273	273	273
R^2	0.024	0.038	0.017	0.029
Adjusted R^2	0.006	0.020	−0.002	0.011
Residual Std. Error (df = 267)	0.054	0.044	0.078	0.046
F Statistic (df = 5; 267)	1.333	2.083	0.897	1.600

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

A3 Descriptive Statistics

Table A3.1: Descriptive statistics of TVRP Variables

Table A3.1 shows descriptive statistics for all variables included in the correlation matrix analysis in chapter 5.3.0.1.

	10-3	Brent	Bulk	CBOND	IP EU	IP NO	IP US	CPI
Mean	0.008	0.005	0.002	-0.002	0.001	0	0	0.041
Median	-0.005	0.014	0.017	-0.006	0.002	0.001	0	0
Maximum	2.197	0.357	0.72	0.373	0.125	0.068	0.071	5.637
Minimum	-3.332	-0.634	-1.054	-0.375	-0.221	-0.051	-0.166	-3.957
Std. Dev.	0.445	0.1	0.181	0.093	0.022	0.016	0.014	0.944
Skewness	-0.481	-1.231	-0.704	0.032	-3.467	-0.018	-5.874	0.363
Kurtosis	21.067	9.422	8.256	4.466	48.715	4.509	78.495	9.340
Jarque-Bera	3723.6	538.0	336.7	24.4	24319.3	25.9	66401.7	463.1
P-value	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
n	273	273	273	273	273	273	273	273

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A3.2: Descriptive statistics for weekly variables

Descriptive table of weekly variables from 12/03/1999 - 30/12/2022. BULKER is the Clarksea average earnings index for bulker freight rates, CLARKSEA is general ClarkSea Index, TANKER is the Clarksea average earnings index for bulker freight rates, OSEBX is Oslo Stock Exchange index, SPX is S&P 500 index, SXXP is STOXX 600 index, MXWO is MSCI World index.

	BULKER	CLARKSEA	MXWO	OSEBX	SPX	SXXP	TANKER
Mean	0.000739	0.000841	0.000650	0.001554	0.000887	0.000287	0.001095
Median	0.003938	0.002433	0.002481	0.004103	0.002339	0.002167	-0.005671
Maximum	0.398833	0.659965	0.116367	0.187916	0.114237	0.137440	1.203895
Minimum	-0.460228	-0.315972	-0.223809	-0.294482	-0.200837	-0.267467	-0.487600
Std. Dev.	0.067385	0.056933	0.024428	0.038114	0.025378	0.029190	0.122083
Skewness	-0.202407	1.260889	-1.092780	-1.193775	-0.848219	-1.301895	1.645874
Kurtosis	8.174882	22.92960	11.99788	11.03055	9.873343	13.59941	16.27075
Jarque-Bera	1395.437	20900.44	4440.537	3635.262	2595.837	6169.795	9682.371
P-value	0.0	0.0	0.0	0.0	0.0	0.0	0.0
n	1243	1243	1243	1243	1243	1243	1243

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

A4 Lag selection for Granger-Analysis

Table A4.1: Akaikes Information Criteria for Granger Causality

Determination of best lag fit based on Akaikes Information Criteria based on a VAR model between dry bulk freight rates and selected stock market indices.

Granger-Causality model Number	(1)	(3)	(5)	(7)	(9)	(11)
Lag 0	-3.929323	-3.871764	-3.538773	-2.812852	-5.210390	-2.340309
Lag 1	-4.009557	-3.952458	-3.616401	-2.920584	-5.351532*	-2.430656
Lag 2	-4.065876	-4.022803	-3.678759	-2.986208	-5.339943	-2.476548
Lag 3	-4.064834	-4.013648	-3.658017	-2.961213	-5.340601	-2.474320
Lag 4	-4.093346*	-4.057535*	-3.714877*	-3.017155*	-5.320204	-2.497229*
Lag 5	-4.067607	-4.033660	-3.699776	-2.994510	-5.312311	-2.487662
Lag 6	-4.084159	-4.050394	-3.701692	-2.998031	-5.306230	-2.465199
Lag 7	-4.077636	-4.035551	-3.680937	-2.977765	-5.287510	-2.444821
Lag 8	-4.071966	-4.022326	-3.665984	-2.964191	-5.276496	-2.446003
Lag 9	-4.076466	-4.029388	-3.672025	-2.970059	-5.279386	-2.449758
Lag 10	-4.063104	-4.019084	-3.666284	-2.960455	-5.257939	-2.435413
Lag 11	-4.046405	-4.003238	-3.655259	-2.944405	-5.247208	-2.432925
Lag 12	-4.024495	-3.985937	-3.643578	-2.936686	-5.244319	-2.441034

*Best fit selected on AIC = **