Volatility modelling in the shipping industry

by

Yang YANG

A thesis submitted for the degree of

Doctor of Philosophy in Finance

University of Nottingham Ningbo China

September 2021

Contents

Contents 2

List of Figures 4

List of Tables 5

1 Introduction 1

2 Methodology 15

2.1 Volatility modelling 15

2.2 Volatility Forecasting 20

3 Forecasting shipping freight rate volatility 23

3.1 Introduction 23

3.2 Baltic Dry Index 25

3.3 Literature review 29

3.4 Data description and summary statistics 32

3.5 Empirical analysis 34

3.5.1 In-sample estimation results 34

3.5.2 Out-of-sample predictions 36

3.6 Conclusion 38

3.7 Limitation 39

4 Impact of crude oil price on shipping freight rate **49**

4.1 Introduction 49

4.2 Literature review 52

4.3 Data description and summary statistics 56

4.4 Empirical analysis 59

4.4.1 In-sample estimation results 59

4.4.2 Out-of-sample predictions 60

4.5 Conclusion 63

4.6 Limitation 64

5 Concluding Remarks **86**

References **89**

List of Figures

1 The evolution of BDI index from 1999-2015. 41

2 (a) Historical index prices for BDI, BDTI and BDCI; (b) Historical price for crude oil price 66

List of Tables

1 Summary statistics of the seven indices 42

2 Sample period of the seven indices 43

3 In-sample estimation results 44

4 Volatility forecasting performance for 1-, 5- and 22-day ahead 46

5 The superior predictive ability (SPA) test of Hansen (2005) 47

6 Summary of the Diebold and Mariano (1995) test results 48

7 Descriptive statistics of Brent and WTI oil spot price 67

8 The in-sample volatility estimation result with HAR and HAR-X models . . 68

9 The in-sample volatility estimation result with GJR-GARCH and GJR-GARCH-X models 70

10 The in-sample volatility estimation result with GARCH and GARCH-X models 72

11 The in-sample volatility estimation result with EGARCH and EGARCH-X models 74

12 Out-of-sample volatility forecasting performance with HAR and HAR-X models 76

13 Out-of-sample volatility forecasting performance with GJR-GARCH and GJR-GARCH-X models 80

14 Out-of-sample volatility forecasting performance with GARCH and GARCH-X models 82

15 Out-of-sample volatility forecasting performance with EGARCH and EGARCH-X models 84

Acknowledgments

First and foremost, I would like to express my deepest gratitude to my supervisors, Professor Xiaoquan Liu, Dr. Conghua Wen, and Dr. Xiafei Li, for their excellent supervision and scholarly guidance through every stage of my PhD studies. I extend my thanks to all my internal assessors, particularly to Dr. Chong You during my first year, Dr. Jing Bie during my second year, and Dr. Xiaogang Bi and Dr. Ying Jiang during my third year. They have all made valuable comments and suggestions crucial at every stage of the writing process of my thesis. Last but not least, I would like to thank my parents, Shizheng Yang and Yuying Zhang, my husband Yi Shu, my son, Tairui Shu, for their unconditional love and support throughout my PhD study. They are my source of motivation and strength whenever I feel despair and become discouraged.

Abstract

This thesis focuses on volatility estimating, modelling, and forecasting by using daily data from the shipping freight market. The topic is studied via two chapters, each with a different focus. After introducing the methodologies to be adopted in this thesis in Section 2, Section 3 introduces the first chapter which explores the performance of three types of mathematical models in volatility prediction by running a horserace among the forecasting precision of five different models, including the Two-component model, the traditional GARCH model, the GJR-GARCH model, the EGARCH model, and the heterogeneous autoregressive (HAR) model. In addition, the forecasting precision is evaluated via 4 different metrics, RMSE, MAE, MAPE, and Mincer-Zarnowitz regress test's R^2. Using the data of seven indices of the shipping freight rate index, ranging from August 1998, to August 2013, this chapter finds that the Two-component model has the best prediction power for the first five indices, while the HAR model ranks second. In addition, the GARCH model has better forecasting capability than the EGARCH model. This is confirmed by Hansen (2005)'s superior predictive ability (SPA) test and Diebold and Mariano (1995)'s pair-wise test.

The second chapter investigates whether the oil index affects the modelling and forecasting of the volatility dynamics for the seven different shipping indices. Using the same dataset as in the first chapter, the addition of the Brent oil index or the West Texas International (WTI) crude oil index is incorporated into the HAR as well as the GARCH-family models to explore whether oil index plays a statistically significant role in volatility modelling and forecasting of the seven shipping freight indices. The in-sample estimation results show that incorporating the oil index could better specify the volatility dynamics for the

shipping freight indices especially for the HAR-X model. Furthermore, the augmented HAR and GARCH-family models are found to outperform their original models in predicting the future volatility. Overall, the results of my thesis aim to provide linkage between crude oil prices and shipping index returns that benefits short-term participants, such as ship owners, charterers, and operators. Accordingly, the use of the appropriate model leads to better forecasting results, thus other players who indirectly participate in the shipping industry, such as investment banks and policy makers, can also optimize their strategies in this market.

Chapter 1

Introduction

Shipping is one of the most important sectors of the world economy as 90% of world trade is transported by sea. Therefore, it is considered a leading indicator of world economic activity (Kilian, 2009). Dry bulk cargo shipping market is a major component of the international shipping market, and it is well known for its properties of high volatility due to the high uncertainty of volume and patterns associated with worldwide trade, the global economy, and government policy. Although it is considered to be a highly competitive market and the volatility of freight rates makes business trends hard to be predicted, it still provides good opportunities to market participants like carriers, operators, and even hedge fund managers.

In the period from 1999 to 2015, the world bulk shipping market experienced an intensive change, especially after 2003 and after the 2007-08 global financial crisis. The boom and retrogression of the market was beyond the expectations of all market participants. Hence, it is worth investigating the volatile properties of freight rates for dry bulk vessels under complicated market conditions.

The Baltic Dry Index (BDI), together with the previous indicator, named Baltic Freight Index (BFI) established in 1985, have received great interest from market participants like ship-owners, vessel operators, hedge fund managers, derivative traders, as well as credit institutions that provide financial support for the construction of vessels, and to maritime operators. The BDI, published by the Baltic Exchange on a daily basis, is an aggregated index calculated by the Baltic Exchange Capesize Index (BCI), the Baltic Exchange Panamax Index (BPI), the Baltic Exchange Supramax Index (BSI), and the Baltic Exchange Handysize Index (BHSI). Each of the sub-indices is based on 30 pre-selected benchmark rates of shipping routes.

The Baltic index values are calculated based on a panel of competitive shipbrokers not trading on their own account, but estimating the prevailing open market rate per route on a daily basis (EU, 2010). The Baltic Exchange compiles and publishes forward rates and options volatilities on the freight derivatives market for the purpose of mark to market and Central Counterparty Clearing House (CCP) margin calls.

During past decades, a considerable amount of literature related to the features of freight rates, the shipping spot market, and the BDI, has been published. It includes issues concerning seasonality, cyclical features, and the unique relationship with macroeconomic trends. Seminal literature relates to freight rates investigations and includes works and publications such as Kavussanos and Alizadeh-M (2001), Adland and Cullinane (2005), Adland and Cullinane (2006), Batchelor et al. (2007) and Lu et al. (2008). More recently, spectral analysis has been the focus of literature, such as Gong et al. (2013), and Papailias et al. (2013).

The BFI, identified above as an accurate indicator of the volatility of the dry bulk shipping market, has been a topic of interest in the shipping industry. In recent years, more researchers have begun to focus on this topic and tried to identify the internal rules and variation patterns by means of econometric measures, which will help to forecast short-term trends and avoid risks.

Cullinane and Gong (2002) provide a simple and accurate model for speculation through the application of the Box-Jenkins approach to time series analysis and forecasting. Due to the limitation of data, they only reach an ARIMA (3,1,0) model. Veenstra and Franses

(1997) study monthly freight rates from September, 1983, to August, 1993, for three Capesize and three Panamax routes by using an augmented Dickey-Fuller test. They conclude that the specification of these long-term relationships does not improve the accuracy of short- or long-term forecasts, which can be interpreted as a corroboration of the efficient market hypothesis. Tvedt (2003) finds that prices processed by an equilibrium model closely relate to the popular means of reverting stochastic price processes used in the finance or real option literature. Therefore, a stochastic optimal control problem of the effect on freight rates of rigidities in yard capacity is presented, while the problems of optimal investment and restructuring policies under switching costs are derived.

Adland and Cullinane (2005) give a simple argument to question the applicability of the expectations theory in bulk shipping freight markets by showing that the risk premium must be time-varied and be in a systematic trend, depending on both the freight market conditions and the duration of a period of time charter.

One of Kavussanos' expertise is studying shipping freight. In 1996, his research was on dry bulk market price issues. By using monthly observations from 1973 to 1992, the paper investigates the volatility in both spot and time charter freight rates of the dry bulk industry. In 1997, a study of the same author is on the volatility of second-hand dry cargo ships. Later, another research of Kavussanos and Nomikos (2000) shows estimation results on time-varying and constant hedge ratios in the BIFFEX market by using a GARCH error structure model and a GARCH-X model; they conclude that the GARCH-X model specification is better than a conventional simple GARCH model in terms of reducing risks. Kavussanos and Alizadeh-M (2001) also investigates the nature of seasonality in dry bulk freight. Their work gives a general introduction to dry bulk shipping markets and the freight rates, and then determines the seasonality pattern based on different vessel sizes, different contract durations, and different market conditions with the utilization of unit root tests, and puts forward some tactical shipping operations separately.

Further remarkable progress was made by Kavussanos and Visvikis in 2004 in terms of the lead-lag relationship. They use data from over-the-counter forward freight agreements in the VECM-GARCH model to investigate the lead-lag relation in both returns and volatilities between spot and futures markets. Furthermore, in another work with Kavussanos et al. (2004), Kavussanos considers how the FFA affects the spot market price volatility in two dry bulk shipping routes. By introducing control variables, the authors find that FFA trading has no detrimental effect on the spot market.

The time-varying volatility model has been used to examine the time-varying behavior of the dry bulk freight rates. The empirical distribution of stock returns displays fat tail, spiked peaks, and persistence in the variance structure. The ARCH of Engle (1982) has been shown to provide a good approximation to many stock return series. Kavussanos (1996, 1997, 1996) apply ARCH and GARCH models to analyze the time-varying behavior in freight rates for dry bulk vessels of different sizes, as well as spot and time charter rates, which is the first time that ARCH and GARCH models are applied in the literature on the dry bulk shipping market. Results have revealed the significance of ARCH and GARCH parameters because better fit is shown when slight compression was made on two alternative approaches of modelling the freight: the classical linear model and the GARCH model.

Based on previous study, Chen and Wang (2004) apply Nelsons EGARCH model to investigate the leverage effect in the phenomenon of an asymmetric impact between past innovations and current volatility, which seems to be an inherent nature of this market. The sample data they use are from April 27th, 1999, to the end of July 2003. Although the time of this data generation is not quite up to date, it provides the foundation of the leverage effect problem in the shipping freight market.

My first chapter contributes to the extant literature in the following ways. First, the sample period ranges from August 1998 to July 2017, i.e., 17 years, which is two times the typical length of sample period suggested by Stopford (2009). Since this typical length of sample period, which is around 6 to 7 years, is considered to cover a shipping business cycle, my 17-year data sample is expected to cover more market up- and downturns during the business cycles in the shipping industry, especially those with high volatility periods, such as the global financial crisis from 2007-2008. Hence, this longer sample period is expected to provide readers with more robust results especially for the periods of market up- and downturns.

Second, I apply three conventional GARCH-family models, GARCH, GJR-GARCH, and EGARCH models to the shipping data. The findings from the above three models show that the past continuous sample paths of the seven indices can be well specified by the GARCH-family models, implying that the indices contain information, such as leverage effect, that is helpful in forecasting their future volatilities. In addition to the conventional GARCH-family models, I further apply two more volatility models, which are the Heterogeneous Autoregressive (HAR) model and the Two-component models, for the first time, and they can also specify the indices well. These results show that the shipping indices can be decomposed into short-term and long-term components and its long-memory property is expected to help forecast future volatility of the indices.

Third, the volatility forecasting performance of the 7 indices using the above five volatility models shows that the Two-component model of Harris et al. (2011) performs the best among the 5 models and the GJR-GARCH model ranks the second, confirmed by the Superior Predictive Ability (SPA) test of Hansen (2005) and the Diebold and Mariano (1995) test of

Diebold and Mariano (1995). This thesis, therefore, contributes to the literature by providing new findings of the volatility predictability of the 5 models for the 7 shipping indices. As a result, in contrast to various literature in financial market which suggests that the HAR model performs the best such as Fei et al. (2019), this thesis finds that the TWO-component model, rather than those conventional GARCH-family models applied in previous literature, is considered the best model in forecasting its future volatility.

The empirical findings of this study are summarized as follows. Firstly, the results from in-sample parameters indicate that the past continuous sample variables in those indices contain forecasting information on their future indices. However, BDTI and BCTI show that both daily and weekly volatility components are close to zero and statistically insignificant.

Secondly, the HAR-RV model fails to well describe the continuous sample path for BDTI, and only the monthly component contains forecasting information for BCTI. In addition, we also observe a decrease in β from the first to the seventh shipping index in the GARCH model, suggesting that the impact of the current volatility shocks on future volatility is the highest for BDI, whereas the lowest is for BCTI.

Thirdly, by running a horserace among the forecasting precision of the five models, it can be concluded that the Two-component model has the best performance for the first five indices, and the HAR-RV model ranks second. In addition, the GARCH model has better forecasting capability than the EGARCH model. For BDTI and BCTI, low RMSE indicates poor forecasting capability. This is consistence with findings from in-sample results.

Finally, according to the results of SPA test, the Two-component model is not inferior to the rest of the competing models. From a DM pairwise test, the Two-component model always outperforms the other four models.

The tanker freight market, which is characterized by high volatility and operating risk, has received full attention. There is much published literature regarding its market volatility. The earliest research work can be dated back to 1978, when Hawdon (1978) proposes a model to simulate the volatility of the tanker freight rate. Nearly a decade later, Beenstock and Vergottis (1989) studied the dynamic impact of factors such as tanker freight rates, second-hand prices, and fleet size, on the tanker market, using an aggregated econometric model. From research work carried out in the 20th century, it is found that Adland and Cullinane (2006) analyzed the volatility of the tanker freight rate using a non-linear stochastic model., while a system identification approach is used to study the structural relation between the tanker freight rate and the influencing factors, according to research from Dikos et al. (2007). In 2011, Alizadeh and Talley (2011) analyze factors that influence the tanker freight rate, including the laycan period, vessel hull type, fixture deadweight utilization ratio, age of vessel, as well as the shipping line. In the same year, Alizadeh and Nomikos (2011) document ana asymmetric relation between the volatility of the tanker freight rate and the term structure where the volatility is higher when the market is in backwardation than in contango.

In spite of the research subjects mentioned above, issues such as the analysis and prediction of different sub-markets with various ship types have also been widely studied. According to Kavussanos (1996), Glen and Martin (1998), their statistical analysis demonstrates that the freight volatility of larger tankers is more volatile than that of smaller tankers. Meanwhile, the same analysis results apply to the operational risk. Kavussanos and Alizadeh-M (2002) discovered the seasonal pattern of the freight volatility of the tanker market by using a Markov regime switching seasonal model. Moreover, comparative analysis of various ship types under different market conditions has been conducted to verify the forecasting performance. Results from Kavussanos (2003) indicate that the conditional volatility is not constant in the VLCC shipping market. Alizadeh et al. (2007) combined it with stochastic demand and then extended the classical partial equilibrium models while he managed to simulate the probability distribution of future tanker spot rates of VLCC.

Although the methods listed above show good performance in both analysis and prediction when the price series is linear, non-linearity and artificial intelligence methods are used to estimate the volatility. Artificial intelligence is not often used in this area, but there is some literature on existing studies. For example, the work of Thanopoulou (2002) analyze the freight volatility of VLCC, and the neural networks is applied in this work to forecast the freight rates. Work by von Spreckelsen,von Spreckelsen et al. (2012) focused on contrastive analysis of different models, including the non-linear neural network and several linear models.

It is a well-established view that the impact of the price of crude oil on the world economy is extensive. For instance, the earliest study from Hamilton (1983) points out that the correlation between recessions and oil shocks is statistically significant and non-spurious, especially in the period 1950-1970. It is proved that crude oil shocks were a significant factor in the US recession period in the 1970s. Furthermore, the upward trend of energy prices may account for much post-OPEC macroeconomic performance. Jones and Kaul (1996) show that the reaction in United States and Canada to the impact of the stock prices can be completely influenced by real cash flows alone in the post war period. By contrast, in the United Kingdom and Japan, changes in crude oil prices appear to cause larger changes in stock prices due to the subsequent changes in real cash flows or to the changes in expected returns.

As a result, the change in crude oil price has been used to predict economic growth for a long while. The areas of production of crude oil are limited, while the demand for it is worldwide. According to BPs statistical review of world energy in June 2011, 68.7% of world crude oil production was undertaken by North America, Europe Eurasia, and the Middle East in 2010.

Crude oil carriers transport crude oil from these limited production regions to global consumption regions. It is not hard to see that the demand for crude oil transport services is derived from the imbalance between the supply and demand sides. Considering the reasons above, a conclusion may be drawn that crude oil price shocks will definitely have significant influence on the world tanker industry.

A number of studies have examined the determinants of tanker freight rates. In pioneering work, Sveistrup and Koopmans (1939) develop a model of supply and demand to investigate the tanker freight rates. Four decades later, Hawdon (1978) suggests that the process of spot freight rate is determined by a series of interactions between the market for tanker services and freight rates both in the short- and long-term. Beenstock and Vergottis (1989) propose a theoretical model in which freight markets and shipping markets are interrelated, and the main reason to support this argument is that second hand vessels are always treated as capital assets.

At the same time, Beenstock and Vergottis (1993) apply this theoretical model empirically to the global tanker market. Lensberg and Rasmussen (1992) model all four shipping sub-categories in a traditional equilibrium framework and discuss the uncertainty by modelling the demand for freight services according to a stochastic function of the crude oil prices. More specifically, Kavussanos (2003) uses co-integrating Error Correction ARCH models to prove that spot and time charter rates (TC rates) for each ship size and time varying risk are important factors.

There is a large amount of literature reporting on the relationship between crude oil price shocks and macroeconomic variables. the work of Kilian and Park (2009) is the most famous of these. They managed to show that the response of aggregate US real stock returns may differ greatly, depending on whether the price increase of crude oil is driven by demand, or by supply shocks in the crude oil market.

In the light of this statement, Lizardo and Mollick (2010) hold the view that crude oil prices significantly explain the value change of the US dollar against other major foreign currencies from 1970 to 2008. In the previous year, Kilian (2009) proposed a structural VAR model of the global crude oil market to evaluate the response of macroeconomic aggregates to exogenous change, which refers to the price change of crude oil. Based on this study, Lin, Fang and Cheng (2010), Basher et al. (2012) contribute to the same subject.

To the best of our knowledge, only a few papers have investigated the linkage between the crude oil market and the tanker market due to the data limitation as well as a lack of clear theoretical relationship. Among the literature, Kennedy (1974) takes the costs of crude oil in sea transportation as a variable when building an economic model of the world crude oil market. He concludes that the price increases for crude oil that occurred in late 1973 are not likely to persist because the largest producing regions, the Persian Gulf and North Africa, may have issues allocating reduced production levels among the individual countries.

Alizadeh and Nomikos (2004) find evidence of the existence of a long term relationship between tanker freight rates and crude oil prices in the United States, however there is no evidence showing that tanker freight rates are related to the physical crude oil market and West Texas Intermediate (WTI) futures price differently.

Furthermore, a very important piece of work from Poulakidas and Joutz (2009) supports the findings above. they use co-integration and Granger causality analysis to examine the lead-lag relationship between oil prices and tanker freight rates. They conclude that the significant increase in freight rates, with a simultaneous increase in crude oil prices will allow identification of relationships between shipping market rates and crude oil prices.

After reviewing almost all the related literature, it is believed there are several crucial points that may have been neglected. Firstly, some prior works discuss the volatility of freight rates among different shipping markets segments (Kavussanos, 1996, 1997, 2003; Kavussanos and Alizadeh-M, 2001; Drobetz et al., 2010); using variables outside of the shipping industry is not normal.

Also, the existing research focuses mainly on the relationship between crude oil prices and the tanker index, the relationship between crude oil prices and the dry bulk index has not been a focus. Secondly, only GARCH family models are used, other models, like the HAR model, have never been applied to the data. Thirdly, time periods are not divided into parts to ensure results are distinguished according to different time lengths.

In my second chapter, based on results in Chapter One, I have added an external variable to the models, i.e., crude oil price. These data are derived from the well-known Brent and WTI crude oil index. The West Texas Intermediate crude oil (WTI) spot contract is regarded as the benchmark price for the international energy market among many investment bank managers on Wall Street. It is also use as the representative price in the description of crude oil price trends in many multimedia articles.

However, from the recent trend, WTI crude oil price is more vulnerable to the impact of local supply and demand, which has nothing to do with the change of global crude oil market fundamentals. At one point, WTI is more like a regional oil price. Brent crude oil supply is generally stable, with limited influence from local factors. From this point of view, compared with the Brent crude oil price in London, the spot contract price of WTI crude oil price looks more like a regional oil price, with limited capability of representing international situations.

All crude oil produced or sold in the United States is priced on the basis of light and low sulfur WTI. As a result of good liquidity and a high degree of price transparency, the crude oil futures contract is one of the three benchmark prices in the crude oil world market.

On the other hand, countries and regions in northwest Europe, the North Sea, the Mediterranean, Africa, and Yemen all use Brent crude oil as the benchmark. Because this futures contract meets the needs of the oil industry in those areas, it is considered to be a highly flexible risk averse and trading tool, and is also one of the three benchmarks of international crude oil prices.

All the crude oil data are monthly data for both Brent and WTI, covering the period from 27 Dec 2001, to 3 Sep 2015, and including 4339 and 3707 observations, respectively.

This chapter contributes to the previous research in the following ways. Firstly, in order to achieve different results related to how the oil price effects the seven freight indices, this study is the first to divide time periods into three different lengths (1, 5, 22 days)

Secondly, the HAR and HAR-X model are firstly used in this field, they are expected to greatly increase the accuracy of the outcomes. Most importantly, the data used in this chapter covers a wide time range of more than 10 years. This implies that the whole cycle of the common shipping industry, which is normally seven to eight years, is included in the above time range. In addition, the famous financial crisis occurred during the time period covered by the data, thereby giving us a complete picture of rising and falling trend of volatility in the shipping industry that is affected by the general world economic environment.

Finally, this paper can support risk management by offering main instructions for both investors and business participants in the shipping area. More specifically, long-term participants such as ship owners, charterers, and operators can be informed ahead of time by using modelling methods applied in our study under circumstances like the deep price shock in 2014. Other players who are indirect participants, like investment banks and policy makers, can possibly optimize their strategies with better forecasting results.

My findings in this thesis are of keen interest and relevance to investors, traders, and portfolio managers in the shipping industry. Firstly, investors may evaluate risks and returns while making investment decisions by searching oil prices over a short time period. Also, it can be of helpful for investors to optimize their investment strategy, and managers with positions in the tanker market would be able to make better decisions based on deeper knowledge of the dependence among the market variables.

Secondly, volatility may inform market participants of the possible spread of turmoil among financial markets, especially during a financial crisis. It will help market participators to facilitate decisions on whether to charter in or charter out ships, set the appropriate freight rate, and whether to increase investments by buying more tankers based on information of the tanker market movements, and so on.

Thirdly, it is useful for market analysts and researchers to further investigate the relationship between the tanker market and the crude oil market in both the short- and long-term. If the economic environment in the tanker market appears much more volatile than usual, they may choose to determine the movement of most of the key variables related to the crude oil index, based on the dependency analysis. At the same time, they can share the analysis and results reported in this thesis with all the participants in the whole shipping industry. The information could help them to better understand the market trends. In return, it could bring down the volatility in the whole tanker market.

Finally, the findings of this study are of importance to oil companies, operators in the tanker market, and investors in crude oil derivatives markets. Tanker operators, for instance, with their position in the tanker market, may be empowered to make better decisions following various shocks.

Chapter 2

Methodology

2.1 Volatility modelling

GARCH and GARCH-X model

The first model to be applied in this thesis is the conventional Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models proposed by Bollerslev (1986) and Engle (1982) and its augmented GARCH-X model (Hwang and Satchell, 2005). This augmented model is a generalized version of Braun et al. (1995) and Glosten et al. (1993) where X refers to the covariates that can be included in the GARCH model, and in this case X is the oil price index. Via incorporating additional information that is considered as important to the volatility process, the main purpose of this part is to understand whether the inclusion of a common heteroscedastic factor such as the oil price index will help to improve the model specification and can further increase the forecasting power of the models applied in the previous part. The GARCH-X model is widely adopted in recent studies on volatility modelling and prediction such as Fei et al. (2019), Han (2015), and Jiang et al. (2019) and is defined as follows:

$$r_t = \mu + \epsilon_t, \;\; \epsilon_t | D_{t-1} \sim t_v(0, \sigma^2_{\epsilon_t}) \tag{2.1}$$

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \phi X_{t-1} \tag{2.2}$$

where r_t is the deseasonalized logarithmic return on day t, the innovation term ϵ_t follows a student's t-distribution t_v of zero mean and variance $\sigma^2_{\epsilon_t}$ with v degree of freedom conditional on the information set D_{t-1}. α and β are the ARCH and GARCH component coefficients to be estimated, respectively. σ^2_t is its variance conditional on the information available at time $t-1$, and its square root is the volatility process we are interested in for the following volatility prediction part. The oil price index at time $t-1$ is augmented as X_{t-1} and forms the GARCH-X model. In this thesis, we are interested the estimated coefficient, ϕ. If it is statistically significant, then the result will indicate that the inclusion of the oil price index is expected to improve the model specification and volatility forecasting.

EGARCH and EGARCH-X model

The second model from the GARCH-type model is the EGARCH model, which stands for exponential GARCH, proposed by Nelson (1991) to handling financial time series. The biggest difference between the conventional GARCH and EGARCH model is that the EGARCH model takes the logarithmic form of the variance in the GARCH model. This enables the model to ensure positivity of the conditional variance at every point of time and to capture the asymmetric effects between positive and negative asset returns on the predicted volatility especially due to the presence of leverage effect. Similarly, X_{t-1}, representing the oil price index, is augmented and then forms the EGARCH-X model as follows:

$$r_t = \mu + \epsilon_t,\ \ \epsilon_t|D_{t-1} \sim t_v(0, \sigma^2_{\epsilon_t}) \tag{2.3}$$

$$\epsilon_t = \sigma_{\epsilon_t} z_t \tag{2.4}$$

$$\log \sigma^2_t = \omega + \alpha \epsilon^2_{t-1} + \beta \log \sigma^2_{t-1} + \phi \log X_{t-1} \tag{2.5}$$

where z follows a standard normal distribution. The variables and coefficients are the same as those in GARCH and GARCH-X models. σ_t is the volatility process that will be evaluated against the *true* volatility proxy in terms of its prediction power.

GJR-GARCH and GJR-GARCH-X model

Similarly, the third GARCH-type model considered in this thesis is the GJR-GARCH model (Glosten et al., 1993), which also captures the leverage effect in the volatility process. The reason to use this model is to act as a natural counterparty against the EGARCH model since the GJR-GARCH model share the same property. Hence the GJR-GARCH and its augmented model is constructed as follows where X_{t-1} represents the oil price index:

$$r_t = \mu + \epsilon_t, \ \epsilon_t | D_{t-1} \sim t_v(0, \sigma^2_{\epsilon_t}) \tag{2.6}$$

$$\sigma^2_t = \omega + (\alpha + \gamma I_{t-1})\epsilon^2_{t-1} + \beta\sigma^2_{t-1} + \phi X_{t-1} \tag{2.7}$$

where the indicator function I_{t-1} captures the leverage effect and reads:

$$I_{t-1} := \begin{cases} 0, & \text{if } r_{t-1} \geq \mu, \\ 1, & \text{if } r_{t-1} < \mu. \end{cases}$$

Hence, a positive and statistically significant coefficient, γ indicates presence of leverage effect.

For the above three GARCH-type models and their augmented ones, the model estimation is performed via Eviews 10.0 as it offers a comprehensive package in estimating (G)ARCH-family models and incorporating additional variables in both return and volatility processes.

HAR and HAR-X model

The popular model we adopted is the Heterogeneous Autoregressive (HAR) model of realized volatility proposed by Corsi (2009). Müller et al. (1993) document a strong seasonality and autoregressive heteroskedasticity of the foreign exchange market due to nonhomogeneous market participants, which goes against the Heterogeneous Market Hypothesis (HMH). This reflects different trading behaviors by market participants due to different risk preferences and constraints, and the way information is interpreted. The HAR model is designed to capture these behaviors by constructing a multi-component volatility structure. It is also able to capture stylized observations of time series of volatility, such as fat tails and long memory. The HAR model is defined as follows:

$$\sigma_{t,t+h} = \alpha + \beta_d Z_t^d + \beta_w Z_t^w + \beta_m Z_t^m + \epsilon_{t+h} \tag{2.8}$$

where $\sigma_{t,t+h} = h^{-1}\left[RV_{t+1} + RV_{t+2} + \cdots + RV_{t+h}\right]$, and Z_t^d, Z_t^w, Z_t^m represent the daily, weekly, and monthly volatility components on day t, which are given by the simple average, given as follows:

$$Z_t^d = \sigma_t^d \tag{2.9}$$

$$Z_t^w = \frac{1}{5}(\sigma_t^d + \sigma_{t-1}^d + \cdots + \sigma_{t-4}^d) \tag{2.10}$$

$$Z_t^m = \frac{1}{22}(\sigma_t^d + \sigma_{t-1}^d + \cdots + \sigma_{t-21}^d). \tag{2.11}$$

where σ_t^d is the daily 5-min RV on day t.

According to previous studies by Corsi (2009), different traders perceive volatility through different time horizons, and therefore react differently. One advantage of the HAR-RV model is that various effects, such as leverage effects (Corsi and Reno, 2012), jumps (Anderson and Vahid, 2007), overnight returns (Tseng et al., 2012), and lunch-break returns (Wang et al., 2015), can be incorporated into the model. In this paper, we include two cross-sectional dispersion measures into the HAR model and form a HAR-X model as follows:

$$\sigma_{t,t+h} = \alpha + \beta_d Z_t^d + \beta_w Z_t^w + \beta_m Z_t^m + \phi X_t + \epsilon_{t+h} \tag{2.12}$$

where X_t represents cross-sectional dispersion variable where h can be 1, 5, 22. One of the biggest advantages of the HAR and HAR-X models is that it is easy to perform model estimation using ordinary least squares (OLS) method. Hence, different from the maximum likelihood estimation applied to the GARCH-type model estimation, Matlab R2020a is used to perform multivariate linear regression to estimate the HAR and HAR-X models.

Two-component model

The 'cyclical' Two-component model is proposed by Harris et al. (2011). By extracting the long-run component of the volatility process, Harris et al. (2011) find that the Two-component model finds that the long-run trend is fully persistent, and the model helps to generate superior out-of-sample forecast of exchange rate volatility over the EGARCH model. In addition, this model also offers substantial computational advantage of the EGARCH model. Assuming the realized volatility follows a Two-component process as follows:

$$\sigma_t = L_t + S_t \tag{2.13}$$

$$S_t = c + \sum_{i=1}^{p} \phi_i S_{t-i} + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} + \epsilon_t \tag{2.14}$$

where σ_t is the realized volatility, L_t and S_t are the long- and short-run components of σ_t, respectively, ϵ_t is the random error term with zero mean and constant variance. The long-term component L_t is obtained using non-parametric filters, namely the low-pass filter Hodrick and Prescott (1997) and the band-pass filter Christiano and Fitzgerald (2003), and then used to estimate the short-term component S_t following a stationary ARMA (1,1) process:

$$\sigma_t - L_t = \alpha\left(\sigma_{t-1} - L_{t-1}\right) + \epsilon_t \tag{2.15}$$

where ϵ_t is the error term. Hence the n-step ahead forecast volatility is obtained:

$$\widehat{\sigma}_{t+n} = \left(1 - \widehat{\alpha}^n\right) L_t + \widehat{\alpha}^n \sigma_t \tag{2.16}$$

Similar to the HAR and HAR-X models, OLS method is used to perform the in-sample estimation for the Two-component model using Matlab R2020a.

2.2 Volatility Forecasting

We use most of the data for in-sample estimation and the remaining 700 observations for out-of-sample prediction. We implement a 1-day rolling window and compute 1-day ahead forecasts for the GARCH(-X) model, and 1-, 5- and 22-day ahead forecasts for the HAR(-X) model. The forecasting accuracy is evaluated by using three popular loss functions, the root mean squared error (RMSE), the mean absolute error (MAE), and the mean absolute percentage error (MAPE). The RMSE is measured as the root of average squared differences between *true* volatility and the forecasted volatility, i.e., the errors between the *true* and the forecasts; the MAE is measured as the average absolute value of squared differences between *true* volatility and the forecasted volatility; and the MAPE is measured as the average absolute value of the percentage deviation of the forecasted volatility from the *true* volatility. These three loss functions are constructed as follows, respectively:

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\hat{\sigma}_{t+h}^2 - \sigma_{rv,t+h}^2\right)^2}, \tag{2.17}$$

$$MAE = \frac{1}{T}\sum_{t=1}^{T}\left|\hat{\sigma}^2_{t+h} - \sigma^2_{rv,t+h}\right|, \tag{2.18}$$

$$\text{MAPE} = \frac{100}{T}\sum_{t=1}^{T}\left|\frac{\hat{\sigma}^2_{t+h} - \sigma^2_{rv,t+h}}{\sigma^2_{rv,t+h}}\right|. \tag{2.19}$$

where T is the number of the out of sample observation, $\hat{\sigma}^2_{t+h}$ is the forecasted variance over horizon h (h =1,5 or 22), $\sigma^2_{rv,t+h}$ is *true* volatility proxy. In this thesis, the *true* volatility proxy is the 5-min realized volatility (RV) of Andersen and Bollerslev (1998) which is widely adopted by scholars (see Andersen et al., 1999; Chortareas et al., 2011). The 5-min RV on day t is constructed as follows:

$$\sigma^2_{rv,t} = \sum_{n=1}^{N} r^2_{t,n}, \tag{2.20}$$

where $r_{t,n}$ is the 5-min log return.

To assess the precision of volatility forecasts, we follow Andersen and Bollerslev (1998) and conduct the Mincer-Zarnowitz regression test (Mincer and Zarnowitz, 1969). Known as the predictive power test, it is defined as follows:

$$\sigma^2_{rv,t+h} = \alpha + \beta\hat{\sigma}^2_{t+h} + \varepsilon_{t+h} \tag{2.21}$$

where $\sigma^2_{rv,t+h}$ is the true volatility proxy at time $t+h$, and $\hat{\sigma}_{t+h}$ is the forecasted volatility at time $t+h$. The forecasting accuracy is captured by the value of the goodness-of-fit, R^2. The higher the R^2 from the Mincer-Zarnowitz regression, the stronger the explanatory power of the model, regardless of its efficiency.

The Diebold and Mariano (1995) statistic:

We employ the pairwise comparison of Diebold and Mariano (1995) and test whether differences in mean squared forecast errors between two models are statistically significant.

The loss differential process, $d_t : t = 1, 2, 3, \ldots, T$, is stationary, following null hypothesis: $H_0 : E[d_t] = 0$, where $d_t = L\left(\epsilon^i_{t+h|t}\right) - L\left(\epsilon^j_{t+h|t}\right)$, $L(\cdot)$ is the loss function. The test statistic is defined as:

$$DM = \frac{\overline{d}}{\sqrt{\widehat{LRV}_{\overline{d}}/T}} \tag{2.22}$$

where $\overline{d}$ is the mean of the loss differential process $\{d_t\}_{t_0}^{T}$ and $\widehat{LRV}_{\overline{d}} = \gamma_0 + 2\sum_{j=1}^{\infty}\gamma_j$, $Y_j = \mathrm{cov}(d_t, d_{t-j})$ the null hypothesis will be rejected at 5% significance level, if the absolute value of DM is greater than critical value, 1.96, from a standard normal distribution. More specifically, the model j has better forecasting power compared with model i, and vice versa.

The Superior Predictive Ability (SPA) test of Hansen (2005):

The pairwise Superior Predictive Ability test evaluates the performances of two competing models. The loss differential process $\{d_t : t = 1, 2, 3, \ldots, T\}$ is defined as:

$$d_t^{(k)} = L\left(\varepsilon^{(b)}_{t+h|t}\right) - L\left(\varepsilon^{(k)}_{t+h|t}\right), k = 1, \ldots, n \tag{2.23}$$

The composite of the SPA test shows there is no predictive ability among all competing volatility models. More precisely, the null hypothesis states that the benchmark model is not inferior to any alternative models. Rejection of the null hypothesis indicates that at least one competing model has more strong predictive power compared with the benchmark.

Chapter 3

Forecasting shipping freight rate volatility

3.1 Introduction

Ships are now involved in approximately 90% of global trade, they generate annual income that accounts for around 5% of the total global economy (International maritime organization). Thus, investment in shipping industry is crucial to the development of shipping enterprises.

As an integral part of the global transportation and logistics network, shipping has always been treated as one of the most volatile industries, and its agents are exposed to substantial unexpected financial and business risks. Such risk predominantly emanates from fluctuations in freight rates which affect the cash flow of different participants, such as ship-owners, operators, and charterers (Alizadeh, 2013).

As it will be discussed in the literature review later, there exist a number of studies on general economic volatility forecasting, while to the best of our knowledge limited work has been done on forecasting the volatility of the shipping freight rate. Since its introduction in 1985, the BDI has become a well-known proxy for the international shipping industry, later quickly establishing itself as a leading indicator used to infer the world-wide economic environment. Nevertheless, the literature on economic growth volatility forecasting focuses on oil price change alone.

This chapter runs a horserace among the forecasting precision of five models, including the Two-component model of Harris et al. (2011), the traditional GARCH model of Bollerslev (1986), the EGARCH model of Nelson (1991), and the heterogeneous auto-regressive (HAR) model of Corsi (2009). The data are returns calculated from seven indices of shipping freight rates from August, 1998, to August, 2013, containing 3,959 and 4,274 daily observations for the dry-bulk sub-segments and the tanker sub-segments, respectively.

The findings of this chapter make contribute to the existing literature. First, the typical length of a shipping business cycle in the existing literature usually ranges from 6 to 7 years, such as Stopford (2009). This research extends sample period up to about 17 years, which is two times the typical length and covers special market downturns with high volatility, such as the global financial crisis of 2007-2008. Hence, this longer sample period provides readers with more sufficient information and help them gain better insight of the topic. Second, the HAR and Two-component models are applied for the first time in shipping data where volatility forecasting is performed among the different carriers and sub-segments of the shipping freight market represented by BDI. Overall, the findings are interesting and worthy of noticing, and they can be summarized into four aspects.

First, there is sufficient evidence to conclude that the 5 of the 7 indices of shipping freight rates can be well specified by the HAR-RV and Two-component models. Their in-sample results suggests that these shipping freight rates contain sufficient forecasting information on their future indices. Second, the only exception is BDTI and BCTI where both HAR-RV and Two-component models fail to well specify their volatility dynamics. For BDTI, its continuous sample path fails to be well described by the HAR-RV model given by the adjusted R^2. This is also the case for BCTI where only the monthly component of the HAR model has forecasting power. In addition, BDI has the highest volatilty for future, while it is the lowest for BCTI, which is indicated by the decreasing β from the first to seventh index in the GARCH model. Third, this study also compared the forecasting capability of the five volatility models. The forecasting result suggests that the Two-component enjoys the best predictive power and fits the data better than the other four models, and the HAR-RV model ranks the second. For BDTI and BCTI, their RMSE indicates relatively poor forecasting capability. This is consistent with the results of in-sample estimation. Finally, the result of the SPA test further suggests that the Two-component model is the least inferior model. This is consistent with the result of the DM pairwise test where the Two-component model outperforms the other four models.

The rest of this chapter is organized as follows. Section 3.2 generates the background of Baltic Dry Index; Section 3.3 discusses the literature; Section 3.4 describes the data set; Section 3.5 presents the estimation results and compares the out-of-sample forecast performances, finally Section 3.6 gives a conclusion to this chapter.

3.2 Baltic Dry Index

The BDI, which is Baltic dry freight index, can determine trends in the shipping industry under normal circumstances as it is the dry bulk vessels which occupy the largest share of this market. It is observed that the BDI hit a recorded low (point 307) immediately after February 2016, and rebounded (to near point 1296) in April, 2017, an increase of more than 4.2 times.

The Baltic Dry Index (BDI) reflects the level of freight rates and mirrors the state of the entire dry bulk market. (Tsioumas et al., 2017)

Figure 1 illustrates the evolution of the BDI from November, 1999, to August, 2015. The lowest point (509) and the peak point (11793) in the figure demonstrate the violent fluctuation. One important reason for this cyclicity is the fluctuation of the world economy, and the dramatic change of BDI is consistent with a large recession at that time. Meanwhile, the intrinsic nature of the shipping industry, for instance shipbuilding cycles and speculative investments (Haralambides et al., 2005), simultaneously contributes to this fluctuation.

The BDI has been published daily by the Baltic Exchange in London since May 1985. Based on daily quotes for booking vessels of various sizes and across multiple maritime routes, the BDI is an indicator of transportation costs for raw materials shipped by sea. More specifically, the BDI is calculated as a weighted average of the Baltic Exchanges indices for the shipping costs of the four largest dry-vessel classes.

By holding the premise that the supply structure of the shipping industry is generally predictable and relatively inflexible, it has been seen that the changes in shipping costs are heavily associated with the changes in the worldwide demand for raw materials (Stopford (2009) provides an in-depth analysis of the shipping industry). The finding of this relationship between shipping costs and global demand for raw materials has prompted interest in the BDI as a leading indicator of world economic activity. Much of the existing literature treats the crude oil price as the leading indicator of the worlds economic environment. For example, Subrahmanyam (2010) writes a detailed review of more than 50 variables that may have predictive power of stock returns, and reaches the conclusion that oil price has the greatest influence. However, Alizadeh and Muradoglu (2014) argue that in many large economies, the main industries have transformed from manufacturing to services and technology, so the importance of oil has decreased considerably. Instead, the shipping industry is only affected by demand for the reason that it will take a certain time period to build new vessels (usually 12 to 24 months), and the supply effect in the short-term could be avoided.

Moreover, the BDI exhibits other advantages as a predictor. Specifically, unlike some other economic indicators, it is never revised ex-post and is largely devoid of speculative content. On the other hand, certain specifics of the shipping industry can be viewed as factors that diminish the indexs predictive potential. For example, highly inelastic supply may generate excessive volatility in shipping costs, causing the index to deviate from the fundamentals of global trade and real economic activity. (Bakshi et al., 2011)

Since most exports from less developed countries comprise primary goods and raw materials, the majority rely on dry bulk carriers in the case of international transportation. BDI is an important component, and thus could reflect the cost of trade. As a result, some prior studies (Bakshi et al., 2011) proved that the movements in the BDI reflect economic activity. The increase in the BDI reflects a stronger demand for commodities, while a downward trend indicates insufficient consumer demand. Firms can take the BDI trend as a factor to form business strategies. Moreover, it could also be treated as a useful indicator for economic recovery because it provides up-to-time alterations and does not avoid speculative purpose movements.

Generally, there are typically four segments of vessels that could be chosen in the shipping industry. The choice of which type of vessel is good for ocean transportation of a commodity depends on various factors such as: type, size, route, and port facilities(Alizadeh and Nomikos, 2009).

Panamax (BPI), launched in 1998, is calculated based on four available routes for a Panamax dry bulker. Each route is calculated with the same weight (25%). Capesize (BCI), launched in 1999, is calculated based on shipping costs of 10 available routes for a Capesize dry bulker in which each route is weighted based on its importance against the other nine routes. Handysize (BHSI), (launched in 2000) carry up to 60,000 tons; there are 200 units in service and they account for carriage of 43 million tons in total. They are very flexible since their smaller size allows them to enter smaller ports. Supramax (BSI) (launched in 2005) vessels have three voyage charter routes and six trip charter routes, however the Baltic Supramax Index (BSI) has only six trip charter routes.

The Capesize carriers, the largest ones, represent 10% of the world fleet and 62%of dry bulk traffic. The second largest, Panamax vessels, as the name implies, can fit in the locks of the Panama Canal, which is 19% of the fleet and 20% of the tonnage. The purpose of this criterion for categorizing dry bulk carriers of different sizes, and to clarify in which ports the carrier will potentially operate (Geman and Smith, 2012).

The BDI is also a proxy to determine the cost of raw materials around the world, such as iron, coal, cement, and grain. The average price of 22 different shipping routes internationally is compiled daily to calculate the BDI. Economic indicators, such as unemployment rate, inflation rate, and oil prices, can be manipulated or influenced by governments and speculators, while the BDI is difficult to manipulate since it is driven by clear forces of supply and demand. One possible explanation is that the number of vessels is limited; and it would be exceptionally costly to increase supply side by building more vessels. Bildirici et al. (2016)

Therefore, these segments of carriers follow quite distinct business cycles primarily driven by the demand for different commodities that can be transported by them (Kavussanos and Visvikis, 2006). As a result, shipping freight rates, being the equilibrium price of the transportation service, also exhibit pronounced segmentation effects among different vessel types and sizes (Kavussanos, 2003, 1996). However, despite the pronounced market segmentation observed in shipping freight markets, shipping segments and sub-segments are not completely isolated from each other (Stopford, 2009). This is due to the fact that different types of vessels can transport the same cargo, and in this way can create competition among different shipping sectors. In addition, investors have the choice to reposition their investment from one shipping sector to another. In fact, several shipping companies are active in all shipping sectors and investors from one sector will enter another whenever they see an opportunity. In the light of the above facts, imbalance of supply and demand in one segment of the market will soon ripple across to the other segments. However, the extant literature remains silent regarding the dynamic evolution of shipping freight market segmentation over time. Tsouknidis (2016) aims to provide novel evidence of the segmentation effect in shipping freight markets by investigating the existence, the severity, and the direction of dynamic volatility spill-overs within the dry-bulk freight segment and between the dry-bulk segment and tanker sub-segments.

3.3 Literature review

In order to better understand the research question in this chapter. A number of literature are studied, mainly including volatility forecasting in different time period with methods, such as, ARCH, ARFIMA and etc.

Since the volatility of financial markets has a direct impact on policy making, volatility forecasts are treated as taking the role of a 'barometer for the vulnerability of financial markets and the economy' (Poon and Granger, 2003). Their wide use can be found in asset pricing, portfolio construction, and risk measurement. modelling volatility, consequently forecasting, has therefore become a popular field of research, and a number of econometrics models have been developed during the past few decades. Conventional models are able to capture stylized facts, for instance volatility persistence and clustering. In order to discover unique price behaviors under specific volatility proxy construction, it is well accepted that the estimator is sure to carry more information related to the true latent volatility and, as a result, superior forecasting capability is expected when modelling volatility forecasting. Such models include Auto-regressive Conditional Heteroskedastic (ARCH) model of Engle (1982), the Generalized ARCH model of Bollerslev (1986), and the Auto-regressive Fractionally Integrated Moving Average (ARFIMA) model of Granger (1980). In addition, Taylor (1994) and Shephard (1996), among others, model volatility as an unobserved component following latent stochastic process, which is theoretically widely used (see Andersen and Bollerslev, 1998; Chernov et al., 2003). Future volatility forecasting and volatility distribution assessment are considered as well through the use of the stochastic volatility model of Kaeck and Alexander (2013).

Volatility component models have attracted attention in the literature since the work of Engle and Lee (1999). The model breaks the volatility dynamics down into two components. One is short-term and temporary, while the other is long-term and persistent. One of the major advantages of this model is not only its ability to capture complicated volatility dynamics, but also its ability to handle structural breaks in asset return volatility (Wang and Ghysels, 2015). Based on existing empirical literature, the Two-component model performs better compared with one-factor models (Chernov et al. (2003)).

Until quite recently, the literature has typically focused on daily returns for forecasting daily volatility and used the daily squared returns as a measure of the true volatility. However, daily squared returns are not an accurate measure of the true volatility because they are calculated from closing prices and, therefore, cannot capture price fluctuations during the day (see Andersen and Bollerslev, 1998). In order to fill the gap created by these limitations, Andersen and Bollerslev (1998) propose the realized volatility as a measure of the true volatility, this has since become very popular. Some existing studies consider forecasting modelling by using those true volatility proxies to forecast future volatility. The Heterogeneous Auto-regressive model of Realized Volatility (HAR-RV) model of Corsi (2009) is widely used in the forecasting literature (see Bollerslev et al., 2016; Patton and Sheppard, 2015).

Unlike the vast literature related to volatility and forecasting in economic markets, only a few studies focus on modelling the volatility of shipping freight rates to identify potential volatility spill-overs across different shipping freight rate segments and sub-segments (Kavussanos, 1996, 1997, 2003; Alizadeh, 2001).

Alexandridis et al. (2017) indicate that the international freight rate market is characterized by some unique features that differentiates it from the other "soft" commodity markets. The high volatility and the seasonality effects are associated with commodities transported by the ocean-going vessels, while the cyclical behavior of rates and prices follow the business cycles, and the non-storable nature of freight rates, amongst others (see Kavussanos and Visvikis, 2006; Kavussanos and Dimitrakopoulos, 2011). It is worth noting that the nature of a non-storable commodity means that the traditional cost-of-carry no-arbitrage arguments of fair pricing do not apply in this case (see Kavussanos and Visvikis, 2004; Alizadeh, 2013, and Kavussanos et al., 2014).

Kilian (2009) and Kilian and Park (2009) develop an index of dry-cargo, shingle-voyage, and ocean-shipping rates to capture shifts in demand for industrial commodities in global business markets; they provide a measure for economic activity by decomposing oil prices into demand and supply driven components. Based on their work, Alizadeh and Muradoglu (2014) investigate the direct relationship between freight rates and stock market activity by using the BDI index. Klovland (2004) and Stopford (2009) argue that world economic activity is the most important single factor that influences ship demand and that freight rates are demand driven. Bakshi et al. (2011) confirm that the growth rate of BDI exhibits a positive and statistically significant relation to global stock returns, commodity returns, and global economic activity.

3.4 Data description and summary statistics

The data examined in this study is comprised of daily prices for the main shipping freight rate indices published by the Baltic Exchange and noted as BDI. All data are from Clarksons Shipping Intelligence Network (SIN).

Shipping freight rates have been shown to exhibit pronounced seasonality effects (Kavussanos and Alizadeh-M, 2001, 2002). In order to ensure that the results are not driven by seasonality, the returns of the indices are calculated as the first logarithmic differences of day-to-day closing index values.

$$r_t = \ln BDI_t - \ln BDI_{t-1} \tag{3.1}$$

The following indices are examined for the dry-bulk cargo segment: the Baltic Dry Index (BDI); the Baltic Capesize Index (BCI); the Baltic Panamax Index (BPI); the Baltic Supramax Index (BSI); and, the Baltic Handysize Index (BHSI). For the tanker segment, the Baltic Dirty Tankers Index (BDTI) and the Baltic Clean Tankers Index (BCTI) are examined; they represent the two major sub-sectors of liquid-bulk shipping. The BDI is a composite index calculated as the equally weighted average of the BCI, BPI, BSI, and BHSI indices. Apart from the BDI, the rest of the indices are calculated as a weighted average of shipping freight rates on major voyage and time charter routes.

Among these seven indices, the Baltic Handysize Index (BHSI) exhibits the shortest available time series since its inception on March 23rd, 2006. For the tanker sub-segments and the general BDI index, the data availability is longer and covers the period from the inception of the BDTI and BCTI shipping freight rate indices, i.e., from August 3rd, 1998, to September 3rd, 2015. Both time periods examined are significantly longer than the typical six- to seven-year length of a shipping business cycle Stopford (2009). As mentioned before, the periods examined also include the 2007-08 global financial crisis, thereby covering both rising and falling trends of the business cycle. In addition, holidays, non-trading days, and missing value are removed from the sample, and the resulting sample period contains 3,959 and 4,274 daily observations for the dry-bulk sub-segments and the tanker sub-segments, respectively.

Table 1 shows the summary statistics of these seven indices, in both dry bulk and tanker carriers. The number of observations, mean, median, standard deviation, skewness and excess kurtosis are presented. The only positive outcome among these is the Baltic Exchange Capesize Index during a particular period. In addition, it can be observed that volatilities of shipping freight rates directly depend on the size of carriers. To further explain the result, the larger vessels display higher levels of volatilities of rates in accordance with different dry-cargo categories. The last column tabulates the Ljung Box statistic for autocorrelation for the first 10 lags. In the Ljung Box tests, the null hypothesis of no autocorrelation is rejected with a high confidence level (95%)

3.5 Empirical analysis

3.5.1 In-sample estimation results

We report the in-sample parameter estimates of the HAR, Two-component, GARCH, GJR-GARCH and EGARCH models for seven indices in Table 3. In panel A, the estimation results of the HAR-RV model are listed with daily, α_d, weekly, α_w, and monthly, α_m, volatility estimators, as well as its intercept, α and their adjusted R^2 .

First, all seven indices have positive intercepts, estimations of α , which are significant at 1% level. Second, we notice that for the first five indices, almost all the coefficients are positive at significant level of 1%. The only exception is the weekly volatility component for the BPI, which is negative and significant at 1% level, and the monthly volatility component for the BHSI, which is positive but statistically insignificant. In addition, the BHI reports the highest adjusted R^2 whereas the BCI has the lowest. Overall, our estimation results indicate that the past continuous sample paths' variables in those indices contain information that is helpful in forecasting their future indices rates.

By contrast, the estimation results of the last two indices, the BDTI and the BCTI, show that the coefficients of both daily and weekly volatility components are close to zero and statistically insignificant. Furthermore, the coefficient of the monthly volatility component for the BCTI is also close to zero and insignificant, while it is positive and significant at 5% level for the BDTI. This suggests that the HAR-RV model fails to well describe the continuous sample path for the BDTI, and for the BCTI only the monthly component contains forecasting information. Additionally, the R^2 for the two indices also suggests that the HAR-RV model cannot describe them well. In panel B, we notice that the coefficient α, are all positive and significant at 1% level, indicating that the short-term component has strong autocorrelation between time $t-1$ and t.

Then, we notice that, with the exception of the BDI and the BPI, the R^2's of the Two-component model are all higher than those of the HAR-RV model, suggesting that, in general, the Two-component model is more likely to capture the continuous sample paths of the indices than the HAR-RV model. However, overall, the Two-component model only reports 8.8% and 7% for the two indices, respectively, suggesting that it still fails to well fit the volatility process for the two indices.

We also implement the ARMA(1,1)-EGARCH(1,1) model to capture possible asymmetric or leverage effects, which is the negative correlation between returns and volatility. In other words, the impacts on conditional volatility of positive and negative shocks of equal magnitude are treated differently.

We firstly observe that the persistence for the indices is very high, except for the BCTI. In addition, the index BSI, is the only one to be negative and significant γ, suggesting the leverage effect of the index process. However, for the BDTI and the BCTI, instead of a positive leverage effect, we identify positive and significant γ, indicating a positive correlation between returns and volatility, which is useful for future research.

In addition, we implement the ARMA(1,1)-GARCH(1,1) model and report the coefficient estimations of the GARCH model, which are all positive and significant. It is interesting to note that the β is decreasing from the first index to the seventh index, suggesting that the impact of the current volatility shocks on future volatility is highest for the BDI, whereas it is lowest for the BCTI. As a result, a high α with relatively low β indicates that the volatility process would be more 'spiky' compared to those having low α and high β. It is worth noting that, for the BCTI, the persistence is particularly low, even compared with that of the BDTI. Therefore, it can be confirmed that, at 5% significance level, the estimation results of the HAR-RV model on the monthly volatility component is statistically insignificant for the BCTI but significant for the BDTI.

3.5.2 Out-of-sample predictions

In Table 4 we summarize the RMSE of realized volatility for all five models. To investigate the forecasting power of these models, we conduct an out-of-sample analysis to forecast one-step-ahead forecasting for all the seven indices. We use the last 700 observations to construct a one-day-ahead rolling window to perform our forecasting. In Table 4 we summarize the RMSE of realized volatility for all four models. We notice that for all seven indices, the RMSEs of the GJR-GARCH model are always the lowest compared to the other four models, suggesting that the Two-component model outperforms the four competing models.

The Two-component model ranks the second in terms of its RMSE statistics. (Our results benefit from Cao et al. (2020), who discovered a neural network enhanced volatility component model, consistent with previous literature that shows the artificial neural network is outstanding when forecasting de-seasonalized data.) For the BDTI and the BCTI, the RMSEs obtained by the Two-component models are very close to the GARCH and EGARCH models RMSEs, suggesting that the Two-component model fails to outperform the two GARCH-family models.

In addition to the two- component model, we also observe that the HAR-RV model performs better than the GARCH model and the EGARCH models for the first five indices; whereas it performs the worst for the BDTI and BCTI indices. This is also the case for the GARCH model as it performs better than the EGARCH model, whereas its forecasting performance is very close to the EGARCH model.

Overall, the Two-component model performs the best and the HAR-RV model ranks second. The GARCH model has better forecasting capability than the EGARCH model. Secondly, in addition to the performance of the forecasting models, we also notice that the BHSI has the lowest RMSEs for all the four models, ranging from 0.037 to 0.052, indicating that the models have higher forecasting capabilities for this index than for others. We can see that, for the BDTI and the BCTI, the RMSEs range from 0.734 to 0.769 and from 0.503 to 0.516, respectively, therefore indicating poor forecasting capability. The results are similar to what we find for the R^2 obtained in Table 3 that lower R^2 's suggest a poor model fit, and therefore lower RMSE. Meanwhile, one exception is for the BCI, which has the highest RMSE, whereas it still has a higher R^2 than those for the BDTI and the BCTI. One possible explanation is that the first five indices are of a different category from the last two indices.

We implement the superior predicative ability (SPA) test of Hansen (2005) and tabulate the stationary bootstrapped p-values, obtained via 1000 replications, in Table 5. The null hypothesis that the benchmark model is not inferior to any of the competing models is resoundingly accepted with a high p-value. Not surprisingly, for the first five indices, the Two-component model always shows p-value of one, indicating that the Two-component model is not inferior to the rest of the competing models, which is the null hypothesis Then, for the indices BDTI and BCTI, we notice that the Two-component model outperforms the HAR-RV and the GARCH family models.

We conduct the Diebold and Mariano (1995) pairwise comparison between the forecasting differences of alternative volatility models, illustrated in Table 6. A positive t-statistic suggests that the model in the row is the preferred one, while a negative t-statistic suggests that the model in the column is the preferred model. Firstly, we observe that for the first five indices, except for the BCI, where the Two-component model dominates the GARCH models at 5% significant level, the Two-component model always outperforms the other three models with 1% significant level. However, for the BDTI and the BCTI, the Two-component model only performs better than the HAR model, whereas it has similar performance to the GARCH and EGARCH models. These points confirm that the forecasting performance of the Two-component model is no different than the GARCH and EGARCH models. Overall, it is found that the Two-component model is always preferred to the others.

3.6 Conclusion

Although there exist a number of studies on general economic volatility forecasting, to the best of our knowledge the number which focus on the volatility of the shipping freight rate is limited. This research contributes to the extant literature in the following ways.

First, the duration of the data examined covers both rising and falling cycles of the shipping industry; secondly, some models are applied for the first time to shipping data and innovative result are achieved. This paper employs some conventional models to analyse volatility and forecasting in the dry bulk index over a longer period (i.e., from August 1998, to August, 2013). From the in-sample parameter, the results indicate that the variable of the past continuous sample paths in those indices contains information that can forecast their future indices. However, the BDTI and the BCTI show that both daily and weekly volatility components are close to zero and statistically insignificant. By running a horserace among five models to determine forecasting precision in terms of RMSE, it is found that the GJR-GARCH performs the best, while the Two-component model ranks.

Second, and the HAR-RV model ranks third. The GARCH model has better forecasting capability than the EGARCH model. According to the results of the SPA test, the Two-component model is not inferior to the rest of the competing models. From a DM pairwise test, the Two-component model always outperforms the other four models.

3.7 Limitation

As with all academic studies, there are several limitations to this study and my future research aims to address those.

First, in the study without oil prices, only the index is involved, and the related derivatives market is not considered. For instance, in recent years, FFA has been widely used as a financial tool; it is highly correlated with the dry bulk index and sub-index, and its lead-lag relation with spot price has also been proven. Therefore, my further study will focus on finding the internal effect, extending to the derivatives market with both general indices and sub-category indices of dry and tanker vessels.

Second, my consideration of time period is also limited. The data I used in my first chapter is from Dr. Dimitris A. Tsouknidis, who very kindly provided the original data that is referenced in his 2016 paper. The data time period is from 1999-2013, and the data is for seven shipping freight indices for four dry bulk and two tanker vessels. It is definitely a remarkable time period worth determining as it is long enough to cover the traditional six to seven year shipping business cycle and includes the great recession period of 2007-2008. However, the data is not quite up to date as the current study takes place in 2020 now. Indeed, some specific events have occurred since 2013, which I believe will influence the study results, which cannot be ignored. Changes in the global economic environment will most certainly affect the models predictive accuracy of volatility. Those factors and events will be taken in to consideration if I am able to expand the topic in further research.

Finally, in addition to those conventional models that are widely studied and applied, my further studies in modelling the shipping indices will focus more on machine learning techniques since various literature suggests that they could deliver better model specification and superior predictability in financial market in recent years (see Gavrishchaka and Banerjee, 2006; Liu, 2019; Ramos-Pérez et al., 2019; Vrontos et al., 2021). This thesis focuses on conventional GARCH-type model as well as the HAR and Two-component models mainly because it is easy to implement the in-sample estimation and out-of-sample forecasting and highly parsimonious especially for the latter two models. Hence, my future studies tend to apply more machine learning approaches to explore algorithms such as long short term memory (LSTM) since it also perform long-term and short-term analysis just like the TWO-component model.

Figure 1: The evolution of BDI index from 1999-2015.

This figure illustrates the evolution of the BDI from November 1999 to August 2015. The low (509) and peaks (11,793) in this figure demonstrate the violent fluctuation.

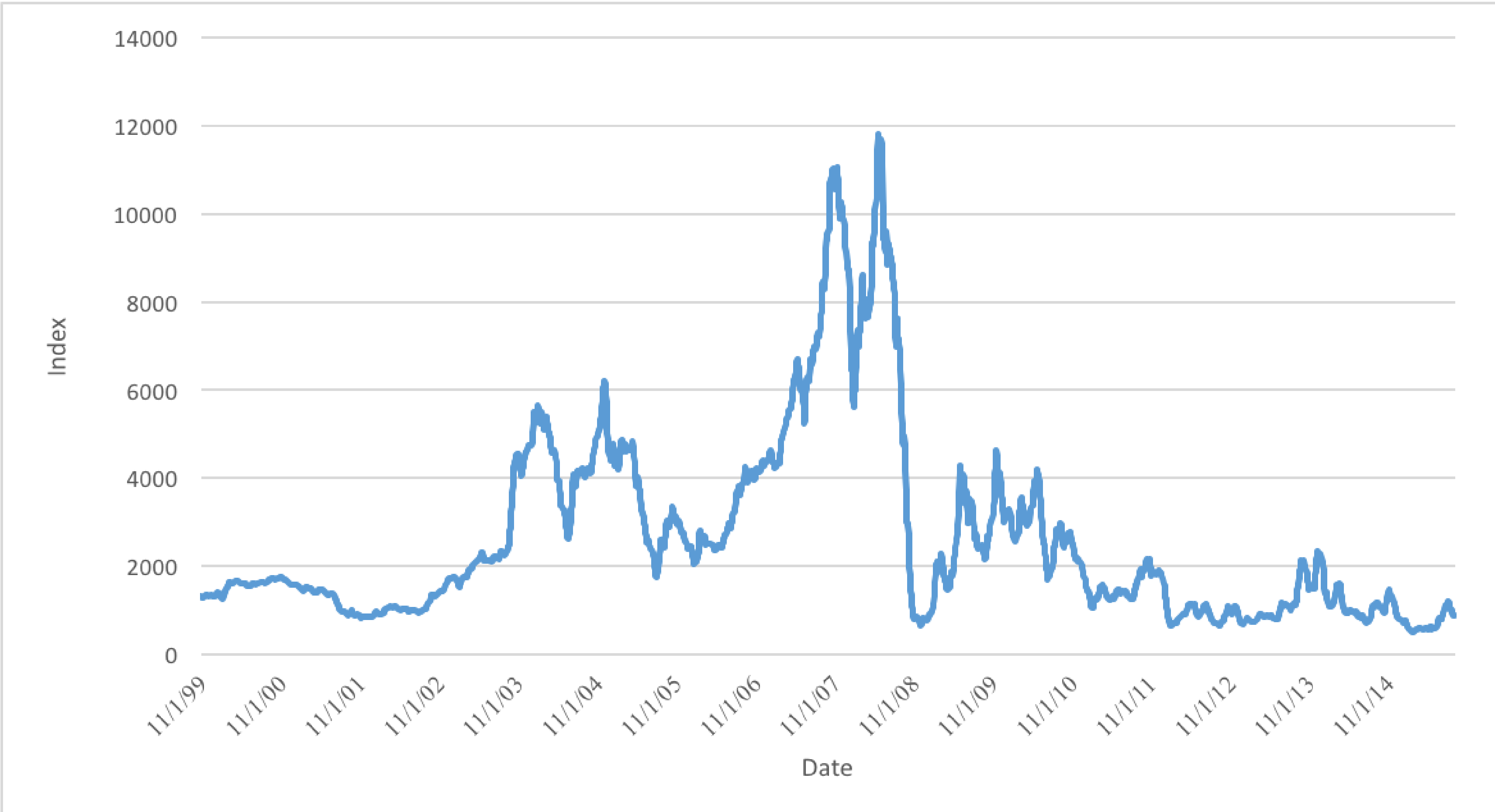


Table 1: Summary statistics of the seven indices

The table shows the number of daily observation for each index, after removing weekends, holidays, and any other missing values. The table also shows the distribution statistics of the daily returns of the seven indices as well as the sample periods

	No. of Obs	Mean ($\times 10^{-4}$)	Median ($\times 10^{-4}$)	S.D. ($\times 10^{-2}$)	Skewness	Kurtosis	LB[10] $\times 10^{-3}$
Baltic Exchange Dry Index	3,959	-1.02	2.4	1.94	0.03	8.71	5.52
Baltic Exchange Capesize Index	4,128	0.43	-4.1	3.16	0.85	15.7	3.19
Baltic Exchange Panamax Index	4,336	-0.33	0	2.3	-0.1	10.8	6.18
Baltic Exchange Supramax Index	2,541	-3.39	1.8	1.59	0.38	22.2	7.79
Baltic Exchange Handysize Index	2,277	-3.2	0	1.31	-1.26	17.7	8.64
Baltic Exchange Dirty Tanker Index	4,274	-1.04	-9.4	2.03	-1.51	43.3	2.76
Baltic Exchange Clean Tanker Index	4,274	-0.21	13	1.4	-1.22	90.4	3.31

Table 2: Sample period of the seven indices

This table illustrates the sample periods for the seven indices according to their different types of vessels.

Index	From	To
Baltic exchange Capesize index	1999-Mar-01	2015-Jul-31
Baltic exchange Panamax index	1998-May-06	2015-Jul-31
Baltic exchange Supramax index	2005-Jul-01	2015-Jul-31
Baltic exchange Handysize index	2006-May-23	2015-Jul-31
Baltic exchange dirty tanker index	1998-Aug-03	2015-Jul-31
Baltic exchange clean tanker index	1998-Aug-03	2015-Jul-31

Table 3: In-sample estimation results

This table reports the in-sample estimation of the HAR, Two-component, GARCH, GJR-GARCH, and EGARCH models for the seven indices.

	Panel A: HAR-RV					Panel B: Two-component	
	α	α_d	α_w	α_m	Adj.R^2	α_m	Adj.R^2
Baltic Exchange Dry Index	0.021***	0.539***	0.062**	0.174***	0.456	0.610***	0.372
	(5.375)	(31.17)	(2.248)	(5.531)		(48.44)	
Baltic Exchange Capesize Index	0.094***	0.245***	0.180***	0.230***	0.205	0.471***	0.221
	(5.429)	(13.77)	(5.331)	(5.596)		(34.26)	
Baltic Exchange Panamax Index	0.027***	0.745***	-0.165***	0.239***	0.572	0.709***	0.503
	(4.939)	(51.13)	(-7.36)	(9.198)		(66.21)	
Baltic Exchange Supramax Index	0.017***	0.517***	0.132***	0.084**	0.402	0.767***	0.588
	(3.36)	(23.32)	(3.833)	(2.13)		(60.18)	
Baltic Exchange Handysize Index	0.007***	0.614***	0.164***	0.048	0.581	0.782***	0.611
	(2.773)	(26.51)	(4.965)	(1.545)		(59.8)	
Baltic Exchange Dirty Tanker Index	0.086***	0.019	0.035	0.152**	0.028	0.296***	0.088
	(6.892)	(1.076)	(0.84)	(2.058)		(20.28)	
Baltic Exchange Clean Tanker Index	0.050***	0.004	0.057	-0.02	0.013	0.265***	0.07
	(6.283)	(0.243)	(1.379)	(-0.252)		(17.94)	

To be continued

	Panel C: GARCH			Panel D: EGARCH				Panel E: GJR-GARCH			
	$\alpha \times 10^{-6}$	γ	β	ω	α	γ	β	ω	α	γ	β
Baltic Exchange Dry Index	35.7**	0.147***	0.853***	-0.171***	0.387***	0.021	0.983***	0.000***	0.000***	0.922***	0.000***
	(1.835)	(13.07)	(93.15)	(-5.29)	(15.21)	(1.542)	(296.9)	(0.000003)	(0.64)	(0.0043)	(0.035)
Baltic Exchange Capesize Index	1.40***	0.200***	0.800***	-0.196***	0.535***	0.009	0.976***	0.186***	0.000***	0.709***	0.000**
	(3.839)	(14.21)	(80.23)	(-5.91)	(15.22)	(0.562)	(257.8)	(0.000003)	(0.493)	(0.011)	(0.500)
Baltic Exchange Panamax Index	1.21***	0.195***	0.805***	-0.304***	0.419***	0.002	0.968***	0.000***	0.000***	0.669***	0.000***
	(3.28)	(13.56)	(69.34)	(-6.43)	(16.41)	(0.138)	(196.6)	(0.000004)	(0.718)	(0.020)	(0.272)
Baltic Exchange Supramax Index	1.21***	0.214***	0.786***	-0.368***	0.265***	-0.046***	0.965***	0.000***	0.000***	0.947***	0.004***
	(2.577)	(8.811)	(43.06)	(-5.11)	(9.663)	(-2.81)	(140.1)	(0.000002)	(0.894)	(0.005)	(0.107)
Baltic Exchange Handysize Index	2.23***	0.176***	0.753***	-0.724***	0.316***	-0.022	0.932***	0.000***	0.000***	0.731***	0.325**
	(4.054)	(6.713)	(20.14)	(-5.04)	(9.192)	(-1.09)	(68.82)	(0.000003)	(0.940)	(0.024)	(0.042)
Baltic Exchange Dirty Tanker Index	0.26***	0.289***	0.696***	-0.387***	0.234***	0.066***	0.954***	0.878***	0.204***	0.064***	0.000***
	(6.742)	(6.955)	(27.9)	(-6.45)	(11.82)	(5.395)	(135.3)	(0.000001)	(0.106)	(0.92)	(0.938)
Baltic Exchange Clean Tanker Index	0.28***	0.406***	0.426***	-2.802***	0.361***	0.107***	0.701***	0.00***	0.000***	0.000***	0.000***
	(8.743)	(7.179)	(10.62)	(-9.39)	(13.05)	(5.582)	(22)	(0.000001)	(0.200)	(0.116)	(0.852)

Table 4: Volatility forecasting performance for 1-, 5- and 22-day ahead

This table summarizes the volatility forecasting performance evaluated by RMSE of realized volatility for the five models: HAR, Two-component, GARCH, EGARCH, and GJR-GARCH.

	HAR	Two	GARCH	EGARCH	GJR-GARCH
Panel A: RMSE					
Baltic Exchange Dry Index	0.23	0.223	0.29	0.296	0.180
Baltic Exchange Capesize Index	1.027	0.956	1.049	1.064	1.023
Baltic Exchange Panamax Index	0.377	0.306	0.453	0.46	0.382
Baltic Exchange Supramax Index	0.296	0.272	0.336	0.404	0.423
Baltic Exchange Handysize Index	0.038	0.037	0.05	0.052	0.047
Baltic Exchange Dirty Tanker Index	0.769	0.734	0.754	0.743	0.680
Baltic Exchange Clean Tanker Index	0.516	0.503	0.506	0.506	0.501
Panel B: MAE					
Baltic Exchange Dry Index	0.894	0.712	0.915	0.966	0.701
Baltic Exchange Capesize Index	2.018	1.887	2.211	2.291	2.115
Baltic Exchange Panamax Index	0.911	0.81	1.069	1.165	0.998
Baltic Exchange Supramax Index	0.746	0.638	0.841	0.883	0.795
Baltic Exchange Handysize Index	0.494	0.408	0.512	0.536	0.501
Baltic Exchange Dirty Tanker Index	1.55	1.316	1.532	1.399	1.265
Baltic Exchange Clean Tanker Index	1.029	0.913	0.928	0.933	0.902
Panel C: MAPE					
Baltic Exchange Dry Index	6.488	5.148	7.416	7.561	5.094
Baltic Exchange Capesize Index	10.49	9.014	11.141	11.56	10.41
Baltic Exchange Panamax Index	8.014	7.913	8.519	9.001	8.010
Baltic Exchange Supramax Index	6.901	6.066	7.118	7.329	6.514
Baltic Exchange Handysize Index	2.065	1.717	2.551	2.618	1.998
Baltic Exchange Dirty Tanker Index	3.642	3.147	3.323	3.265	3.117
Baltic Exchange Clean Tanker Index	3.158	3.009	3.139	3.13	2.998
Panel D: Mincer-Zarnowitz regress test					
Baltic Exchange Dry Index	0.455	0.501	0.409	0.463	0.527
Baltic Exchange Capesize Index	0.689	0.718	0.605	0.62	0.691
Baltic Exchange Panamax Index	0.512	0.592	0.547	0.499	0.577
Baltic Exchange Supramax Index	0.505	0.553	0.544	0.487	0.530
Baltic Exchange Handysize Index	0.201	0.234	0.218	0.191	0.210
Baltic Exchange Dirty Tanker Index	0.603	0.694	0.597	0.631	0.701
Baltic Exchange Clean Tanker Index	0.517	0.561	0.502	0.493	0.599

Table 5: The superior predictive ability (SPA) test of Hansen (2005)

This table reports the SPA test for models: HAR, Two-component, GARCH, EGARCH, and GJR-GARCH. The null hypothesis is that the benchmark model is not inferior to any of the competing models, which is resoundingly accepted with a high p-value .

	HAR	Two	GARCH	EGARCH	GJR-GARCH
Panel A: RMSE					
Baltic Exchange Dry Index	0.000	1.000	0.000	0.000	0.000
Baltic Exchange Capesize Index	0.000	1.000	0.034	0.023	0.057
Baltic Exchange Panamax Index	0.000	1.000	0.000	0.000	0.000
Baltic Exchange Supramax Index	0.000	1.000	0.000	0.000	0.000
Baltic Exchange Handysize Index	0.000	1.000	0.000	0.000	0.000
Baltic Exchange Dirty Tanker Index	0.000	1.000	0.030	0.317	0.000
Baltic Exchange Clean Tanker Index	0.000	1.000	0.066	0.364	0.612
Panel B: MAE					
Baltic Exchange Dry Index	0.000	1.000	0.000	0.000	0.651
Baltic Exchange Capesize Index	0.000	1.000	0.000	0.000	0.000
Baltic Exchange Panamax Index	0.000	1.000	0.000	0.000	0.000
Baltic Exchange Supramax Index	0.000	1.000	0.000	0.000	0.000
Baltic Exchange Handysize Index	0.009	1.000	0.005	0.000	0.891
Baltic Exchange Dirty Tanker Index	0.000	1.000	0.000	0.000	0.715
Baltic Exchange Clean Tanker Index	0.008	1.000	0.066	0.000	0.643
Panel C: MAPE					
Baltic Exchange Dry Index	0.000	1.000	0.000	0.000	0.556
Baltic Exchange Capesize Index	0.000	1.000	0.034	0.000	0.000
Baltic Exchange Panamax Index	0.058	1.000	0.000	0.000	0.005
Baltic Exchange Supramax Index	0.000	1.000	0.000	0.000	0.001
Baltic Exchange Handysize Index	0.000	1.000	0.000	0.000	0.489
Baltic Exchange Dirty Tanker Index	0.000	1.000	0.030	0.000	0.293
Baltic Exchange Clean Tanker Index	0.015	1.000	0.066	0.000	0.477

Table 6: Summary of the Diebold and Mariano (1995) test results

In this table, we tabulate the proportion of significant p-values for the Diebold and Mariano (1995) pairwise comparison between these five models: HAR, Two-component, GARCH, EGARCH and GJR-GARCH in terms of RMSE. In addition, the results are qualitatively very similar for MAE andthe results are qualitatively very similar MAPE.

Baltic Exchange Dry Index

	HAR	Two	GARCH	EGARCH	GJR-GARCH
HAR		12.31	-2.18	-2.47	-2.33
Two			-5.19	-5.45	-5.56
GARCH				-3.35	-3.63
EGARCH					-3.52
GJR-GARCH					

Baltic Exchange Capesize Index

	HAR	Two	GARCH	EGARCH	GJR-GARCH
HAR		9.95	0.48	0.33	0.38
Two			-1.83	-1.96	-1.93
GARCH				-1.73	-1.67
EGARCH					-1.62
GJR-GARCH					

Baltic Exchange Panamax Index

	HAR	Two	GARCH	EGARCH	GJR-GARCH
HAR		4.62	-4.42	-4.89	-5.01
Two			-7.35	-7.83	-7.92
GARCH				-7.56	-7.33
EGARCH					-7.65
GJR-GARCH					

Baltic Exchange Supramax Index

	HAR	Two	GARCH	EGARCH	GJR-GARCH
HAR		9.33	-1.38	-2.09	-1.98
Two			-3.56	-3.98	-3.77
GARCH				-1.67	-1.75
EGARCH					-1.82
GJR-GARCH					

Baltic Exchange Handysize Index

	HAR	Two	GARCH	EGARCH	GJR-GARCH
HAR		15.21	-2.37	-2.93	-2.88
Two			-6.21	-6.73	-6.97
GARCH				-8.28	-8.36
EGARCH					-8.78
GJR-GARCH					

Baltic Exchange Dirty Tanker Index

	HAR	Two	GARCH	EGARCH	GJR-GARCH
HAR		14.08	-1.64	-1.92	-1.82
Two			-0.77	-0.5	-0.43
GARCH				1.58	1.61
EGARCH					1.48
GJR-GARCH					

Baltic Exchange Clean Tanker Index

	HAR	Two	GARCH	EGARCH	GJR-GARCH
HAR		13.57	1.41	1.47	1.51
Two			-0.36	-0.29	-0.23
GARCH				1.58	1.47
EGARCH					1.52
GJR-GARCH					

Chapter 4

Impact of crude oil price on shipping freight rate

4.1 Introduction

As mentioned before, sea shipping is a leading indicator of world economic activity as 90% of world trade activities need vessels to complete the transport process (Kilian, 2009). Thus, shipping enterprises consider investment in the shipping industry to be crucial to its development. At the same time, it is a well-accepted view that sea shipping, as an integral part of the global transportation and logistics network, is a most volatile industry, and therefore its agents are exposed to substantial unexpected financial and business risks, which predominantly emanate from fluctuations in freight rates. In addition, it will greatly affect the cash flows of different participants, such as ship-owners, operators, and charterers. (Alizadeh, 2013).

Prices in the bulk and tanker shipping markets are clearly highly uncertain. It is generally believed that the impact of crude oil price on the world economy is extensive (Shi et al., 2013). Hamilton (1983) discover that the correlation between recessions and oil shocks is statistically significant and non-spurious over the period 19481972, which supports the proposition that oil shocks were a contributing factor in at least some of the US recessions prior to 1972. In a more detailed study, Jones and Kaul (1996) show that the reaction of the United States and Canadian stock prices to oil shocks can be completely accounted for by the influence of these shocks on real cash flows alone in the post-war period.

For a very long time, the change in crude oil price has commonly been used to predict economic growth. However, the supply of crude oil is controlled by a few oil-production areas, while the demand for crude oil is global. According to the BP Statistical Review of World Energy, June 2011, 68.7% of world crude oil production was undertaken by North America, Europe and Asia, and the Middle East in 2010. Crude oil carriers transport crude oil from the producing regions to meet the consumption worldwide, which means that the demand for crude oil transport services is derived from the imbalance between the supply and demand of crude oil. Therefore, it is quite conceivable to conclude that crude oil price shocks have significant effects on the tanker market.

As stated in Gavriilidis et al. (2018), crude oil price shocks affect the tanker market in two different ways. Firstly, the volatilities in crude oil prices are directly caused by the demand for crude oil transport services, which is influenced by the supply side of the crude oil market. For example, an unexpected increase in crude oil production causes an immediate increase in the demand for crude oil transport services. It is easy to understand that since normally vessels are in different routes over the world, at a practical level there would be a huge workload if existing routes altered. It is worth noting that the number of existing vessels remains constant over a short time period. According to Strandenes in Wayne (2012), new vessels are the basic source that drives an increase in transport capacity in the shipping industry. The time required to deliver a new vessel may be three to four years when shipbuilding capacity is scarce in relation to contracting activities. The second aspect on which crude oil price shocks can impact the tanker market is related to the transportation costs of shipping companies. Transportation costs in the tanker market comprise three parts: capital costs; running costs; and voyage costs. These costs vary according to different travel distances and routes. To explain it in a more detailed way, those costs mainly include fuel and port costs. For companies in the tanker freight market, oil price is a notable expense since it is a product of crude oil. The higher oil price the higher the freight rate, and thus a decrease in profit for tanker freight companies.

There are several crucial points that may be neglected in the previous work. Firstly, it has not been general practice to use variables outside the shipping industry in some of the prior research which discusses the volatility of freight rates among different shipping market segments e.g., Kavussanos, 1996, 1997, 2003; Alizadeh, 2001; Drobetz et al., 2010. Moreover, the existing research focus is mainly on the relationship between crude oil prices and the tanker index, the relationship between crude oil prices and the dry bulk index have not been bought to attention. Secondly, only the GARCH family of models are used, other models, such as the HAR model, have never been applied to these data. Thirdly, time periods have not been divided into parts to understand how results may differ over different time periods.

This study contributes to the extant literature in the following ways: firstly, it is the first to divide time periods into three different lengths (1, 5, 22 days) with the purpose of gaining different results related to how the oil price effects the seven freight indices. Secondly, the HAR and HAR-X models are used for the first time in this field to increase the accuracy of forecasting outcomes. Finally, our data has a very wide time range of more than 10 years. In other words, It means that this time range covers the whole common business cycle of the shipping industry, which is normally seven to eight years, and also includes the indices data for the period of the famous financial crisis, thus giving a complete picture of rising and falling trends of volatility affected by the general global economic environment.

Finally, this paper supports risk management by offering important advice for both investors and business participants in the shipping area. More specifically, more accurate volatility forecasting provided in this study can serve as an alarm for those stakeholders especially during the market downturns. Further, other indirect participants, such as investment banks and policy makers, may adjust their strategies by using better forecasting tools.

The rest of this paper is organized as the follows: Section 4.2 gives a review of the existing literature; Section 4.3 describes the dataset; Section 4.4 discusses the empirical results, and finally Section 4.5 draws conclusions.

4.2 Literature review

It is widely accepted that crude oil plays a crucial role in the world economy, and the dynamics of the volatility of oil prices nowadays causes deep concern among market participants and government regulators. For instance, due to the financial crisis in 2008, WTI decreased by approximately 80% and was only around $33 per barrel, even at the end of 2008 (F. Chen et al., 2017). Thus, many researchers think it is worth investigating the relationship between crude oil price shocks and macroeconomic variables. Kilian and Park (2009) reveal the response of aggregate US real stock returns to crude oil price increases may differ greatly, depending on whether the increase in crude oil price is driven by demand or supply shocks in the crude oil market. In the same year, Kilian build a structural VAR model of the global crude oil market to evaluate the response of macroeconomic aggregates to exogenous changes in oil prices. Another similar study is that of Basher et al. (2012). In addition, it is found that oil prices could fully explain movements in the value of the US dollar against major foreign currencies from the 1970s to 2008 (Lizardo and Mollick, 2010).

Tanker carriers, which include three main ship types, are mainly used to transport crude oil and play a significant role in the international transportation market nowadays. According to Kavussanos (1996) and Kavussanos and Alizadeh-M (2002), the vessel size in the tanker industry determines an operations flexibility, which is constrained by the different natural conditions of routes and ports. For instance, there are three main routes for VLCCs, each originates in the Persian Gulf and ends in the Far East, North America, or north-west Europe via the Cape. Suezmax tankers mainly operate between the Persian Gulf and north-west Europe through the Suez Canal. but also West Africa to the US Gulf and the US east coast. Aframax vessels mainly operate from West Africa and the North Sea to the US east coast, from North Africa to the Mediterranean and North Europe, and from the Persian Gulf to the Far East. Handysize tankers are mainly used for regional oil product shipping. The Worldwide Tanker Nominal Freight Scale (WS) is used to standardize tanker freight rates, while the Baltic Dirty Tanker Index (BDTI) and the Baltic Clean Tanker Index (BCTI), published by the Baltic Mercantile and Shipping Exchange, are used to reflect the whole situation of the tanker spot freight market.

Previous studies pay a lot of attention to high risk and fickle changes, and also show the need and significance for more work to be done. Shi et al. (2013) does further research about relationship between tanker freight rates and oil price shocks of different origins , which is based on the work of Kilian (2009), who is the first researcher to reveal that the origin of an oil-price shock determines its influence on the global economy and the stock market (Kilian and Park, 2009).

The majority of previous studies focus on the relationship between crude oil price and tanker freight rate in two different aspects. Some consider the fact that tankers are mainly used to transport crude oil which can be described as a synergetic effect. For example, Tsouknidis (2016) documents evidence of large time-varying volatility spill-overs within and between the dry bulk and tanker sub-segments, which are seen to be far larger during and after the period of the global financial crisis. Other studies also focus on volatility modelling and forecasting in tanker freight markets such as Chen and Wang (2004) and Adland and Cullinane (2006).

Meanwhile, some studies put their emphasis on modelling. The earliest of these is from Sveistrup and Koopmans (1939) , who propose a model of supply and demand to determine tanker freight rates. Decades later, Beenstock and Vergottis (1989) improve the theoretical model of the world tanker market. This model includes all four shipping markets in a classic equilibrium framework and introduces uncertainty by modelling the demand for freight services as a stochastic function of the crude oil price. As mentioned, ARCH and GARCH family models are popular in this area. For instance, Kavussanos (1996) estimates a set of GARCH models to establish that using oil price as an exogenous variable significantly improves forecasting accuracy of tanker volatility. Later in his paper in 2003, he uses co-integrating Error Correction ARCH models to model spot and time charter (TC) rates for each ship size, while the associated time varying risks are involved in his models. He shows that risks are lower for TC rates in comparison to the spot rates, and are also lower in smaller vessels in comparison to larger vessels. Therefore, for risk averse owners, It would be optimal to operate tankers in TC markets and use smaller vessels to diversify the involved higher risks.

Similar studies from Kavussanos (1996) and Drobetz et al. (2012) include oil price as an exogenous variable in a GARCH-X model setting. Especially in Drobetz et al. (2012), they examine the dynamics of time-varying volatility in both dry bulk and tanker freight markets, using a GARCH model with exogenous variables (GARCH-X) and an EGARCH model, which is able to show how macroeconomic factors could provide additional explanatory power when included in the conditional variance equation of these models. Chen et al. (2017) and Zhou (2012) investigate the cross-correlations between the West Texas International crude oil index (WTI) and the Baltic Exchange Dirty Tanker Index (BDTI) by applying the Multifractal Detrended Cross-Correlation Analysis (MF-DCCA).

Other researchers, such as Zheng and Lan (2016) point out that the fluctuation of the tanker freight rate is heavily dependent on fuel cost. It is also worth noting that among other studies, Joutz (2009) investigates the lead-lag relationship between oil prices and tanker freight rates, and successfully finds relations between spot and future crude oil prices, crude oil inventories, and tanker rates.

In addition, Sun et al. (2014) discover two series that are significantly correlated in the medium- and long-term when taking the relevant structure into consideration. In addition to the above literature, Gavriilidis et al. (2018) are the first researchers to investigate if oil price shocks of different origin can improve volatility forecasts drawn from a wide set of popular GARCH models for tanker freight rates across freight contracts (spot and 1-year time charter contracts) and vessel sizes (VLCC, Suezmax, Aframax, MR).

Previous studies focus on oil price influence as well. Hamilton (2003) argues that there are three factors at work together to determine the crude oil prices: in the short-term, the balance between supply and demand; in the medium-term, the structure of the oil industry; and in the long-term, the marginal production cost, which is consistent with world oil demand. Higher crude oil prices increase the production cost of goods and services, and therefore it is well established view that higher crude oil prices may have a negative influence on the world economy.

The famous study by Kilian (2009) investigates the response of stock returns to oil price shocks and shows they may differ greatly depending on whether the increase in the price of crude oil is driven by demand or supply shocks in the crude oil market. It is important for ship-owners and operators in the crude oil tanker market to distinguish crude oil supply shocks from crude oil non-supply shocks since they affect the tanker market through different channels.

Based on these results, Shi et al. (2013) conclude the impact of crude oil production on the world economy is comprehensive. Firstly, decreasing crude oil production would hinder the progress of economic development if the worlds energy demands cannot be meet. Secondly, it is hard to find substitutes for crude oil in the short-term. Decreases in crude oil supply may result in a sharp rise in its price and, as a result, the costs of economic activities increase, which is harmful to the economy. Thirdly, as for the crude oil tanker market, since the demand for crude oil transport services depends on the amount of international trade in crude oil, decline in its production also directly decreases the demand for crude oil transport services.

4.3 Data description and summary statistics

We obtained the Baltic Dirty Tanker Index (BDTI) from the Baltic Exchange. The indices are published by the Baltic Exchange and are calculated daily based on the reports of the Baltic Exchange partners, shipbrokers, and panelists. Alizadeh and Talley (2011) argue that BDTI reflects the conditions of tanker market as well as the effects of macroeconomic determinants of tanker freight rates. The BDTI is classified into four sub-indices, namely Capsize, Panamax, Superamax, and Handysize, based on different ship types.

Shipping freight rates have been shown to exhibit pronounced seasonality effects (Kavussanos and Alizadeh-M, 2001, 2002). In order to ensure that the results are not driven by seasonality, the returns of the indices are calculated as the first logarithmic differences of day-to-day closing index values.

$$r_t = \ln BDI_t - \ln BDI_{t-1} \tag{4.1}$$

For the dry-bulk cargo segment the following indices are examined: the Baltic Dry Index (BDI); the Baltic Capesize Index (BCI); the Baltic Panamax Index (BPI); the Baltic Supramax Index (BSI); and, the Baltic Handysize Index (BHSI). For the tanker segment, the Baltic Dirty Tankers Index (BDTI) and the Baltic Clean Tankers Index (BCTI) are examined; they represent the two major sub-sectors of liquid-bulk shipping. The BDI is a composite index calculated as the equally weighted average of the BCI, BPI, BSI, and BHSI indices. Apart from the BDI, the rest of the indices are calculated as a weighted average of shipping freight rates on major voyage and time charter routes.

The Baltic Handysize index (BHSI) has the shortest time series data available as its inception as a tool from March 23rd 2006. Meanwhile the tanker sub-segments and the general BDI index has the longest data availability, which is from August 3rd, 1998, when the inception of the BDTI and the BCTI took place, to September 3rd, 2015. However, both time periods for these data are longer than the typical length of a sea shipping business cycle, which usually is six to seven years Stopford (2009). Moreover, the time period during which the global financial crisis occurred is covered by all the data, which means there is sufficient information to observe both up and down periods of the business cycle. After filtering out the data for holidays, missing values, and non-trading days, the final sample contains 3959 and 4274 daily observations for the dry-bulk sub-segments and the tanker sub-segments, respectively. When building models, we use most of the data for in-sample estimation, and the last 700 observation for testing, i.e., out-of-sample predictive power testing.

Table 7 shows the summary statistics of these seven indices, both in dry bulk and tanker carriers. The number of observations, mean, median, standard deviation, skewness, and excess kurtosis are presented. The only positive income among these is the Baltic Exchange Capesize Index during some specific periods. In addition, it can be observed that the volatilities of shipping freight rates depend directly on the size of carriers. That is, larger vessels gain higher levels of volatility in their rates, which is in accordance with the dry-cargo categories. The last column tabulates the Ljung Box statistic for autocorrelation for the first ten lags. In the Ljung Box tests, the null hypothesis of no autocorrelation is strongly rejected.

Our data include a measure of the crude oil production in the world, and crude oil is the most important commodity traded around the world because it is the main energy source for all kinds of production activities. It is believed that the impact of oil price changes on the world economy is extensive, and therefore oil prices have been used as an indicator of global economic development. The impact of crude oil production on the world economy can be summarized from three aspects.

Firstly, a decline in crude oil production may slow down the process of industry development as there is not enough energy supply. Secondly, for the reason that substitutes for crude oil as an energy source are rare, oil prices will definitely go up in the short-term when production decreases. Lastly, especially for the tanker market, on which many previous studies focus, the demand side for crude oil transport services mainly depends on the amount of crude oil in the international market.

The sample data consists of crude oil prices of Brent and WTI spot crude prices. All the oil data used in this article are monthly data for both Brent and WTI, covering the period from 27 Dec, 2001, to 3 Sep, 2015, which are 4339 and 3707 observations, respectively. In

Figure 2, the top panel (a) illustrates the average value of Brent and WTI index as well as indices of BDI, BDCI, and BDTI. The bottom panel (b) demonstrates the historical average value of the crude oil price. Comparing the evolution patterns of three index series in Panel (a), there seems to be a similar decreasing trend in latter part of 2007. In Panel (b), an obvious decline occurs in the second half of 2008. It is believed that the drop in crude oil tanker market levels is due to the decline in both crude oil production and prices.

Table 7 summarizes the number of observations, mean, standard deviation, minimum and maximum value of the two cross-sectional dispersion measures: Brent and WTI oil spot price indices. It also reports the serial correlation for 1, 3, 5, 20 lags together with t-statistics of the Augmented Dickey-Fuller test. The sample period is from 27 Dec, 2001, to 3 Sep, 2015. The two oil price indices have similar values of mean and maximum numbers, thus both can be treated as an important indicator of crude oil prices. Therefore, we use both indices in further research.

4.4 Empirical analysis

4.4.1 In-sample estimation results

Table 8 reports the in-sample volatility estimation result of the HAR and HAR-X models in seven panels over the whole sample period. The exogenous variables X are the Brent and WTI, respectively, which are able to capture the crude oil price change in different periods.

Firstly, we observe that the β_m coefficient is positive and significant for all of the HAR-X models, showing that the cross-sectional dispersion variable plays a substantial role in describing daily volatility processes, and that incorporating the cross-sectional dispersion can better specify the daily volatility dynamics. This result is consistent with the findings of Gavriilidis et al. (2018) who show that the inclusion of oil price shocks of different origin as exogenous variables in a wide set of models improves the accuracy of their volatility forecasts. Furthermore, the statistically significant results for the two tanker indices also suggest that transportation of raw materials by tanker vessels highly correlates with oil prices. It is consistent with existing literature from Lin and Sim (2013), who argue that the spillover effect of the BDI was insignificant during the sample period from 2007 to 2018, when applying the VAR-BEKK-GARCH-X model.

In addition to the HAR and HAR-X models, Table 9, Table 10 and Table 11 also illustrate the in-sample estimation results of the GARCH-family models including the GJR-GARCH, the conventional GARCH, and the EGARCH with their augmented models, respectively. Overall, their in-sample estimation yields qualitatively similar results which are in line with the HAR-X model. This is in line with prior literature, such as Lu et al. (2008). Overall, augmenting the cross-sectional dispersion variable, X, could better specify the modelling of the daily volatility dynamics for the seven indices, suggesting that X is expected to further contribute to volatility forecasting.

4.4.2 Out-of-sample predictions

As the significance level for estimates of the parameters are slightly different from the in-sample result and the out-of-sample result, we conduct out-of-sample tests of the shipping industry indices to examine the forecasting performance of the benchmark and augmented models. Table 12, Table 13, Table 14, and Table 15 summarizes the results for the seven different indices. We report three loss functions of forecasting errors, namely RMSE, MAE, and MAPE with the Mincer-Zarnowitz regress test, to evaluate whether the difference in forecasting performance between volatility models is significant.

First, the results of the Table 12 show that the predictive power of the HAR-X model is significantly better than that of the HAR model for several specific indices for 1-, 5-, and 22-day ahead, in terms of the RMSE, MAE, and MAPE with their t-statistics by incorporating Brent or WTI oil price indices as the X variable. For example, via incorporating the Brent oil price index in the Baltic Exchange Supramax Index in panel D, the forecasting performance is significantly improved in terms of the RMSE, MAE, and MAPE with the Mincer-Zarnowitz regress test especially for 5- and 22-day ahead. This is also the similar case for panel A and C where the volatility forecasting performance is improved as well for the Baltic Exchange Dry Index and Baltic Exchange Panamax Index in terms of the MAE and MAPE. It is worth noting that the small size carriers in Panel E, which are under the Handysize category, have RMSE, MAE, and MAPE that are mostly insignificant due to the limited liquidity of those carriers in the market. Furthermore, the Mincer-Zarnowitz adjusted R^2 also fails to improve in Panel E as well as Panel G.

For the HAR and HAR-X models, we trained our data over 1-, 5-, and 22-day ahead horizons to correspond to different volatility components underlying the HAR model. By augmenting the two cross-sectional dispersion measures, we observe that, except for the one-day ahead horizon for the RMSE in panel A as general dry bulk index, the augmented models show great decreases in forecasting errors across all horizons and across all loss functions. Moreover, according to the R^2 of the Mincer-Zarnowitz regression, the augmented HAR-X model exhibits stronger explanatory power with a higher R^2 especially for the 5- and 22-day ahead. Overall, at the different indice levels, we provide clear evidence that the information content in the oil price helps improve the forecasting performance of HAR-X models.

It is noteworthy that, at a more detailed level, it seems that the augmented HAR-X models do not perform better than the benchmark HAR model over the 1-day ahead forecast horizon. The HAR-X outperforms the benchmark HAR model in two indices, namely the Panama and the Dirty Tanker index. At the same time, the difference among the other four indices is slightly significant. However, for 5- and 22-day ahead forecast horizons, the HAR-X model dominates the HAR model by having significantly larger forecasting errors. Overall, all panels suggest that the information content of the different dispersion is more pronounced at the 1-day ahead horizons.

Table 13, table 14, and table 15 provide testing results of the GARCH-family models, which include: standard GARCH v.s GARCH-X ; GJR-GARCH v.s. GJR-GARCH-X; and, EGARCH v.s. EGARCH-X models, within 1-day ahead on out-of-sample data. Generally, the RMSE and MAE are the basis used here to evaluate whether the difference in forecasting performance between volatility models is significant.

The GARCH family models show similar improvement when adding the exogenous variable X (oil price index in this thesis). It is sufficient to compare the GJR-GARCH with the HAR to see whether adding an oil price as an exogenous variable could improve forecasting power. We also report the R^2 of the Mincer-Zarnowitz regression.

Firstly, the results show that for the four indices, Panels B, C, E, and F, bringing in an external variable X, which denotes the WTI crude oil prices, helps to improve the models predictive power in the short-term. Since no previous literature about the relationship between indices and crude oil price in the dry bulk shipping industry can be found, we can only accept that, based on the result of the GJR-GARCH model, crude oil price can be used as an external variable in short-term forecasting with indices of any segment in dry bulk carriers. For those two tanker indices, the WTI seems do better as its MAE value are all statistically significant in short time periods.

Secondly, speaking of the R^2 of the Mincer-Zarnowitz regression, the GJR-GARCH-X model did not exhibit stronger explanatory power with a higher R^2. It is worth noting that, in last two tanker indices, namely Panels F and G, two crude oil indices do not seem to help in forecasting, which is not in alignment with the results from the previous four indices in dry bulk segments.

In addition to the above information, the R^2s are all quite low compared with the other four dry bulk segments for the GARCH and GARCH-X model. Especially in the dirty tanker part, the original GARCH model has 22.8% within 1-day ahead, while with the WTI it can only explain 19.7% of the data variation. This result may be caused by model selection. To my best knowledge, there are only a few literature except for Gu et al. (2010) which studied the multifractality of WTI and Brent crude oil markets by MF-DFA analysis, they found that the two crude oil markets become more and more efficient in the long-term. On the contrary, Ruan et al. (2016) investigated the degree of cross-correlations between the Baltic Dry Index and crude oil price with the MF-DCCA method, and the empirical results show that the cross-correlations are strongly persistent in the short-term. My research contributes to the above literature and provides more evidence in oil price volatility modelling and forecasting.

4.5 Conclusion

In this paper, we examine the impact of the oil price on volatility modelling and its forecasting power with the seven shipping indices. Motivated by the evidence in the literature that documents the information content of this dispersion measure, we are interested in investigating whether it helps in volatility forecasting.

By using the Brent and the WTI oil price indices from 27 Dec 2001, to 3 Sep 2015 with

4339 and 3707 observations, respectively, and applying the HAR models augmented by the dispersion measure, our empirical evidence shows that the HAR-X models obtain a better fit in the in-sample estimation tests and improve volatility forecasting accuracy in short term (1-day ahead horizon). In the meantime, although applying the GARCH family models in this chapter did not perform as well as the HAR models, adding the exogenous variable X , which represents two crude oil price indices, does help forecasting in the short time period.

Later, in the forecasting part, the output of HAR models indicate that oil price has a statistically significant effect on short-term prediction rather than for long term. Meanwhile, the results of GJR-GARCH models are consistent with previous literature that there is statistically significant finding in all four Dry Baltic indices with the exogenous variable Brent crude oil price for 1-day ahead. However, for tanker carriers, WTI has a better fit.

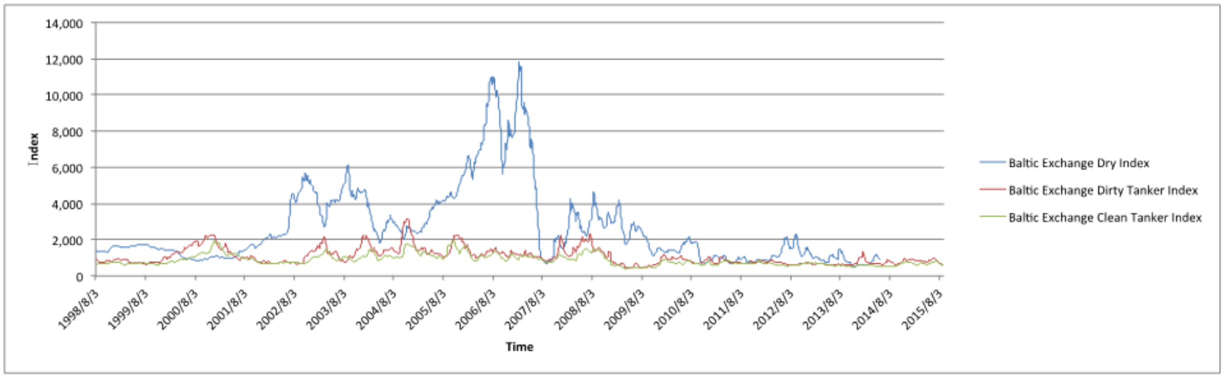
Our findings are of keen interest and relevance to investors, traders, and portfolio managers etc. in shipping industry. Firstly, investors may evaluate risk and returns while making investment decisions using oil prices in short time periods. Secondly, volatility may inform market participants ahead of time of the possible spread of turmoil among financial markets, especially during a financial crisis. Finally, the findings of this study are of importance to oil companies, operators in the tanker market, and investors in the oil derivatives markets. Tanker operators, for instance, with positions in the tanker market may be empowered to make better decisions, facing various shocks.

4.6 Limitation

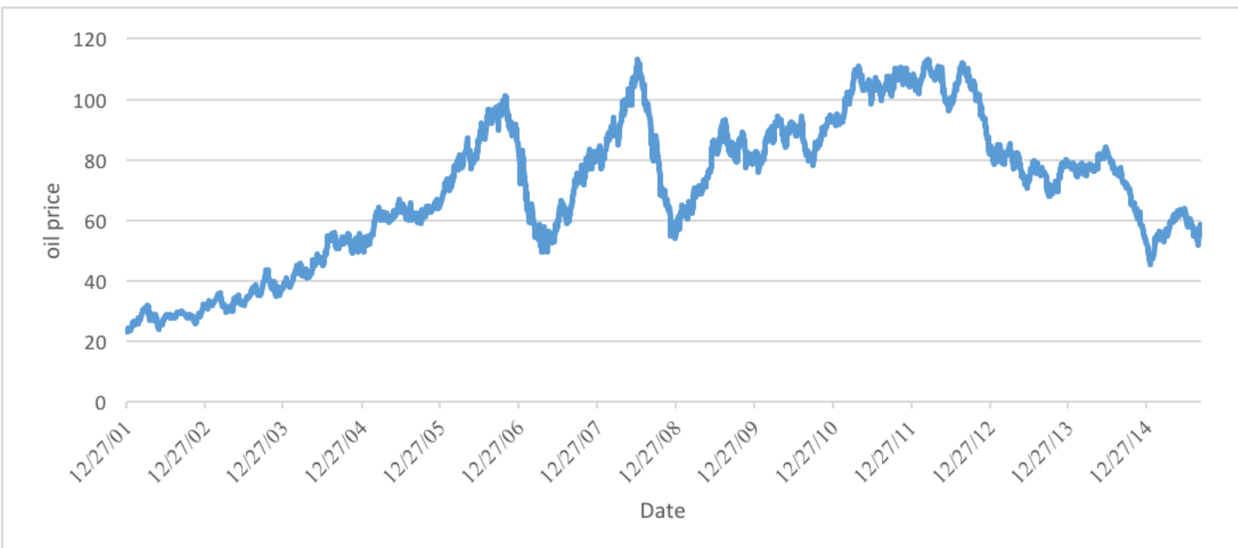
In the research that includes oil price data, in addition to the external variable of the Brent and WTI crude oil prices, more macroeconomic proxies should be taken as variables that may influence the study results, such as GDP. Secondly, when thinking of the division of time periods into different lengths, it is worth trying to include occurrences of major events to provide more accurate volatility forecasting results. Finally, I employ volatility models in my study, such as the GJR-GARCH-X model, only because that it takes into account the asymmetric properties of volatility. Alternatively, other volatility models in the GARCH family could be tested, comparing them with bench model. Furthermore, according to previous literature from F. Chen et al. (2017), models like multifractal cross-correlation analysis method (MF-CCA) and the multifractal detrended partial cross-correlation analysis method (MF-DPXA) can also be considered. In addition, more performance measures that could examine the economic value of volatility forecasts will be extensionally included, and the statistical significance of these performance measures should also be tested as well.

Figure 2: (a) Historical index prices for BDI, BDTI and BDCI; (b) Historical price for crude oil price

This figure illustrates the historical data of crude oil price which calculated by average value of Brent and WTI index, and index of BDI, BDCI and BDTI.



(a)



(b)

Table 7: Descriptive statistics of Brent and WTI oil spot price

This table summarizes the number of observations, mean, standard deviation, minimum and maximum value of the two cross-sectional dispersion measures: Brent and WTI oil spot prices. It also reports the serial correlation for 1, 3, 5, 20 lags together with t-statistics of the Augmented Dickey-Fuller test. The sample period is from 27 Dec 2001 to 3 Sep 2015.

Oil price	No. obs.	Mean	S.D.	Min	Max	Serial correlation at lag					ADF Test
						1	3	5	10	20	
Brent	4339	69.003	29.426	18.02	144.22	0.999	0.997	0.994	0.988	0.975	-0.313
WTI	3707	69.115	24.627	23.7	145.31	0.998	0.994	0.99	0.981	0.959	-0.462

Table 8: The in-sample volatility estimation result with HAR and HAR-X models

This table reports the in-sample volatility estimation of HAR and HAR-X models of 7 indices. The exogenous X variable γ_d is the Brent/WTI. Standard errors are in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Panel A: Baltic Exchange Dry Index

	HAR-X					HAR			
	α	β_d	β_w	β_m	$\gamma_d \times 10^{-3}$	α	β_d	β_w	β_m
Brent	0.026***	0.604***	0.031	0.177***	0.233**	0.04***	0.605***	0.031	0.19***
	(0.01)	(0.02)	(0.03)	(0.03)	(0.1)	(0.01)	(0.02)	(0.03)	(0.03)
WTI	0.028***	0.604***	0.031	0.183***	0.192**				
	(0.01)	(0.02)	(0.03)	(0.03)	(0.12)				

Panel B: Baltic Exchange Capesize Index

	HAR-X					HAR			
Brent	0.047***	0.455***	0.116***	0.225***	0.364**	0.069***	0.455***	0.116***	0.235***
	(0.02)	(0.02)	(0.03)	(0.04)	(0.2)	(0.01)	(0.02)	(0.03)	(0.04)
WTI	0.061***	0.455***	0.116***	0.234***	0.124**				
	(0.02)	(0.02)	(0.03)	(0.04)	(0.24)				

Panel C: Baltic Exchange Panamax Index

	HAR-X					HAR			
Brent	0.028***	0.78***	-0.131***	0.21***	0.162**	0.038***	0.781***	-0.13***	0.214***
	(0.01)	(0.02)	(0.02)	(0.03)	(0.1)	(0.01)	(0.02)	(0.02)	(0.03)
WTI	0.025**	0.78***	-0.13***	0.207***	0.226**				
	(0.01)	(0.02)	(0.02)	(0.03)	(0.13)				

Panel D: Baltic Exchange Supramax Index

	HAR-X					HAR			
Brent	0.03**	0.817***	-0.039	0.102***	-0.116**	0.02***	0.817***	-0.04	0.106***
	(0.01)	(0.02)	(0.03)	(0.03)	(0.14)	(4.0E-05)	(0.02)	(0.03)	(0.03)
WTI	0.026*	0.817***	-0.04	0.106***	-0.063**				
	(0.02)	(0.02)	(0.03)	(0.03)	(0.16)				

To be continued

	HAR-X					HAR			
	α	β_d	β_w	β_m	$\gamma_d \times 10^{-3}$	α	β_d	β_w	β_m
Panel E: Baltic Exchange Handysize Index									
Brent	0.017	0.805***	0.015	0.077**	0.004**	0.017***	0.805***	0.015	0.077**
	(0.01)	(0.03)	(0.04)	(0.03)	(0.15)	(4.9E-03)	(0.03)	(0.04)	(0.03)
WTI	0.022*	0.804***	0.015	0.077**	-0.063**				
	(0.01)	(0.03)	(0.04)	(0.03)	(0.14)				
Panel F: Baltic Exchange Dirty Tanker Index	HAR-X					HAR			
Brent	0.104***	0.281***	0.141***	0.217***	-0.338**	0.073***	0.282***	0.141***	0.242***
	(0.01)	(0.02)	(0.04)	(0.05)	(0.13)	(0.01)	(0.02)	(0.04)	(0.05)
WTI	0.085***	0.282***	0.14***	0.239***	-0.161**				
	(0.01)	(0.02)	(0.04)	(0.05)	(0.16)				
Panel G: Baltic Exchange Clean Tanaker Index	HAR-X					HAR			
Brent	0.073***	0.192***	0.311***	0.042	-0.124**	0.063***	0.193***	0.312***	0.047
	(0.01)	(0.02)	(0.04)	(0.05)	(0.09)	(0.01)	(0.02)	(0.04)	(0.05)
WTI	0.052***	0.192***	0.312***	0.038	0.18**				
	(0.01)	(0.02)	(0.04)	(0.05)	(0.12)				

Table 9: The in-sample volatility estimation result with GJR-GARCH and GJR-GARCH-X models

This table reports the in-sample volatility estimation of GJR-GARCH and GJR-GARCH-X models of 7 indices. The exogenous X variable is the Brent/WTI. P-value of Standard error is in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	GJR-GARCH-X					GJR-GARCH			
Panel A: Baltic Exchange Dry Index									
	$\omega \times 10^{-5}$	α	γ	β	$\phi \times 10^{-5}$	$\omega \times 10^{-5}$	α	γ	β
Brent	-1.875***	0.433***	-0.161***	0.668***	1.44**	0.046***	0.207***	-0.055***	0.858***
	(0.08)	(0.02)	(0.02)	(0.01)	(0.06)	(0.01)	(0.01)	(0.01)	(0.002)
WTI	-1.757***	0.415***	-0.141***	0.699***	1.242***				
	(0.08)	(0.01)	(0.02)	(0.01)	(0.06)				
Panel B: Baltic Exchange Capesize Index									
	GJR-GARCH-X					GJR-GARCH			
Brent	-3.1***	0.368***	-0.099***	0.725***	2.4***	0.282***	0.324***	-0.063***	0.781***
	(0.19)	(0.02)	(0.02)	(0.01)	(0.14)	(0.03)	(0.01)	(0.02)	(0.01)
WTI	-3.25***	0.364***	-0.092***	0.74***	2.29***				
	(0.25)	(0.01)	(0.02)	(0.01)	(0.17)				
Panel C: Baltic Exchange Panamax Index									
	GJR-GARCH-X					GJR-GARCH			
Brent	20.2	0.024	-0.313***	0.49	-10.5	0.305***	0.298***	-0.039**	0.735***
	(35.3)	(0.28)	(0.1)	(0.68)	(19.4)	(0.04)	(0.01)	(0.02)	(0.01)
WTI	12.874	-0.019	0.46	0.428	-66.40				
	(-199.99)	(-0.35)	(-0.09)	(-0.49)	(28.08)				
Panel D: Baltic Exchange Supramax Index									
	GJR-GARCH-X					GJR-GARCH			
Brent	-0.082	0.41***	-0.111***	0.744***	0.073	0.057***	0.412***	-0.107***	0.742***
	(0.16)	(0.02)	(0.02)	(0.01)	(0.09)	(0.01)	(0.02)	(0.02)	(0.01)
WTI	0.063	0.412***	-0.107***	0.742***	-0.004				
	(0.08)	(0.02)	(0.02)	(0.01)	(0.05)				

To be continued

	GJR-GARCH-X					GJR-GARCH			
	$\omega \times 10^{-5}$	α	γ	β	$\phi \times 10^{-5}$	$\omega \times 10^{-5}$	α	γ	β
Panel E: Baltic Exchange Handysize Index									
Brent	0.62**	0.194***	0.03	0.745***	-0.221	0.193***	0.191***	0.027	0.753***
	(0.28)	(0.02)	(0.03)	(0.02)	(0.14)	(0.02)	(0.02)	(0.03)	(0.01)
WTI	-0.495***	0.189***	0.016	0.748***	0.376***				
	(0.16)	(0.02)	(0.03)	(0.02)	(0.09)				
Panel F: Baltic Exchange Dirty Tanker Index									
	GJR-GARCH-X					GJR-GARCH			
Brent	5.18***	0.166***	-0.159***	0.914***	-2.48***	20.6***	0.214***	-0.061**	0.10*
	(0.23)	(0.01)	(0.01)	(0.002)	(0.11)	(1.22)	(0.03)	(0.03)	(0.05)
WTI	8.93***	0.212***	-0.067**	0.127**	6.1***				
	(2.35)	(0.03)	(0.03)	(0.06)	(1.2)				
Panel G: Baltic Exchange Clean Tanaker Index									
	GJR-GARCH-X					GJR-GARCH			
Brent	20.8***	0.15	0.05	0.60***	1.245	11.9***	0.097***	-0.04	0.048
	(5.81)	(0.11)	(0.18)	(0.11)	(1.24)	(0.67)	(0.03)	(0.03)	(0.05)
WTI	20.8***	0.15	0.05	0.6***	0.941				
	(7.55)	(0.11)	(0.18)	(0.11)	(3.15)				

Table 10: The in-sample volatility estimation result with GARCH and GARCH-X models

This table reports the in-sample volatility estimation of GARCH and GARCH-X models of 7 indices. The exogenous X variable is the Brent/WTI. P-value of Standard error is in parentheses. $^{*}P < 0.1$; $^{**}P < 0.05$; $^{***}P < 0.01$.

Panel A: Baltic Exchange Dry Index

	GARCH-X				GARCH		
	$\mu \times 10^{-}5$	α	β	$\phi \times 10^{-}5$	μ	α	β
Brent	1.184***	0.881***	0.206***	2.787**	2.497***	0.748***	0.261***
	(0.021)	(0.072)	(0.047)	(1.301)	(0.10)	(0.06)	(0.09)
WTI	1.547***	0.788***	0.340***	3.148***			
	(0.068)	(0.09)	(0.05)	(1.108)			

Panel B: Baltic Exchange Capesize Index

	GARCH-X				GARCH		
Brent	0.847***	0.591***	0.694***	2.771***	0.987***	0.495***	0.510***
	(0.074)	(0.056)	(0.071)	(0.784)	(0.049)	(0.06)	(0.08)
WTI	1.078***	0.703***	0.469***	2.014***			
	(0.046)	(0.03)	(0.01)	(0.667)			

Panel C: Baltic Exchange Panamax Index

	GARCH-X				GARCH		
Brent	1.050***	0.899***	0.290***	-0.891	1.194***	0.761***	0.244***
	(0.09)	(0.05)	(0.02)	(0.701)	(0.127)	(0.04)	(0.03)
WTI	1.783***	0.918***	0.124***	-1.008			
	(0.104)	(0.04)	(0.02)	(0.991)			

Panel D: Baltic Exchange Supramax Index

	GARCH-X				GARCH		
Brent	1.493***	0.985***	0.174***	0.875***	2.271***	0.934***	0.061***
	(0.078)	(0.09)	(0.01)	(0.167)	(0.182)	(0.06)	(0.01)
WTI	2.074***	0.925***	0.231***	0.398***			
	(0.128)	(0.05)	(0.09)	(0.108)			

To be continued

Panel E: Baltic Exchange Handysize Index

	GARCH-X				GARCH		
	$\mu \times 10^{-5}$	α	β	$\phi \times 10^{-5}$	μ	α	β
Brent	2.174***	0.092	0.066	-0.018	1.118***	0.958***	0.054
	(0.098)	(5.16)	(1.87)	(0.080)	(0.103)	(0.09)	(0.04)
WTI	1.737***	0.997	0.021	1.110***			
	(0.110)	(0.06)	(0.03)	(0.311)			

Panel F: Baltic Exchange Dirty Tanker Index

	GARCH-X				GARCH		
Brent	0.749***	0.117	0.927***	-3.377***	1.871***	0.154***	0.884***
	(0.069)	(0.11)	(0.05)	(0.359)	(0.218)	(0.03)	(0.03)
WTI	1.418***	0.137***	0.881***	4.21***			
	(0.987)	(0.01)	(0.01)	(1.06)			

Panel G: Baltic Exchange Dirty Tanker Index

	GARCH-X				GARCH		
Brent	0.977***	0.071***	0.948***	1.211	0.101***	-0.048	0.051***
	(0.120)	(0.02)	(0.04)	(0.921)	(0.06)	(0.08)	(0.008)
WTI	1.578***	0.064***	0.927***	2.360			
	(0.079)	(0.07)	(0.05)	(2.154)			

Table 11: The in-sample volatility estimation result with EGARCH and EGARCH-X models

This table reports the in-sample volatility estimation of EGARCH and EGARCH-X models of 7 indices. The exogenous X variable is the Brent/WTI. *P*-value of Standard error is in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Panel A: Baltic Exchange Dry Index

	EGARCH-X					EGARCH			
	$\mu \times 10^{-5}$	α	γ	β	$\phi \times 10^{-5}$	$\mu \times 10^{-5}$	α	γ	β
Brent	-3.58***	0.01	1.22***	0.66***	1.89***	-2.18***	0.02	1.08***	0.74***
	(0.24)	(0.03)	(0.05)	(0.02)	(0.76)	(0.27)	(0.21)	(0.05)	(0.02)
WTI	-2.41***	0.02	1.07***	0.75***	1.26***				
	(0.22)	(0.02)	(0.05)	(0.02)	(0.27)				

Panel B: Baltic Echange Capsize Index

	EGARCH-X					EGARCH			
Brent	-1.94***	0.01	1.07***	0.80***	1.44***	0.95 ***	0.03	0.96***	0.87***
	(0.17)	(0.02)	(0.04)	(0.02)	(0.11)	(0.09)	(0.02)	(0.04)	(0.01)
WTI	-1.15***	0.01	0.96***	0.86***	2.18***				
	(0.1)	(0.02)	(0.04)	(0.01)	(0.56)				

Panel C: Baltic Exchange Panamax Index

	EGARCH-X					EGARCH			
Brent	-2.75***	0.01	1.39***	0.70***	-0.16	-2.44***	0.01	1.39***	0.75***
	(0.18)	(0.03)	(0.05)	(0.02)	(0.11)	(0.17)	(0.03)	(0.05)	(0.02)
WTI	-2.90***	0.01	0.39***	0.68***	-1.88				
	(0.32)	(0.03)	(0.05)	(0.03)	(1.66)				

Panel D: Baltic Exchange Supramax Index

	EGARCH-X					EGARCH			
Brent	-1.94***	-0.002	1.42***	0.79***	0.87**	-1.99***	-0.01	1.45***	0.79***
	(0.25)	(0.04)	(0.08)	(0.03)	(0.45)	(0.23)	0.03	(0.08)	(0.003)
WTI	-2.05***	-0.01	1.48***	0.79***	0.81**				
	(0.27)	(0.03)	(0.08)	(0.03)	(0.41)				

To be continued

Panel E: Baltic Exchange Handysize Index

	EGARCH-X					EGARCH			
	$\mu \times 10^{-5}$	α	γ	β	$\phi \times 10^{-5}$	$\mu \times 10^{-5}$	α	γ	β
Brent	-2.57***	-0.05	1.33***	0.72***	-0.24	-2.59***	-0.47***	1.32**	0.73***
	(0.34)	(0.04)	(0.09)	(0.03)	(0.67)	(0.3)	(0.04)	(0.09)	(0.03)
WTI	-2.75***	-0.04	1.32***	0.73***	1.81***				
	(0.33)	(0.04)	(0.09)	(0.03)	(0.66)				

Panel E: Baltic Exchange Dirty Tanker Index

	EGARCH-X					EGARCH			
Brent	-0.15***	0.10***	0.18***	0.97***	-2.26***	-0.11***	0.09***	0.17***	0.98***
	(0.01)	(0.01)	(0.01)	(0.05)	(0.75)	(0.01)	(0.01)	(0.01)	(0.08)
WTI	-0.11***	0.09***	0.18***	0.98***	2.70***				
	(0.01)	(0.01)	(0.01)	(0.09)	(0.487)				

Panel G: Baltic Exchange Clean Tanker Index

	EGARCH-X					EGARCH			
Brent	-2.26***	0.21***	0.32***	0.72**	-2.87	0.76***	0.16***	0.48***	0.90**
	(0.31)	(0.03)	(0.04)	(0.04)	(2.14)	(0.08)	(0.04)	(0.09)	(0.08)
WTI	-3.14***	0.22***	0.42**	0.68***	1.81***				
	(0.29)	(0.02)	(0.03)	(0.03)	(0.23)				

Table 12: Out-of-sample volatility forecasting performance with HAR and HAR-X models

This table reports the out-of-sample forecasting performance of HAR models and corresponding augmented HAR-X models with the Brent and WTI oil spot prices. The root mean square error (RMSE) and the mean absolute error (MAE) are used. The t-statistic of the Diebold and Mariano (1995) test between the benchmark and augmented models is also reported.$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Panel A: Baltic Exchange Dry Index

	RMSE	t-stat	MAE	t-stat	MAPE	t-stat	Mincer-Zarnowitz regress test
1-day ahead	0.264		0.101		4.256		0.379
5-day ahead	0.183		0.08		3.561		0.236
22-day ahead	0.103		0.056		3.321		0.162
Brent							
1-day ahead	0.264	-0.143	0.101	2.296**	4.021	2.196**	0.380
5-day ahead	0.183	-1.545	0.079	2.167**	3.121	2.594***	0.236
22-day ahead	0.103	1.56	0.054	3.746***	2.989	3.041***	0.170
WTI							
1-day ahead	0.264	-0.493	0.101	1.448	4.211	1.091	0.379
5-day ahead	0.183	-2.576**	0.08	-0.313	3.566	-0.112	0.234
22-day ahead	0.104	-3.722***	0.056	-2.315**	3.367	-1.645*	0.154

To be continued

Panel B: Baltic Exchange Capesize Index

	RMSE	*t*-stat	MAE	*t*-stat	MAPE	*t*-stat	Mincer-Zarnowitz regress test
1-day ahead	1.459		0.363		5.218		0.130
5-day ahead	0.555		0.231		4.331		0.159
22-day ahead	0.262		0.15		2.982		0.225
Brent							
1-day ahead	1.441	1.215	0.364	-1.245	5.001	1.596	0.150
5-day ahead	0.541	1.587	0.231	-0.065	3.916	1.691*	0.202
22-day ahead	0.258	0.478	0.147	1.291	2.545	1.323	0.304
WTI							
1-day ahead	1.458	0.383	0.362	2.367**	4.780	2.981	0.131
5-day ahead	0.554	0.979	0.231	0.978	4.012	1.688*	0.162
22-day ahead	0.26	1.706*	0.151	-1.577	2.414	1.707*	0.234
Panel C: Baltic Exchange Panamax Index							
1-day ahead	0.361		0.123		6.252		0.530
5-day ahead	0.306		0.119		5.920		0.238
22-day ahead	0.161		0.079		5.114		0.288
Brent							
1-day ahead	0.361	-1.439	0.123	2.669***	5.569	3.021***	0.531
5-day ahead	0.306	-1.16	0.118	5.058***	5.400	3.590***	0.239
22-day ahead	0.161	1.307	0.077	4.461***	4.612	4.002***	0.299
WTI							
1-day ahead	0.361	-1.809*	0.123	1.687*	5.778	1.798*	0.530
5-day ahead	0.307	-3.483***	0.119	1.659*	5.701	1.912*	0.237
22-day ahead	0.163	-4.992***	0.079	0.718	4.892	1.604	0.283

To be continued

Panel D: Baltic Exchange Supramax Index

	RMSE	*t*-stat	MAE	*t*-stat	MAPE	*t*-stat	Mincer-Zarnowitz regress test
1-day ahead	0.058		0.027		2.218		0.434
5-day ahead	0.049		0.03		1.963		0.186
22-day ahead	0.025		0.02		1.561		0.096
Brent							
1-day ahead	0.058	0.612	0.026	3.805***	1.715	2.621***	0.436
5-day ahead	0.049	2.524**	0.029	8.091***	1.529	5.610***	0.195
22-day ahead	0.024	10.138***	0.018	12.057***	1.061	9.972***	0.154
WTI							
1-day ahead	0.058	-0.202	0.027	1.208	2.001	1.649*	0.434
5-day ahead	0.049	-0.223	0.03	0.267	1.855	1.453	0.186
22-day ahead	0.025	1.615	0.02	1.779*	1.327	1.981**	0.101

Panel E: Baltic Exchange Handysize Index

	RMSE	*t*-stat	MAE	*t*-stat	MAPE	*t*-stat	Mincer-Zarnowitz regress test
1-day ahead	0.011		0.008		0.905		0.435
5-day ahead	0.011		0.009		0.618		0.199
22-day ahead	0.008		0.007		0.411		0.272
Brent							
1-day ahead	0.011	1.045	0.008	0.399	0.893	1.327	0.435
5-day ahead	0.011	2.15**	0.009	2.326**	0.502	2.980***	0.199
22-day ahead	0.008	-1.502	0.007	0.213	0.409	0.601	0.278
WTI							
1-day ahead	0.011	0.717	0.008	0.894	0.887	1.221	0.435
5-day ahead	0.011	1.101	0.009	0.825	0.581	1.089	0.197
22-day ahead	0.008	1.753*	0.007	1.376	0.379	1.668*	0.265

To be continued

Panel F: Baltic Exchange Dirty Tanker Index

	RMSE	t-stat	MAE	t-stat	MAPE	t-stat	Mincer-Zarnowitz regress test
1-day ahead	0.702		0.099		10.210		0.010
5-day ahead	0.144		0.058		8.369		0.069
22-day ahead	0.058		0.037		8.011		0.135
Brent							
1-day ahead	0.701	1.027	0.099	1.432	10.117	0.932	0.010
5-day ahead	0.144	0.465	0.058	1.834*	7.335	1.974**	0.071
22-day ahead	0.058	0.302	0.036	2.536**	7.012	2.813***	0.142
WTI							
1-day ahead	0.702	-0.908	0.099	4.481***	9.350	2.299**	0.010
5-day ahead	0.144	-0.919	0.057	5.907***	7.114	2.891***	0.071
22-day ahead	0.058	1.793*	0.036	7.196***	6.853	3.459***	0.150

Panel G: Baltic Exchange Clean Tanaker Index

	RMSE	t-stat	MAE	t-stat	MAPE	t-stat	Mincer-Zarnowitz regress test
1-day ahead	0.588		0.053		7.329		0.001
5-day ahead	0.085		0.027		6.365		0.020
22-day ahead	0.024		0.016		5.641		0.039
Brent							
1-day ahead	0.588	1.252	0.053	0.555	7.121	1.565	0.001
5-day ahead	0.085	2.035**	0.027	-0.056	6.003	1.654*	0.025
22-day ahead	0.024	2.314**	0.016	-0.442	5.431	1.771*	0.081
WTI							
1-day ahead	0.588	1.192	0.053	-0.054	7.238	1.097	0.001
5-day ahead	0.085	1.519	0.027	0.371	6.241	1.165	0.023
22-day ahead	0.024	-0.484	0.016	0.006	5.577	0.950	0.050

Table 13: Out-of-sample volatility forecasting performance with GJR-GARCH and GJR-GARCH-X models

This table reports the out-of-sample forecasting performance of GJR-GARCH models and corresponding augmented GJR-GARCH-X models with the Brent and WTI oil spot prices. The root mean square error(RMSE) and the mean absolute error (MAE) are used. The t-statistic of the Diebold andMariano (1995) test between the benchmark and augmented models is also reported. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Panel A: Baltic Exchange Dry Index

	RMSE	t-stat	MAE	t-stat	MAPE	t-stat	Mincer-Zarnowitz regress test
1-day ahead	6.769		2.818		21.059		0.957
Brent							
1-day ahead	7.506	-1.712*	3.065	-4.009***	22.913	-1.059	0.946
WTI							
1-day ahead	7.305	-1.248	2.98	-2.762***	22.263	-0.196	0.949

Panel B: Baltic Exchange Capesize Index

	RMSE	t-stat	MAE	t-stat	MAPE	t-stat	Mincer-Zarnowitz regress test
1-day ahead	22.105		9.821		30.364		0.881
Brent							
1-day ahead	20.742	3.424***	8.92	6.935***	27.236	2.963***	0.891
WTI							
1-day ahead	22.003	0.478	9.914	-1.058	29.398	1.203	0.879

Panel C: Baltic Exchange Panamax Index

	RMSE	t-stat	MAE	t-stat	MAPE	t-stat	Mincer-Zarnowitz regress test
1-day ahead	7.904		2.77		16.238		0.985
Brent							
1-day ahead	8.22	-1.25	2.645	2.358**	14.389	2.412**	0.982
WTI							
1-day ahead	7.546	2.547**	2.753	0.37	14.022	2.598***	0.985

To be continued

Panel D: Baltic Exchange Supramax Index

	RMSE	*t*-stat	MAE	*t*-stat	MAPE	*t*-stat	Mincer-Zarnowitz regress test
1-day ahead Brent	6.769		2.818		21.059		0.957
1-day ahead WTI	7.506	-1.712*	3.065	-4.009***	22.913	-1.059	0.946
1-day ahead	7.305	-1.248	2.98	-2.762***	22.263	-0.196	0.949
Panel E: Baltic Exchange Handysize Index							
1-day ahead Brent	22.105		9.821		30.364		0.881
1-day ahead WTI	20.742	3.424***	8.92	6.935***	27.236	2.963***	0.891
1-day ahead	22.003	0.478	9.914	-1.058	29.398	1.203	0.879
Panel F: Baltic Exchange Dirty Tanker Index							
1-day ahead Brent	7.904		2.77		16.238		0.985
1-day ahead WTI	8.22	-1.25	2.645	2.358**	14.389	2.412**	0.982
1-day ahead	7.546	2.547**	2.753	0.37	14.022	2.598***	0.985
Panel G: Baltic Exchange Clean Tanaker Index							
1-day ahead Brent	10.289		4.476		60.148		0.736
1-day ahead WTI	14.972	-1.006	4.739	-1.157	61.012	-0.178	0.458
1-day ahead	10.939	-1.202	4.634	-3.148***	64.187	-3.198***	0.685

Table 14: Out-of-sample volatility forecasting performance with GARCH and GARCH-X models

This table reports the out-of-sample forecasting performance of GARCH models and corresponding augmented GARCH-X models with the Brent and WTI oil spot prices. The root mean square error (RMSE) and the mean absolute error (MAE) are used. The t-statistic of the Diebold and Mariano (1995) test between the benchmark and augmented models is also reported. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Panel A: Baltic Exchange Dry Index

	RMSE	t-stat	MAE	t-stat	MAPE	t-stat	Mincer-Zarnowitz regress test
1-day ahead	0.0233		0.0152		8.215		0.968
Brent 1-day ahead	0.0234	-1.615*	0.0170	-4.014***	9.514	-3.541***	0.951
WTI 1-day ahead	0.0229	-1.158	0.0166	-2.765***	9.125	-2.891***	0.953
Panel B: Baltic Exchange Capesize Index							
1-day ahead	0.0473		0.0298		5.165		0.880
Brent 1-day ahead	0.0474	2.424**	0.0297	3.938***	4.598	2.894***	0.898
WTI 1-day ahead	0.0473	1.481	0.0297	-1.060	5.012	1.165	0.881
Panel C: Baltic Exchange Panamax Index							
1-day ahead	0.0262		0.195		4.658		0.990
Brent 1-day ahead	0.0262	-2.255**	0.196**	3.360***	4.012	2.123**	0.988
WTI 1-day ahead	0.0261	1.550	0.195	1.375	4.512	0.687	0.995

To be continued

	RMSE	t-stat	MAE	t-stat	MAPE	t-stat	Mincer-Zarnowitz regress test
Panel D: Baltic Exchange Supramax Index							
1-day ahead Brent	0.0132		0.0102		6.144		0.990
1-day ahead WTI	0.0133	-1.557	0.0103	-0.351	6.078	0.145	0.990
1-day ahead	0.0133	2.325**	0.0102	-2.469**	6.002	0.987	0.990
Panel E: Baltic Exchange Handysize Index							
1-day ahead Brent	0.109		0.0087		6.654		0.998
1-day ahead WTI	0.091**	-1.815*	0.0086	-3.320***	7.647	-2.654***	0.995
1-day ahead	0.092	2.874***	0.0087	2.117**	5.098	2.461**	1.000
Panel F: Baltic Exchange Dirty Tanker Index							
1-day ahead Brent	0.0154		0.015		3.169		0.228
1-day ahead WTI	0.0153	1.880*	0.0101	-1.131	3.299	-1.012	0.197
1-day ahead	0.0156	-2.124**	0.0198**	-3.835***	3.965	-2.981***	0.115
Panel G: Baltic Exchange Clean Tanaker Index							
1-day ahead Brent	0.0125		0.0078		1.096		0.591
1-day ahead WTI	0.0122	-0.952	0.0077	-0.927	1.198	-0.813	0.425
1-day ahead	0.0124	-2.378**	0.0077	-2.110**	1.645	-2.987***	0.535

Table 15: Out-of-sample volatility forecasting performance with EGARCH and EGARCH-X models

This table reports the out-of-sample forecasting performance of EGARCH models and corresponding augmented EGARCH-X models with the Brent and WTI oil spot prices. The root mean square error (RMSE) and the mean absolute error (MAE) are used. The t-statistic of the Diebold and Mariano (1995) test between the benchmark and augmented models is also reported. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Panel A: Baltic Exchange Dry Index

	RMSE	t-stat	MAE	t-stat	MAPE	t-stat	Mincer-Zarnowitz regress test
1-day ahead	0.233		0.169		5.198		0.894
Brent 1-day ahead	0.0235	-0.821	0.0171***	-3.228***	5.598	-1.978**	0.901
WTI 1-day ahead	0.0233	-2.223**	0.0169**	-1.661*	5.781	-2.221**	0.895
Panel B: Baltic Exchange Capesize Index							
1-day ahead	0.0473		0.0298		4.154		0.880
Brent 1-day ahead	0.0473***	1.420	0.0297***	4.934***	3.077	3.489***	0.895
WTI 1-day ahead	0.0473	2.488**	0.0297	-2.065**	4.481	-0.975	0.889
Panel C: Baltic Exchange Panamax Index							
1-day ahead	0.0262		0.195		6.147		0.971
Brent 1-day ahead	0.0262	-3.214***	0.196**	3.337***	5.178	2.981***	0.965
WTI 1-day ahead	0.0261	2.734***	0.195	1.360	6.871	1.001	0.961

To be continued

Panel D: Baltic Exchange Supramax Index

	RMSE	t-stat	MAE	t-stat	MAPE	t-stat	Mincer-Zarnowitz regress test
1-day ahead Brent	0.0132		0.0102		1.089		0.990
1-day ahead WTI	0.0133	-2.341**	0.0103	-0.355	1.091	-0.712	0.995
1-day ahead	0.0133	3.216***	0.0102	-1.520	1.273	-1.153	0.991
Panel E: Baltic Exchange Handysize Index							
1-day ahead Brent	0.109		0.0087		3.193		0.998
1-day ahead WTI	0.091**	-1.815**	0.0086	-3.225***	3.724	-1.913*	0.991
1-day ahead	0.092	2.871***	0.0087	2.115**	2.612	2.478**	1.000
Panel F: Baltic Exchange Dirty Tanker Index							
1-day ahead Brent	0.0154		0.01		4.089		0.228
1-day ahead WTI	0.0153	1.881*	0.0101	-1.130	4.178	-0.089	0.197
1-day ahead	0.0156	-2.125**	0.015	-3.384***	4.914	-2.458**	0.116
Panel G: Baltic Exchange Clean Tanaker Index							
1-day ahead Brent	0.0125		0.0078		2.749		0.59
1-day ahead WTI	0.0122	-0.954	0.0077	-0.927	2.812	-0.412	0.42
1-day ahead	0.0124	-2.382**	0.0077	-2.115**	3.011	-2.478**	0.53

Chapter 5

Concluding Remarks

In this thesis, I investigated the volatility of seven shipping freight indices, including five dry bulk and two tanker indices for the time period from 1999 to 2013. Several mathematical models are applied to discover the patterns of market volatility. In addition to those mathematical models, their predictive accuracy is tested. Considering the external factors, in the second part of my study two crude oil prices are added as new variables for all models to determine if these factors increase the predictive power of those models.

As mentioned before, there exist a number of studies on general economic volatility forecasting, but the amount of literature that focuses on the volatility of shipping freight rates is limited. This thesis contributes to the extant literature in the following ways. Firstly, the time period of the data used in the research covers both up and down cycles of the shipping industry; this is unique in forecasting shipping market volatility and gives much more complete information compared to existing works. Secondly, innovative results are given by some models which have been applied to shipping data for the first time.

Furthermore, this paper implements some conventional models to analyse and forecast volatility on the dry bulk index over a longer time period (i.e., from Aug 1998, to Aug 2013). The results from the in-sample parameters indicate that the past continuous sample path variables in those indices have forecasting power for its future indices. However, the BDTI and BCTI show that both the daily and the weekly volatility components are close to zero and statistically insignificant. By running a horserace among the forecasting precision of five models, we find that the Two-component model preforms the best and the HAR-RV model ranks second. In addition to the above findings, the GARCH model has better forecasting capability than the EGARCH model. According to the results of the SPA test, the Two-component model is not inferior to the rest of the competing models, while the DM pairwise test shows the Two-component model always outperforms the remaining three models.

In the second part of the study, where oil price data are added, I examine the impact of the oil price on volatility modelling and forecasting of the seven shipping indices. Motivated by the evidence in the literature that documents the information content of this dispersion measure, we are interested in investigating whether it helps to improve volatility forecasting, using the Brent and the WTI oil price index from 27 Dec 2001, to 3 Sep 2015, including 4339 and 3707 observations, respectively.

Using the HAR models augmented by the dispersion measure, our empirical evidence shows that the HAR-X models are a better fit in the in-sample estimation tests and improve volatility forecasting accuracy in the short-term (1-day ahead horizon). In the meantime, although the GJR-GARCH models did not perform as well as the HAR models, adding variable X, which represents two crude oil price indices, does help forecasting in short time periods. Later, in the forecasting part, HAR models show that oil prices have a statistically significant effect on short-term, rather than long-term, prediction. Meanwhile, by using GJR-GARCH models, the results are consistent with previous literature, i.e., that there is statistical significance found in all four dry Baltic indices with the exogenous variable, namely the Brent crude oil price, for forecasts 1-day ahead. However, for tanker carriers, WTI has the better fit.

Findings in this research contribute to the sea shipping industry in the following aspects.

Firstly, they may help investors evaluate risk and returns by paying more attention to oil price changes in the short-term in order to make the most optimal investment decisions. Secondly, using the models which have the greatest predictive power to forecast volatility can efficiently inform market participants ahead of time of any possible spread of turmoil among financial markets, especially during a financial crisis. Finally, oil companies, operators in the tanker market, and investors in oil derivatives markets can use the results in this study and, if they do so efficiently, find them of great benefit to their business. Tanker operators, for instance, with positions in the tanker market, may be empowered to make better decisions when faced with various shocks.

Nonetheless, my future research will focus on the following different perspectives. Firstly, there should be a strong, long-range, persistent, and multi-fractal cross-correlation volatility between crude oil price and tanker indices. Furthermore, a volatility transmission network for the tanker freight market could be continuously investigated, this may help market participants to better understand the tanker freight market and to devise better investment strategies as a result. Study related to the above subject will help offer more practical suggestions. Secondly, other external variables, such as GDP, should also be considered in addition to the two crude oil prices in order to compare the accuracy of forecasting power with the bench model.

References

Adland, R., and Cullinane, K. (2005). A time-varying risk premium in the term structure of bulk shipping freight rates. *Journal of Transport Economics and Policy (JTEP)*, *39*(2), 191–208.

Adland, R., and Cullinane, K. (2006). The non-linear dynamics of spot freight rates in tanker markets. *Transportation Research Part E: Logistics and Transportation Review*, *42*(3), 211–224.

Alexandridis, G., Sahoo, S., and Visvikis, I. (2017). Economic information transmissions and liquidity between shipping markets: New evidence from freight derivatives. *Transportation Research Part E: Logistics and Transportation Review*, *98*, 82–104.

Alizadeh, A. H. (2013). Trading volume and volatility in the shipping forward freight market. *Transportation Research Part E: Logistics and Transportation Review*, *49*(1), 250–265.

Alizadeh, A. H., Ådland, R. O., and Koekebakker, S. (2007). Predictive power and unbiasedness of implied forward charter rates. *Journal of Forecasting*, *26*(6), 385–403.

Alizadeh, A. H., and Muradoglu, G. (2014). Stock market efficiency and international shipping-market information. *Journal of International Financial Markets, Institutions and Money*, *33*, 445–461.

Alizadeh, A. H., and Nomikos, N. K. (2004). The efficiency of the forward bunker market. *International Journal of Logistics Research and Applications*, *7*(3), 281–296.

Alizadeh, A. H., and Nomikos, N. K. (2009). Performance of statistical arbitrage in petroleum futures markets. *The Journal of Energy Markets*, *1*(2), 3–33.

Alizadeh, A. H., and Nomikos, N. K. (2011). Dynamics of the term structure and volatility of shipping freight rates. *Journal of Transport Economics and Policy (JTEP)*, *45*(1), 105–128.

Alizadeh, A. H., and Talley, W. K. (2011). Microeconomic determinants of dry bulk shipping freight rates and contract times. *Transportation*, *38*(3), 561–579.

Andersen, T. G., and Bollerslev, T. (1998). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *International Economic Review*, 885–905.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Labys, P. (1999). Realized volatility and correlation. *LN Stern School of Finance Department Working Paper*, *24*.

Bakshi, G., Panayotov, G., and Skoulakis, G. (2011). The baltic dry index as a predictor of global stock returns, commodity returns, and global economic activity. *Commodity Returns, and Global Economic Activity*, *67*, 37–42.

Basher, S. A., Haug, A. A., and Sadorsky, P. (2012). Oil prices, exchange rates and emerging stock markets. *Energy Economics*, *34*(1), 227–240.

Batchelor, R., Alizadeh, A., and Visvikis, I. (2007). Forecasting spot and forward prices in the international freight market. *International Journal of Forecasting*, *23*(1), 101–114.

Beenstock, M., and Vergottis, A. (1989). An econometric model of the world tanker market. *Journal of Transport Economics and Policy*, 263–280.

Beenstock, M., and Vergottis, A. (1993). The interdependence between the dry cargo and tanker markets. *Logistics and Transportation Review*, *29*(1), 3.

Bildirici, M., Kayıkçı, F., and Onat, I. Ş. (2016). Bdi, gold price and economic growth. *Procedia Economics and Finance*, *38*, 280–286.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3), 307–327.

Bollerslev, T., Patton, A. J., and Quaedvlieg, R. (2016). Exploiting the errors: A simple approach for improved volatility forecasting. *Journal of Econometrics*, *192*(1), 1–18.

Braun, P. A., Nelson, D. B., and Sunier, A. M. (1995). Good news, bad news, volatility, and betas. *The Journal of Finance*, *50*(5), 1575–1603.

Cao, Y., Zhai, J., and Liu, X. (2020). A neural network enhanced volatility component model. *Quantitative Finance*, 1–15.

Chen, and Wang, S. T. (2004). The empirical evidence of the leverage effect on volatility in international bulk shipping market. *Maritime Policy and Management*, *31*(2), 109–124.

Chen, F., Miao, Y., Tian, K., Ding, X., and Li, T. (2017). Multifractal cross-correlations between crude oil and tanker freight rate. *Physica A: Statistical Mechanics and Its Applications*, *474*, 344–354.

Chernov, M., Gallant, A. R., Ghysels, E., and Tauchen, G. (2003). Alternative models for stock price dynamics. *Journal of Econometrics*, *116*(1-2), 225–257.

Chortareas, G., Jiang, Y., and Nankervis, J. C. (2011). Forecasting exchange rate volatility using high-frequency data: Is the euro different? *International Journal of Forecasting*, *27*(4), 1089–1107.

Christiano, L. J., and Fitzgerald, T. J. (2003). The band pass filter. *International Economic Review*, *44*(2), 435–465.

Corsi, F. (2009). A simple approximate long-memory model of realized volatility. *Journal of Financial Econometrics*, *7*(2), 174–196.

Cullinane, K., and Gong, X. (2002). The mispricing of transportation initial public offerings in the chinese mainland and hong kong. *Maritime Policy and Management*, *29*(2), 107–118.

Diebold, F. X., and Mariano, R. S. (1995). Comparing predictive accuracy. *Journal of Business and Economic Statistics*, *13*(3), 253–263.

Dikos, G., Marcus, H. S., and Papadatos, M. P. (2007). Old ideas may still be new: a system identification approach to tanker freight modelling. *Systems Research and Behavioral Science: The Official Journal of the International Federation for Systems Research*, *24*(6), 627–644.

Drobetz, W., Richter, T., and Wambach, M. (2012). Dynamics of time-varying volatility in the dry bulk and tanker freight markets. *Applied Financial Economics*, *22*(16), 1367–1384.

Drobetz, W., Schilling, D., and Tegtmeier, L. (2010). Common risk factors in the returns of shipping stocks. *Maritime Policy and Management*, *37*(2), 93–120.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation. *Econometrica: Journal of the Econometric Society*, 987–1007.

Engle, R. F., and Lee, G. (1999). A long-run and short-run component model of stock return volatility. *Cointegration, Causality, and Forecasting: A Festschrift in Honour of Clive WJ Granger*, 475–497.

Fei, T., Liu, X., and Wen, C. (2019). Cross-sectional return dispersion and volatility prediction. *Pacific-Basin Finance Journal*, *58*, 101218.

Gavriilidis, K., Kambouroudis, D. S., Tsakou, K., and Tsouknidis, D. A. (2018). Volatility forecasting across tanker freight rates: The role of oil price shocks. *Transportation Research Part E: Logistics and Transportation Review*, *118*, 376–391.

Gavrishchaka, V. V., and Banerjee, S. (2006). Support vector machine as an efficient framework for stock market volatility forecasting. *Computational Management Science*, *3*, 147–160.

Geman, H., and Smith, W. O. (2012). Shipping markets and freight rates: an analysis of the baltic dry index. *The Journal of Alternative Investments*, *15*(1), 98–109.

Glen, D., and Martin, B. (1998). Conditional modelling of tanker market risk using route specific freight rates. *Maritime Policy and Management*, *25*(2), 117–128.

Glosten, L. R., Jagannathan, R., and Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance*, *48*(5), 1779–1801.

Gong, S. X., Ye, H.-Q., and Zeng, Y. Y. (2013). Impacts of the recent financial crisis on ship financing in hong kong: a research note. *Maritime Policy and Management*, *40*(1), 1–9.

Granger, C. W. (1980). Long memory relationships and the aggregation of dynamic models. *Journal of Econometrics*, *14*(2), 227–238.

Gu, R., Chen, H., and Wang, Y. (2010). Multifractal analysis on international crude oil markets based on the multifractal detrended fluctuation analysis. *Physica A: Statistical Mechanics and its Applications*, *389*(14), 2805–2815.

Hamilton, J. D. (1983). Oil and the macroeconomy since world war ii. *Journal of Political Economy*, *91*(2), 228–248.

Hamilton, J. D. (2003). What is an oil shock? *Journal of Econometrics*, *113*(2), 363–398.

Han, H. (2015). Asymptotic properties of GARCH-X processes. *Journal of Financial Econometrics*, *13*, 188–221.

Hansen, P. R. (2005). A test for superior predictive ability. *Journal of Business and Economic Statistics*, *23*(4), 365–380.

Harris, R. D., Stoja, E., and Yilmaz, F. (2011). A cyclical model of exchange rate volatility. *Journal of Banking and Finance*, *35*(11), 3055–3064.

Hawdon, D. (1978). Tanker freight rates in the short and long run. *Applied Economics*, *10*(3), 203–218.

Hodrick, R. J., and Prescott, E. C. (1997). Postwar us business cycles: an empirical investigation. *Journal of Money, Credit, and Banking*, 1–16.

Hwang, S., and Satchell, S. E. (2005). Garch model with cross-sectional volatility: GARCHX models. *Applied Financial Economics*, *15*(3), 203–216.

Jiang, Y., Cao, Y., Liu, X., and Zhai, J. (2019). Volatility modeling and prediction: the role of price impact. *Quantitative Finance*, *19*, 2015–2031.

Jones, C. M., and Kaul, G. (1996). Oil and the stock markets. *The Journal of Finance*, *51*(2), 463–491.

Kaeck, A., and Alexander, C. (2013). Continuous-time vix dynamics: On the role of stochastic volatility of volatility. *International Review of Financial Analysis*, *28*, 46–56.

Kavussanos, M. G. (1996). Comparisons of volatility in the dry-cargo ship sector: Spot versus time charters, and smaller versus larger vessels. *Journal of Transport Economics and Policy*, 67–82.

Kavussanos, M. G. (1997). The dynamics of time-varying volatilities in different size second-hand ship prices of the dry-cargo sector. *Applied Economics*, *29*(4), 433–443.

Kavussanos, M. G. (2003). Time varying risks among segments of the tanker freight markets. *Maritime Economics and Logistics*, *5*(3), 227–250.

Kavussanos, M. G., and Alizadeh-M, A. H. (2001). Seasonality patterns in dry bulk shipping spot and time charter freight rates. *Transportation Research Part E: Logistics and Transportation Review*, *37*(6), 443–467.

Kavussanos, M. G., and Alizadeh-M, A. H. (2002). The expectations hypothesis of the term structure and risk premiums in dry bulk shipping freight markets. *Journal of Transport Economics and Policy (JTEP)*, *36*(2), 267–304.

Kavussanos, M. G., and Dimitrakopoulos, D. N. (2011). Market risk model selection and medium-term risk with limited data: Application to ocean tanker freight markets. *International Review of Financial Analysis*, *20*(5), 258–268.

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

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

Kavussanos, M. G., Visvikis, I. D., and Batchelor, R. A. (2004). Over-the-counter forward contracts and spot price volatility in shipping. *Transportation Research Part E: Logistics and Transportation Review*, *40*(4), 273–296.

Kennedy, M. (1974). An economic model of the world oil market. *The Bell Journal of Economics and Management Science*, 540–577.

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, *99*(3), 1053–69.

Kilian, L., and Park, C. (2009). The impact of oil price shocks on the us stock market. *International Economic Review*, *50*(4), 1267–1287.

Lin, F., and Sim, N. C. (2013). Trade, income and the baltic dry index. *European Economic Review*, *59*, 1–18.

Liu, Y. (2019). Novel volatility forecasting using deep learning–long short term memory recurrent neural networks. *Expert Systems with Applications*, *132*, 99–109.

Lizardo, R. A., and Mollick, A. V. (2010). Oil price fluctuations and us dollar exchange rates. *Energy Economics*, *32*(2), 399–408.

Lu, J., Marlow, P. B., and Wang, H. (2008). An analysis of freight rate volatility in dry bulk shipping markets. *Maritime Policy and Management*, *35*(3), 237–251.

Müller, U. A., Dacorogna, M. M., Davé, R. D., Pictet, O. V., Olsen, R. B., and Ward, J. R. (1993). Fractals and intrinsic time: A challenge to econometricians. *Unpublished Manuscript, Olsen and Associates, Zürich*, 130.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the Econometric Society*, 347–370.

Papailias, F., Thomakos, D. D., and Liu, J. (2013). The baltic dry index: cyclicalities, forecasting and hedging strategies. *Empirical Economics*, *52*(1), 255–282.

Patton, A. J., and Sheppard, K. (2015). Good volatility, bad volatility: Signed jumps and the persistence of volatility. *Review of Economics and Statistics*, *97*(3), 683–697.

Poon, S.-H., and Granger, C. W. (2003). Forecasting volatility in financial markets: A review. *Journal of Economic Literature*, *41*(2), 478–539.

Poulakidas, A., and Joutz, F. (2009). Exploring the link between oil prices and tanker rates. *Maritime Policy and Management*, *36*(3), 215–233.

Ramos-Pérez, E., Alonso-González, P. J., and Núñez-Velázquez, J. J. (2019). Forecasting volatility with a stacked model based on a hybridized Artificial Neural Network. *Expert Systems with Applications*, *129*, 1–9.

Ruan, Q., Wang, Y., Lu, X., and Qin, J. (2016). Cross-correlations between baltic dry index and crude oil prices. *Physica A: Statistical Mechanics and Its Applications*, *453*, 278–289.

Shephard, N. (1996). Statistical aspects of arch and stochastic volatility. *Monographs on Statistics and Applied Probability*, *65*, 1–68.

Shi, W., Yang, Z., and Li, K. X. (2013). The impact of crude oil price on the tanker market. *Maritime Policy and Management*, *40*(4), 309–322.

Stopford, M. (2009). *Maritime economics*. Routledge.

Sveistrup, P., and Koopmans, T. (1939). : Tanker freight rates and tankship building. an analyses cyclical fluctuations. *NationaløKonomisk Tidsskrift*.

Taylor, S. J. (1994). Modeling stochastic volatility: A review and comparative study. *Mathematical Finance*, *4*(2), 183–204.

Thanopoulou, H. (2002). Investing in ships: an essay on constraints, risk and attitudes. *The Handbook of Maritime Economics and Business*, 623–641.

Tsioumas, V., Papadimitriou, S., Smirlis, Y., and Zahran, S. Z. (2017). A novel approach to forecasting the bulk freight market. *The Asian Journal of Shipping and Logistics*, *33*(1), 33–41.

Tsouknidis, D. A. (2016). Dynamic volatility spillovers across shipping freight markets. *Transportation Research Part E: Logistics and Transportation Review*, *91*, 90–111.

Tvedt, J. (2003). A new perspective on price dynamics of the dry bulk market. *Maritime Policy and Management*, *30*(3), 221–230.

Veenstra, A., and Franses, P. H. (1997). A cointegration approach to forecasting freight rates in the dry bulk shipping sector. *Transportation Research. Part A: Policy and Practice*, 447–458.

von Spreckelsen, C., von Mettenheim, H.-J., and Breitner, M. H. (2012). Spot and freight rate futures in the tanker shipping market: Short-term forecasting with linear and non-linear methods. In *Operations research proceedings* (pp. 247–252). Springer.

Vrontos, S. D., Galakis, J., and Vrontos, I. D. (2021). Implied volatility directional forecasting: a machine learning approach. *Quantitative Finance*, 1–20.

Wang, X., Wu, C., and Xu, W. (2015). Volatility forecasting: The role of lunch-break returns, overnight returns, trading volume and leverage effects. *International Journal of Forecasting*, *31*, 609–619.

Zheng, S., and Lan, X. (2016). Multifractal analysis of spot rates in tanker markets and their comparisons with crude oil markets. *Physica A: Statistical Mechanics and Its Applications*, *444*, 547–559.