GRA 19502

Master Thesis

Component of continuous assessment: Forprosjekt, Thesis MSc

Master Thesis Preliminary

Start: 01.12.2016 09.00

Finish: 16.01.2017 12.00

MSc in Business, Major in Finance

A Study of the Volatility in the Dry Bulk Market

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CONTENT

INTRODUCTION

Volume of seaborne trade accounts for about 80% of total world merchandise trade. Two thirds of the seaborne trade volume is dry cargo, raw materials including primarily ore, coal, grains that will be further processed to make all kinds of end products. The freight shippers pay to charter bulk carriers, ships built to transport dry cargo, has long been closely watched by the shipping industry and the financial market as it is perceived as a leading indicator of global economic state. In February 2016, BDI, an index that measures dry cargo freight, fell to its historical low, a time described by some as "the worst market since the Viking age". Currently hit hard by the downturn, the dry bulk shipping market is characterized by its high volatility with the example of a 94% dive between May and December 2008. As bulk carriers account for about 43% of world fleet and carry two thirds of the seaborne cargo, a better understanding of the volatility of the freight will not only help the struggling dry bulk industry make future investment decisions, but also provide insight into global economy.

In our study we want to explore the nature and development of dry bulk market in order to gain a better outlook on its properties and underlying factors that determine its behaviour. We will try to analyze previous papers, some of which are presented on the reference list, on the market structure and volatility estimation to develop an insight on gaps in research studies. We want to primarily focus on the volatility in the market, trying to properly measure it and understand its qualitative impact on the market. Our final goal is developing a model which can help to explain the underlying processes which leads to the unusual properties of the market. More precisely, we plan to test for asymmetry, heteroscedasticity, exo and endogenous variables in the market and study the relations between the dry bulk market and global economic processes. To do this we will try to look into the microstructure of the market, analyzing not only aggregated data, but also types of the freight and the routes. We believe that this study should help to develop an intuitive understanding of the high volatility in dry bulk market, which will be of great importance to future investors and entrepreneurs.

LITERATURE REVIEW

Making shipping investment is risky. Stopford (1997) discussed this point by first observing shipowners' anxiety about daily fluctuations of freight rates and went on

to elaborate on "shipping risk" - risk about the return on shipping investment that comes from the cyclical nature of the shipping business. An increase in trade volume would result in a disproportion between supply and demand of shipping capacity and push up freight rate to restore the balance. As a result, shipowners may be tempted to increase fleet size hoping to capture more profit in a good market. In the end a good market may eventually wind down as the supply of shipping capacity restores the balance. This uncertainty about the future of the shipping market motivates some companies to take the shipping risk and others to transfer the shipping risk. In Cullinane's (1995) study on risk and return of investment in drybulk shipping, he referred to Gray's (1987) perspective on major commercial risks faced by shipowners: (1) Interest rate risk, (2) Exchange rate risk, (3) Bunker price risk, (4) Market risk. Out of four, market risk involves factors that could negatively affect the freight rate. It is industry specific and has the most direct impact on the revenues of shipowners. He argued that it is the most important risk for shipowners because the revenues are more affected by the uncertainties than the costs.

The freight market is a market place where shipowners provide ships for hire and charterers/shippers hire the ships to transport cargoes. When a freight rate is agreed along with other terms on the "charter-party" (contract specifying all the terms) the ship is "fixed". There are different charter types such as "Voyage Charter", "Contract of Affreightment", "Period Charter", and "Bare boat charter" with different contract execution and risk transfer mechanism to suit the needs of different counterparties (Stopford, 1997). The most common approach to systematically understand the freight market is the supply and demand model that is often used in the commodities market. Table 1 presents a general supply and demand model proposed by Stopford (1997) for the shipping market.

Demand	Supply
The world economy	World fleet
Seaborne commodity trades	Fleet productivity
Average haul	Shipbuilding production
Political events	Scrapping and losses
Transport costs	Freight rates

Table 1: Ten variables in the shipping market model (Stopford, 1997, 115)

Any imbalance between supply and demand feed into the freight market, which acts as a control valve for the money paid from the shipper to the shipowner. This model also demonstrates key characteristics of the shipping market as the demand is unpredictable and prone to fluctuate in the short run but the supply is slow to catch up. This process of capacity adjustment explains the volatile and cyclical nature of the shipping market (Randers and Göluke, 2007).

Bulk carriers are built to transport homogenous dry bulk commodities in large quantities by sea. Five major bulk commodities iron ore, coal, grain, bauxite/alumina, phosphate rock account for about 60% of total dry bulk trade (UNCATD, 2015). Although each vessel has its own specification, for the purpose of conducting analysis, they are usually grouped with other similar vessels by their capacity (tonnage) for carrying cargoes (Stopford, 1997; Alizadeh and Nomikos, 2009; UNCATD, 2015). Table 2 shows a common way to group different bulk carriers.

Group	Tonnage
Capesize	100,000 dwt plus
Panamax	60,000–99,999 dwt
Handymax	40,000–59,999 dwt
Handysize	10,000–39,999 dwt

Table 2: Four vessel groups (UNCATD, 2015, ix)

Each group of vessels has its unique trading advantage depending on the parcel size of the cargo, cargo handling, distance, routes, and ports. When choosing the vessel to hire or build, trade-offs are general made between three factors: economies of scale, the parcel sizes of the available cargoes, port draught and cargo handling facilities (Stopford, 1997; Alizadeh and Nomikos, 2009). In the new millennium, two trends stood out in the drybulk sector. First, it has attracted more attention from players outside shipping who search for new investment class and leading economic indicators. Second, chartering chains have grown longer and more fragile. One single company that fails to perform could trigger a series of disastrous events (Gratsos et al., 2012).

Adland and Strandenes (2007) saw primarily two schools of modeling the freight market. One attempted to capture the supply and demand fundamentals for equilibrium prices (Hawdon, 1978; Beenstock and Vergottis, 1989; Hale and Vanags, 1989; Beenstock and Vergottis 1989, 1993). The other one used univariate stochastic model (Kavussanos, 1996; Kavussanos and Nomikos, 1999; Kavussanos, and Alizadeh, 2002; Adland and Cullinane, 2005). The first school is limited by the difficulty of data collection as the number of variables increases, weak econometric relationships, and its deterministic nature. The second school relies on the assumption that all the information is embedded in the current price.

Recent development in the drybulk market analysis was summarized by Glen (2006) as the reduced form autoregressive model has become the popular choice for empirical research while traditional structural modeling has grown out of fashion. Beenstock and Vergottis's (1989, 1993) work highlighted the application of structural models in the drybulk market. They built their model on top of assumptions of rational expectations of freight rates and market efficiency. The freight rates predicted by the model were the expectations of all the market participants. Market efficiency then ensured that ship prices would be adjusted by arbitrageurs to new information known to the market. The tide started to shift when new econometric techniques and data of higher frequency were made available in the 1990s. Stationarity testing and co-integration examination have become the launching pad for new research that focused on statistical properties of data. In particular, new statistical models that relaxed the restriction of constant variance have made modeling the time-varying volatility of the drybulk freight rate increasingly popular. A wide variety of studies have emerged in the past twenty years to explore seasonality, term structure, stationarity, forecasting ability of financial derivatives, and conditional heteroscedasticity in the drybulk market..

Traditional statistic models such as classical linear regression model require the data series to have constant variance or the estimated parameters would be inefficient. However, the variance of financial time series is most likely not constant. In addition, the presence of volatility clustering in financial time series, meaning large (small) changes tend to be followed by large (small) changes (Mandelbrot, 1963), indicating that the market is more volatile in some periods of time than others (Brooks, 2014). Engle (1982) developed the class of

Autoregressive Conditional Heteroscedasticity (ARCH) model which models risks by allowing the conditional variance (h_t) of the time series to depend on the previous values of squared error ($\epsilon_{t-1}, \epsilon_{t-2}, \dots, \epsilon_{t-p}$). The conditional mean of y_t is determined by $x_t\ \beta$, a linear combination of lagged variables (x_t) that could take almost any forms and is included in the information set φ_{t-1} with a vector of parameters β. An ARCH (p) model can be written as:

$$y_t\ |\varphi_{t-1} \sim N(x_t\ \beta, h_t)$$
$$h_t = \alpha_0 + \ \alpha_1 \epsilon_{t-1}^2 + \ \dots + \alpha_p \epsilon_{t-p}^2$$
$$\epsilon_t = y_t\ - \ x_t\ \beta$$

The model has the desirable econometric application where the previous forecast errors are used to predict the next forecast variance. Most importantly, if the observed time-varying volatility or volatility clustering could be explained by an ARCH process, the researcher could continue to operate on the assumption of unconditional stationarity. One question to consider when applying ARCH models is the number of lagged errors. In order to capture the dependence in the conditional variance, the number can be very large and increase the chance of violating the non-negativity constraint for the conditional variance (Brooks, 2014). Aware of this relatively arbitrary selection of lag structure in ARCH models, Bollerslev (1986) extended ARCH models in a way similar to extending AR process to ARMA process of time series data. The result is a general ARCH (GARCH) model. A GARCH (p,q) model can be written as:

$$y_t\ |\varphi_{t-1} \sim N(x_t\ \beta, h_t)$$
$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}$$
$$\epsilon_t = y_t\ - \ x_t\ \beta$$

Letting past conditional variance enter the adaptive learning mechanism, GARCH models essentially have the one-period-ahead conditional variance determined by a weighted average of its long-term average value, past errors, and past conditional variance. As a GARCH (1,1) model can be proven to be a restricted infinite order ARCH model, it is parsimonious and more unlikely to violate the non-negativity constraints for the conditional variance.

Kavussanos (1996) used GARCH class of model to capture the time-varying dynamics of volatilities in the drybulk freight market. With monthly data of spot freight index of different vessel groups (Handysize, Panamax, Capesize) from 1973 to 1992, he found the GARCH process to be stationary and volatilities in the spot and time-charter freight market to behave differently. Handysize vessels were found to have lower volatilities than Panamax and Capesize vessels and Panamax vessels are found to have lower volatilities than Capsize vessels. He argued that it is due to the capability of smaller vessels to serve more markets and cargoes that made the demand for them less volatile.

Glen and Rogers (1997) examined weekly series of Capesize indices of different key trading routes published from 1989 to 1996 that recorded both spot and time-charter drybulkl freight rates. They found the levels to be all nonstationary under both Augmented Dickey-Fuller test and Phillips-Perron test but their first differences to be stationary. Cointegration between each route was identified and attributed to common external drivers such as industrial production, world trade, seaborne cargo movements, and bunker prices. Tvedt (2003) reviewed prior works on the stationarity of drybulk freight rates and second-hand vessels (Kavussanos, 1996; Glen and Rogers, 1997; Glen 1997; Kavussanos, 1997) which all pointed to a random walk process. He argued that a transformation of indices and freight rates into Japanese yen denomination could yield a different result as Asia accounted for a majority of activities in drybulk commodities trading and shipbuilding. After the transformation of data from 1980s to 1999, the indices and freight rates did become stationary. The BFI index was downward mean reverting potentially implying the dynamic where high freight rates induced an increased new building activities and vessel utilization while low freight rates encouraged vessel lay-up and scrapping.

Motivated by the nonstationarity and deterministic seasonal pattern of macroeconomic variables (Osborn, 1990; Canova and Hansen, 1995), Kavussanos and Alizadeh (2001) used monthly data to search for systematic seasonal patterns in freight rate fluctuations within a year between different group of vessels (Capesize, Panamax and Handysize), different contract durations (spot, 1-year and 3-year time charters), and different market conditions (peaks and troughs). They concluded ARIMA and VAR models are most appropriate to model the series and found

deterministic seasonality showing freight rates rose in March and April and dropped in June and July. Freight rates of larger vessels fluctuated more than smaller vessels. Longer contracts had smaller seasonal fluctuations than shorter contracts. Seasonal fluctuations were sharper when the market picked up than going down.

When examining term structure, the drybulk market has two unique features that make it difficult to establish relationships between spot and forward contract with traditional approach. First, the non-storability character makes the usual cash-and-carry strategy inapplicable. Second, the non-tradability character makes constructing replicating portfolios very difficult (Adland and Cullinane, 2005). Kavussanos and Alizadeh's (2002) study on term structure of the drybulk market began from elaborating on the duration of freight contract. Freight rate of shorter-duration or spot contracts was thought to depend on current supply and demand (Stopford ,1997) while freight rate of longer-duration period contracts was believed to depend on expectations of future short-duration freight rates from rational market participants. This was in line with the expectations hypothesis covered by classic financial economics literature (Campbell and Shiller, 1987, 1991). In reviewing the studies done by Hale and Vanags (1989) and Veenstra (1999) on this topic, they considered the studies inconclusive due to insufficient sample size and inappropriate model formulation. Using the tests proposed by Campbell and Shiller (1987, 1991), monthly data from 1980 to 1997 of contracts matured in one year and three years in different vessel group (Handysize, Panamax, and Capesize), they found negative time-varying risk-premia through GARCH-in-mean specifications. Defying traditional belief of expectation hypothesis, they provided four arguments for explanation: higher fluctuations in the spot market, unemployment risk, vessel relocation costs, uncertainty over voyage costs. Adland and Cullinane (2005) explored theoretical argument of risk premium behind important risk factors faced by charterers and shipowners. Risk of spot market volatility and liquidity risk could contribute to both a positive and negative risk premium as both shipowners and charterers are risk-averse against future spot freight movements. Without further restrictions of their risk preference and bargaining power, it is difficult to tell the influence. Unemployment risk usually motivates shipowners to offer a lower forward freight rate compared with expected future spot rate to make sure the vessels are chartered. Default risk had the opposite

effect as it motivated shipowners to demand a higher forward freight rate to account for the possibility that charterers may walk away from a long-term contract. The risk of transport shortage encourages charterers to pay a higher forward freight rate to ensure their ability to transport future cargoes. Technological/legislative risk prompts charterers to pay a lower forward freight rate to compensate increased costs of trading older vessels. They concluded that the net risk premium should in most cases be negative and time-varying depending on the market conditions.

Alizadeh and Nomikos (2011) investigated the relationship between dry bulk freight volatility and the term structure. The idea was from commodities market as a backwardation (spot price is higher than forward prices) market indicates a temporal urge for the buyer to get hold of the commodity hence paying a higher price when the supply is fairly inelastic. If the drybulk market follows the same logic, they expected to find higher volatility in a backwardation market compared with contango (spot price is lower than forward prices) and flat (spot price is close to forward prices). Using weekly observations from 1992 to 2007, they found higher volatility in the spot contract than 1-year and 3-year time charters contract, and by using an EGARCH-X specification, they found shocks to be persistent and have sign effects where market participants actually strengthened the possibility of a downturn by their reaction to bad news. Most importantly, they found much higher volatility in backwardation market and the rate of increased as the degree of backwardation increased. This confirmed the theory that the freight rate was highly sensitive when the supply is tight but when there was excess supply in the market to absorb shocks to the market the volatility would not move much.

Xu et al. (2011) used a two-step model to analyze the relationship between fleet size and volatility of spot and time-charter freight rate of Capesize and Panamax with monthly data from 1973 to 2010. They first generated one-step ahead conditional volatilities by using an AR-GARCH model and had it regressed against the changes of fleet size, freight rates, industrial production, and bunker price. They found nonstationarity in variance under the GARCH process and confirmed previous results in the literature that volatility of both spot and time-charter drybulk freight rates is time-varying and clustering (Kavussanos, 1996; Kavussanos, 2003; Adland and Cullinane, 2005). In addition fleet size is found to positively affect the volatility in particular the volatility of spot Capesize freight rate, which echoed Kavussanos's (1996) finding.

METHODOLOGY

Our methodology would evolve around conducting an autoregressive model in order to test the volatility characteristic of BDI index. As suggested in the theoretical studies, we are going to first test for copious autoregressive effects and try to create a forecasting model which would fit the available data. In order to do that we are going to follow classic econometric procedure. First, we would test the data for stationarity and unit roots in the composite index and its groups. Next, If the processes appear to be stationary, we are going to test for heteroscedasticity and AR effects. In order to enhance the model, we are going to test for volatility clustering, shock-persistence, information asymmetries and GARCH effects, level of lags, as well as, possibly, include other factors and error-correction terms. In case the data appear to be non-stationary, we would try to understand the type, reason and degree of non-stationarity. Our next step would be an attempt to conduct a cointegration model or deal with non-stationarity by differencing or other mathematical tools, however, at this point our study would show a strong deviation from the underlying empirical researches and theoretical frameworks, provided in the theoretical part of the text. Hence, we would be very cautious while moving from the classic ARIMA models and would be mindful of trade-off between information lost to get stationarity in the process.

After getting the model we are going to evaluate its quality and make an effort to provide a theoretical and practical explanation for it. We are particularly interested, as our topic suggests, in analyzing abnormal shocks in volatility and return parity, such as asymmetry shocks, increased or decreased risk premium, mean reversion tendency etc. We would also try to look into the differences in the reactions of different groups of the index and explain the results. All in all, we expect to be able to either broaden the and specify the studies, which have been done on the marine finance in general and BDI index in particular, or to question their conclusions, based on our research.

DATA

In order to conduct the preliminary analysis, we had to collect the data. We used the data from Baltic Stock Exchange, provided via the Bloomberg Terminal system. We also include the data for Dirty and Clean Tanker indexes to compare their

variances with the targeted indexes. We have collected the data s and would try to analyze the indexes separately and compare the obtained results, focusing on the BDI, as the main objective. The available timeframes are the following:
04.01.1985– 03.11.2016 for BDI; 31.12.1998 – 03.11.2016 for Panamax;
01.07.2005– 03.11.-2016 for Supramax; 02.01.2007 – 03.11.2016 for Handysize;
10.04.2014   – 03.11.2016 for Capesize; 03.08.1998 – 03.11.2016 for Clean and Dirty Tanker Indexes. The data descriptive statistics is presented in the table 3.

Name	BDI	Panamax	Supramax	Handysize	Capesize	Dirty	Clean
Mean	1936	2398	1837	925	1216	1047	853
St.Err.	19,20	31,53	27,3	14,96	29,02	6,68	4,61
Median	1394	1607	1380	658	1046	884	749
Mode	978	1020	721	444	1248	723	680
St.Dev.	1717	2105	1454	742	736	451	311
Var	2946471	4430015	2114263	550985	542183	203434	96944
Kurtosis	9,22	3,74	2,13	1,68	0,69	2,48	0,77
Skewness	2,85	1,91	1,64	1,63	0,88	1,49	1,04
Range	11503	11431	6713	3224	3620	2741	1610
Minimum	290	282	243	183	161	453	345
Maximum	11793	11713	6956	3407	3781	3194	1955
Sum	15475306	10688945	5208380	2277218	783056	4767632	3885760
Count	7994	4457	2836	2462	644	4554	4558
Conf.lev. (95,0%)	38	62	54	29	57	13	9

Table 3: Descriptive statistics of index data (Baltic Stock Exchange, 2016)

By the snapshot of the descriptive statistics, we observe that the indexes differ in all of the parameters, which, however, can be partly explained by the difference in the number of observations and the general volume. However, we can notice straight

away an abnormally high variance, difference in Skewness and Kurtosis, as well as a significant difference in variance in the groups.

Therefore, we are going to investigate and try to build a model which would help to understand what exactly causes the differences in the underlying behavior.

The skewness of the indexes is quite remarkable, as all the groups show the positive skewness coefficient. This indicates that all of them are unlikely to have big losses, but rather have frequent small losses.

Kurtosis is also positive, hence the distributions are leptokurtic, therefore, have fatter tails and the extreme outcomes are less likely. This corresponds to the empirical studies, which discovered mean-tendency in the process.

Given the differences in the indexes' statistics, we might expect to include the extra terms from some additional factors, or lags of index groups in our GARCH(p,q) model, if they show to be consistent and relevant for the model. If we will have a need to collect extra data on additional factors which might come efficient in explaining the abnormal riskiness of drybulk shipping, we would focus on gathering and adapting it in order to include it either as a direct explanatory variable, or as a synthetic factor of a number of external variables, endogenous variables or a mix of both.

Given the different time-frames of the datasets, which vary from index to index, we might expect the structural breaks in the final model, hence, we would try to deal with it by either breaking the model by appropriate timesets or using a rolling forecast. Given the high variance, we might expect an autocorrelation in the results, which we are going to test for in the beginning of the analytical part. We are then going to proceed with testing for unit root in the series by using the ADF

(Augmented Dickey-Fuller test. If we are going to discover a plausible error-correction relation, we will start our analysis by using a standard Engle-Granger approach, followed by vector error-correction model to discover multidimensional relations, if those are to be found.

Another point, which shall be tested, according to the data and might contribute to the explanatory power of our model, is examining the time-varying volatility. According to basic theory, the rising trade volume shall balance out the market and, hence, decrease the volatility and extreme shocks. We are going to test, whether it is indeed true, as the initial conclusions from the data set do not support this statement. Below we present the graphs of daily log-returns[1] for BDI, Panamax, Supramax, Handysize and Capesize, created in Stata 14 software:
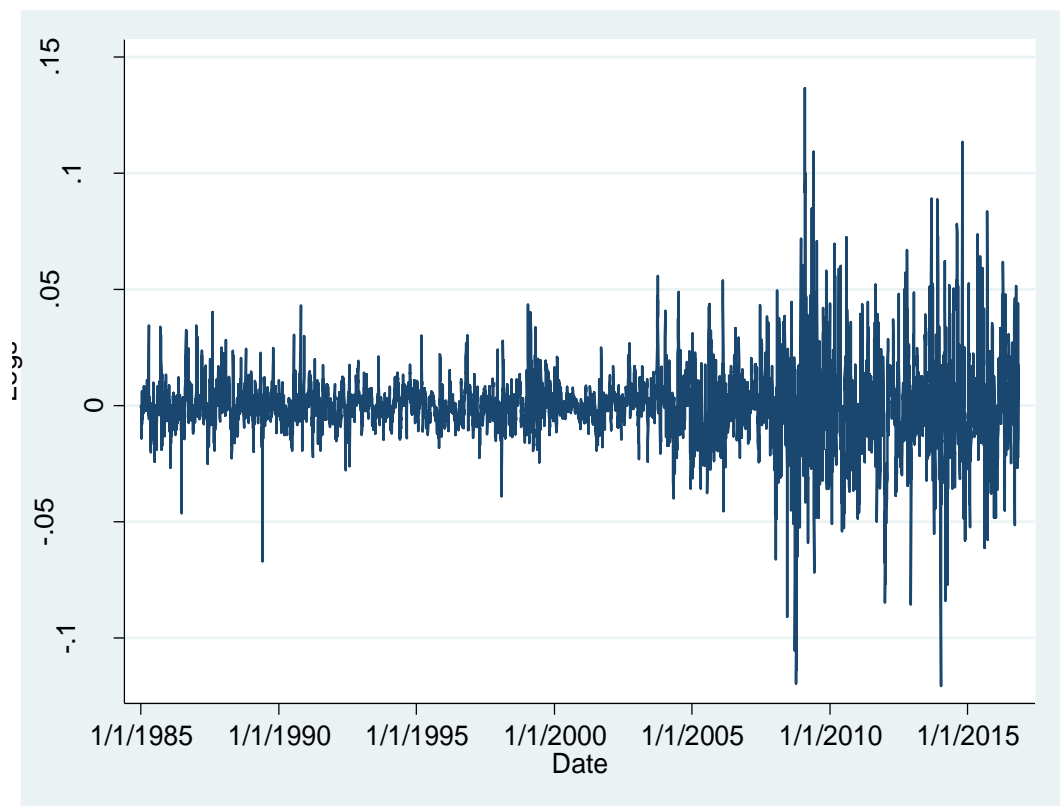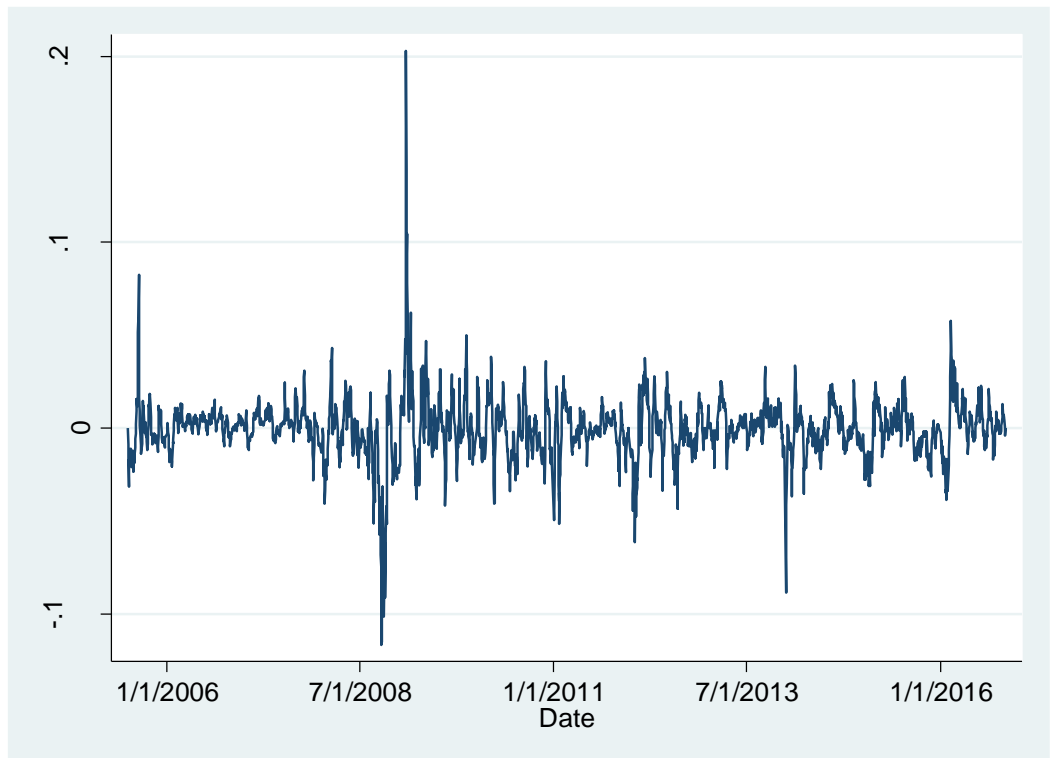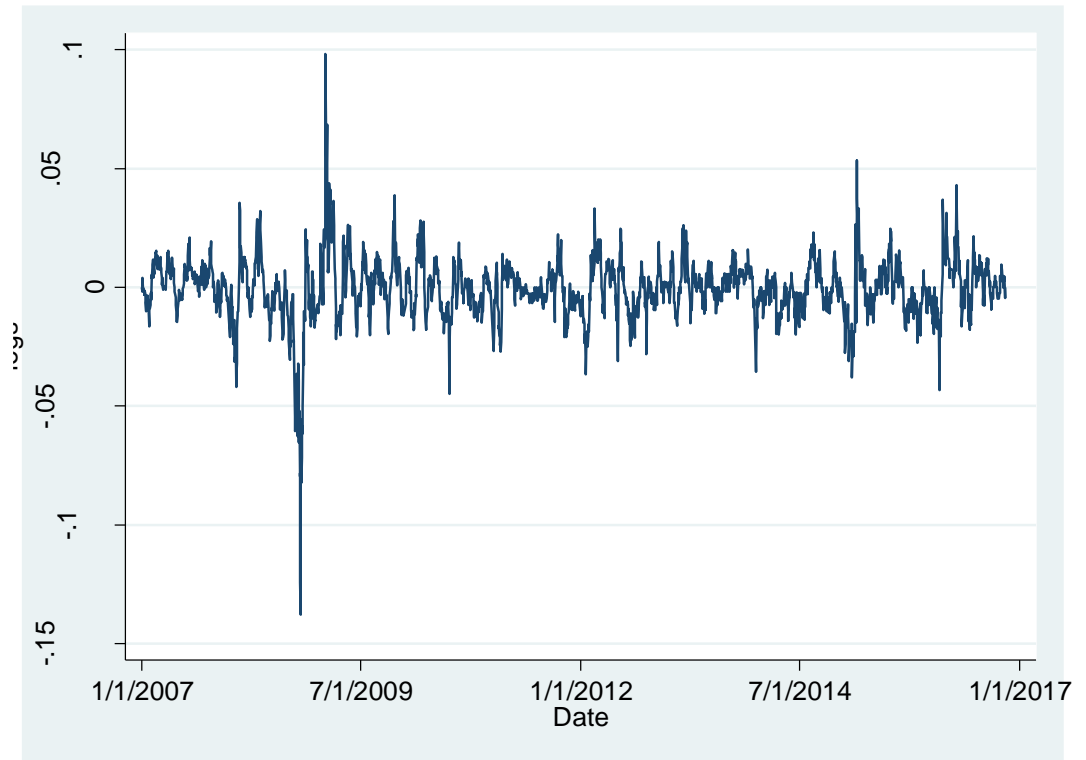

Graph 1: Daily log-returns of BDI

[1] Logreturns have been calculated as $Ln(P_{n+1}/P_n)$, where P_n is the index value for the day N
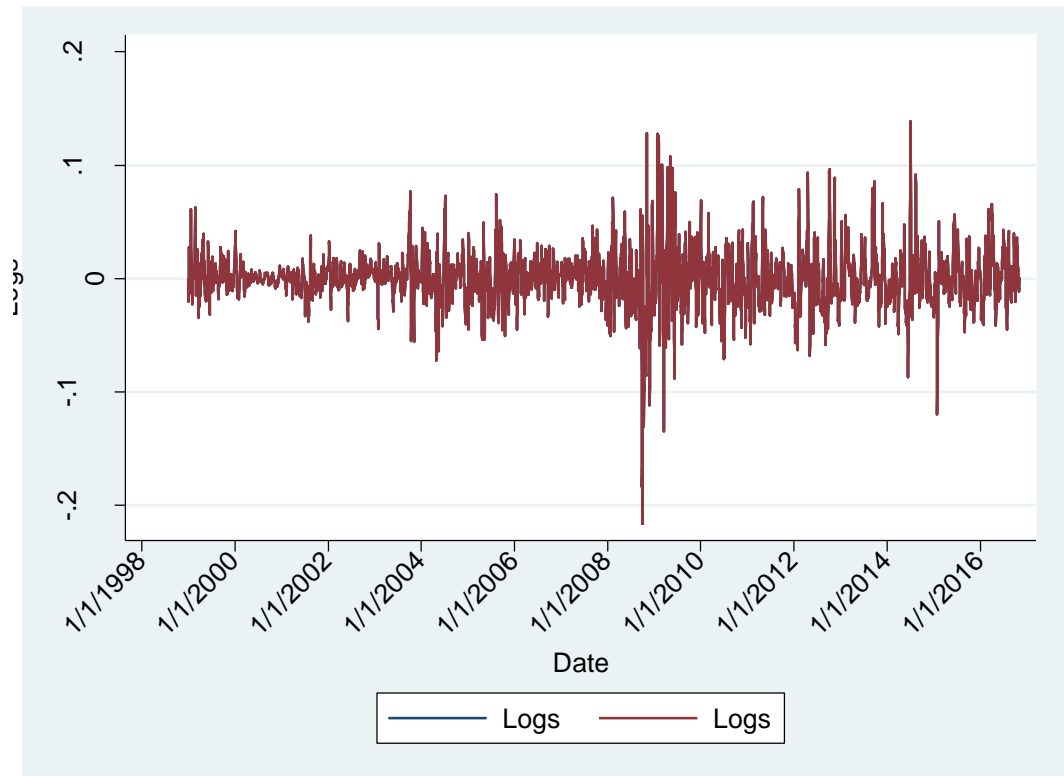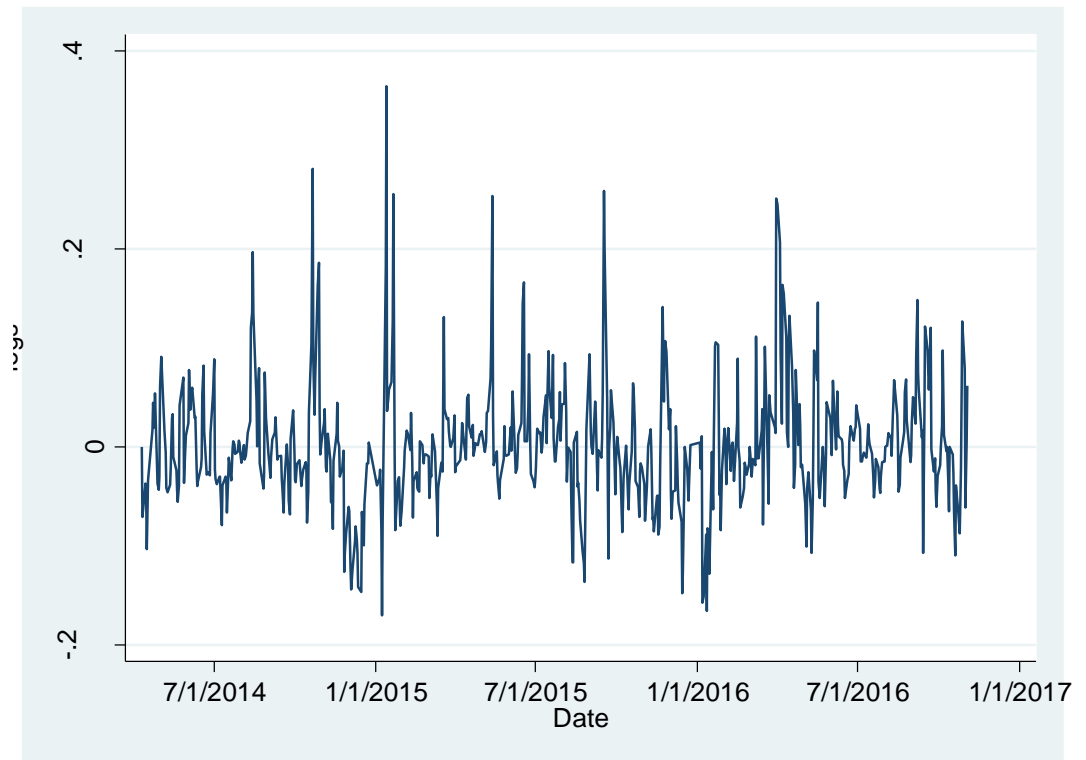
Graph 2: Daily log-returns of Panamax

Graph 3: Daily log-returns of Supramax

Graph 4: Daily log-returns of Handysize

Graph 5 Daily log-returns of Capesize

We can clearly observe extremely high volatility, especially at the time of last global financial crisis during 2008. In addition, we can see some serious spikes in volatility during the years 2014 and 2015. Overall, we can suspect a serious degree of volatility clustering and will test for EGARCH effects in our model. By the snapshot of the graphs, we can clearly anticipate the abnormal amount of risk, involved in the drybulk market price formulation.

However, examining the causality is our main goal, rather than pointing out the correlations, therefore, we are going to deeply look into the volatility-volume relation too, in order to find whether this unusual factor is significant for our model.

One of the possible explanations of the abnormalities in the data might lay in the behavioral field: risky external traders, attracted by the rising market volume, might have shifted the balance of risk-return payoff by "noise trading", however, we do not focus on behavioral explanations, which might be suitable for the research question.

Despite a great amount of possible explanatory factors, we would try to create a parsimonious model, including only the most relevant variables and trying to save and give as much information as possible. All in all, we plan to find a feasible model, which would capture the unusual riskiness of the dry bulk market and provide some inside on its price-to-risk relations.

TIME PLAN

After submitting the preliminary of the thesis, we plan to finalize the introduction, theory, literature review and methodology parts by the time we will have presented the intermediate results. After the presentation we will proceed with perfecting the data preliminary analysis and then start working on the alalytical part, where we

will try to build an appropriate econometric model. Finally, we will work on presenting the results of our research and its conclusions in a compehensive and cohearant manner. The preliminary schedule for our further work is presented in the table below:

Deadline	Task
31.01.2017	Finalizing Introduction and Literature Review
28.02.2017	Finalizing Methodology, Preparing a Presentation
15.04.2017	Finalizing Data Description and Preliminary Data Analysis
31.05.2017	Reporting the Results and Finalizing Conclusions
31.06.2017	Finalizing the Master Thesis

Table 4: Time Plan of Further work

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