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Modelling Volatility in Dry Bulk Freight Markets

Abstract

Shipping market is considered as a seasonal, cyclical and highly volatile market. Due to the nonstationary and nonlinear nature of freight series and the complexity of influencing factors, it is difficult to analyze the fluctuations in the dry bulk shipping market. Baltic Dry Index (BDI) consisting of sub-indices namely Baltic Supramax Index (BSI), Baltic Panamax Index (BPI) and Baltic Capesize Index (BCI) has been developed by the Baltic Exchange to reflect the overall fluctuation level of international dry bulk shipping market. These indices are considered as one of the leading economic indicators by worldwide institutions such as United Nations Council of Trade and Development (UNCTAD). This study mainly focuses on the econometric modelling of the volatility in dry bulk shipping. Modelling the of volatility of dry bulk shipping will allow us to understand the risk factor and risk structure of the Capesize, Supramax, and Panamax segments of the dry bulk freight market. The purpose of this study is to examine the properties of volatility in the sub-indices of highly respected dry bulk freight index BDI, namely BSI, BPI and BCI return values by employing an Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) based model. The freight index data were received from Bloomberg Professional Database. The results of empirical analysis indicate that both volatility persistence and leverage effect are obvious for all three freight index returns, meaning the impact of external shocks in dry bulk shipping market are asymmetric. Also dry bulk freight market, especially the Capesize segment, requires a long time for the effects of the shocks to be disperse on their own. Lastly the results revealed high index sensitivity ratios for all three models, which supports the phenomenon of shipping industry being one of the quickest and harshest reflecting sectors to the developments in the global economy.

Keywords: *Baltic Dry Index, Freight Rate, Volatility, Leverage Effect, Dry Bulk Shipping, Financial Time Series, EGARCH*

1. Introduction

Following years after its formation, The Baltic Exchange recognized as the most important independent source of maritime market information for the trading and settlement of physical and derivative shipping contracts. Currently, the Baltic Exchange houses 600 companies and more than 3000 individuals which makes it the most important market for shipping (Geman and Smith, 2012). With its large database and reflective status of the market, the data provided by the Baltic Exchange are extensively studied through the years.

Baltic Dry Index (BDI), which is the successor of Baltic Freight Index (BFI), is a composite index that is calculated as the weighted average of three sub-indices: Baltic Capesize Index (BCI), Baltic Supramax Index (BSI), and Baltic Panamax Index (BPI) (Baltic Exchange, 2019). It incorporates the cost of transporting various raw materials worldwide. Furthermore, it is a fundamental indicator for direction of input prices and economic activity (Papailias et al, 2017) as average raw material prices such as coal, iron ore, cement and grains are embedded. Thus, it is closely related to economic conditions and therefore global trade. It is recognized as a predictor especially for economic crashes. In this context, it is critical to understand the risk factor of these indices and build a useful model for each of the sub-indices to discover their volatility properties. Kavussanos (1996a) pointed out the necessity of employing Autoregressive Conditional Heteroscedasticity (ARCH) type modelling when assessing risks in spot and time charter dry bulk markets, as their variances are not constant over time. Kavussanos (1996b) then examined the volatility in the world tanker market for second hand vessels via ARCH modelling. He found that larger segments of tanker prices such as VLCC fluctuate wilder than smaller segments and suggested that risks in the tanker industry have decreased since the first part of the 1980s. Kavussanos (1997) then proceeds to examine the volatility properties of second hand market for different size dry bulk vessels with ARCH type modelling. The study reveals volatility clustering for all segments and higher volatility for larger size ship prices. As the dry bulk shipping market is volatile and cyclical, companies are constantly searching for ways to evaluate the changes in freight rates, and reducing the business risk and uncertainties. Development of a volatility assessment method using the historical BCI, BSI, and BPI data could be an utmost importance for interested parties. In this paper, the concept of Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model is proposed for the modelling the volatility of BCI, BSI, and BPI. With it, the volatility properties and risk structure for all three indices are thoroughly investigated. This study contributes to the literature by considering a recent time horizon and modelling volatility of different segments of dry bulk freight market rather than analyzing it as a whole.

The remainder of this paper is organized as follows: Section 2 presents data for BCI, BSI, and BPI and their preparation for financial econometric modelling. Construction of the time series model with EGARCH methodology is also given in Section 2; Section 3 presents the empirical results and discussions; and Section 4 gives conclusions and recommendations for future research.

2. Methodology

This study employs a financial time series analysis as the main research methodology. After conducting a research upon the changing and asymmetric volatility models to decide on which time series approach to be taken, an EGARCH model was constructed in order to model the volatility and understand its properties in BCI, BSI, and BPI.

2.1. Data

The data used on analysis consists of weekly BSI, BCI, and BPI data published by the Baltic Exchange between 2 January 2011 – 3 February 2019. All indices consist of 419 observations, which is a considerable number to capturing the changes in asymmetric volatility over time and volatility clustering. All of the necessary data were gathered from Bloomberg to prevent the mismatch and missing value problems that may occur from gathering data from different databases which do not perfectly correspond with each other. Figure 1 provides the time trend graph of raw BSI, BCI, and BPI data in order to provide an understanding of the trend in the dry bulk freight rates across different vessel types. Also the descriptive statistics of raw series are given below in Table 1.

Table 1 - Descriptive Statistics of BSI BCI and BPI Index Values

	BSI	BCI	BPI
Mean	914.6969	1760.986	1111.518
Median	900.0000	1593.000	1052.000
Maximum	1607.000	4246.000	2132.000
Minimum	243.0000	164.0000	287.0000
Std. Dev.	273.3886	857.9295	429.1760
Skewness	0.325380	0.608412	0.289963
Kurtosis	2.818200	3.059953	2.192834
Jarque-Berra	7.970416	25.91262	17.24586
Probability	0.018589	0.000002	0.000180

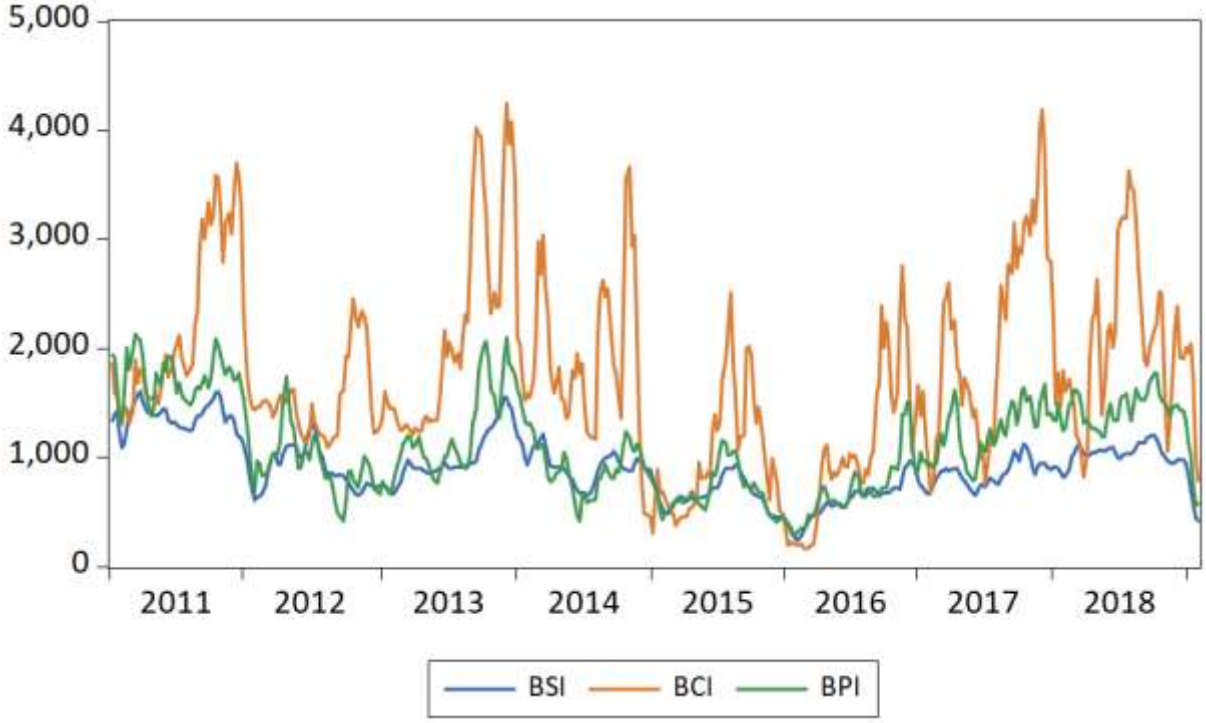

Figure 1 – Time Trend of BSI BCI and BPI Index Values

When Figure 1 is inspected closely, one can argue that volatility clustering and cyclical patterns are obvious for all three indices. While all of the freight rates show similar movements, the wild fluctuations of BCI index values set the series apart from other two. After the visual inspection we can make preliminary judgements that all of the indices possess volatility patterns that are very large and unstable.

2.2. Preparation of the Data

Firstly, the index values must to be converted into logarithmic returns in order to be applied in the financial time series analysis especially for EGARCH model and improve the estimation performance. The raw data converted into return series by applying the equation below to raw BSI, BCI, and BPI index values;

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

Which P_t is the freight index value and R_t is the freight index rate of return value. After the conversion of BCI, BSI, and BPI to return series, time trend graphs were given for the visual inspection at the Figure 2 below.

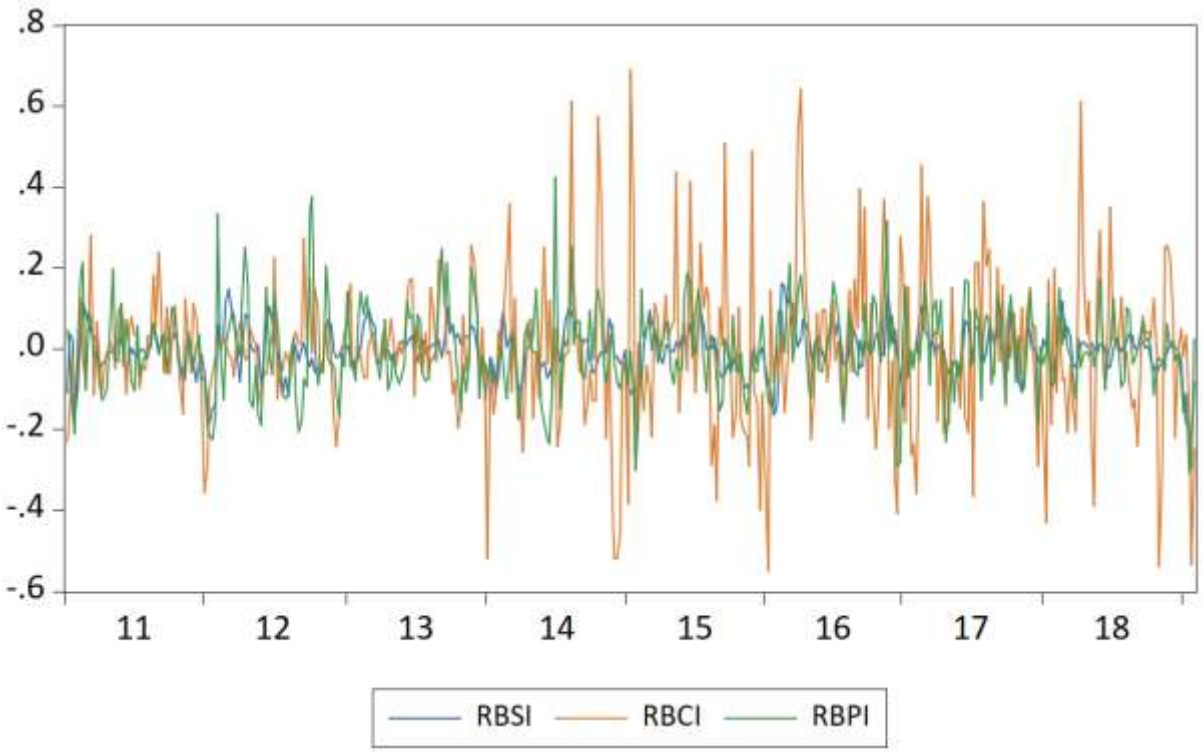

Figure 2 – Time Trend of BSI BCI and BPI Index Return Values

When the BSI, BCI, and BPI rate of return graph at Figure 2 is examined, we can make preliminary calls that all of the series are stationary and constantly waving by the zero mean. Also the volatility clustering is visually obvious for both of the series. Although time stream graphs give first glance information and some insights regarding the stationarity of the series, it is a must to conduct a unit root test and to ensure the stationarity. For this matter Augmented Dickey-Fuller (ADF) unit root test (Said and Dickey, 1984) is applied for all of the return series and the results of the unit root tests are given in the Table 2 below.

Table 2 – ADF Unit Root Tests

	R(BSI)	R(BCI)	R(BPI)
ADF Test Statistic	-8.972007***	-10.80290***	-10.50687***
1% level critical value	-3.445739	-3.445739	-3.445739
5% level critical value	-2.868219	-2.868219	-2.868219
10% level critical value	-2.570392	-2.570392	-2.570392

Note: *** refers to rejection of the null hypothesis for non-stationarity at 1%.

2.3. Modelling and Estimation

In order to produce a useful model, several steps have been followed in the scope of this study. First of all, the weekly series of BCI, BSI, and BPI were converted into their index rate of return forms to start the modelling procedure. After that unit root tests were conducted to

ensure stationarity of all three index rate of return series. For the model selection process, after the quick glance of the correlograms of the series it was obvious that the series must be modelled with AR and MA components. The AR and MA orders for the models were determined using an automated search over all possible models considering up to 4 orders for both AR and MA components with an automated search with the framework outlined by Hyndman and Khandakar (2008). The search is set to minimization of Akaike Information Criterion (Akaike, 1973) equated as;

$$\mathrm{AIC} = -2\mathrm{LL} + 2n_p$$

where LL is the log-likelihood value and n_p is the number of parameters. As for AR and MA orders, the search has given the order of AR (2) and the order of MA (3) for RBCI resulting in an ARMA (2,3) structure, order of AR (0) and the order of MA (2) for RBSI resulting in an ARMA (0,1) structure, and order of AR (0) and the order of MA (1) for RBPI resulting in an ARMA (0,4) structure.

After the ARMA(p,q) structures of the series are determined simple Ordinary Least Squares (OLS) models for BCI, BSI, and BPI were constructed. All three of the models were tested against the heteroscedasticity with Autoregressive Conditional Heteroscedasticity-Lagrange Multiplier (ARCH-LM) test and the results are given at the Table 3 below.

Table 3 - ARCH Test Results for RBCI ARMA(2,3), RBSI MA(2) and RBPI MA(1) Models

		RBCI ARMA(2,3)	**RBSI MA(2)**	**RBPI MA(1)**
ARCH-LM Test	F-Statistic	7.297884	6.027275	3.232360
	Prob.	0.0072	0.0026	0.0405

ARCH-LM test checks for the existence of heteroscedasticity by regressing squared residuals of the model on lagged values of the squared residuals and a constant (Engle, 1982). With the H_0 null hypothesis representing homoscedasticity, all OLS models were tested. When looked at the results, all of the models reject the homoscedasticity assumption of the test, it can be safely said that all three time series models possess strong heteroscedastic structures which are applicable for EGARCH type modelling.

In this study EGARCH (1,1,1) models for all three RBCI, RBSI, and RBPI series were employed. The general equation proposed by Nelson (1991) is in the form:

(3)

$$ln(\sigma_t^2) = \omega + \beta\, ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right]$$

Where parameter ω is variance intercept of the model, parameter β is the measurement of volatility persistence which also known as the GARCH effect, parameter α is the return coefficient of the model, which is also known as the ARCH effect, and the parameter γ is the magnitude of models asymmetric volatility, which also known as the leverage effect parameter.

3. Results and Discussion

The modelling procedure aforementioned in the previous chapter has resulted in a EGARCH (1,1,1) ARMA (2,3) model for RBCI, EGARCH (1,1,1) MA (2) model for RBCI, and EGARCH (1,1,1) MA (1) for RBPI series. Estimation results are presented in Table 4, Table 5, and Table 6 below.

Table 4 – RBCI EGARCH (1,1,1) ARMA (2,2) Estimation Results

Variable	Coefficient	P-value	Variable	Coefficient	P-value
C	-0.000929	0.9184	MA(1)	-1.493167***	0.0000
AR(1)	1.724860***	0.0000	MA(2)	0.603700***	0.0000
AR(2)	-0.999651***	0.0000	MA(3)	0.217520***	0.0000
Variance Equation					
ω	-0.121716***	0.0001	γ	-0.054804*	0.0707
α	0.101763***	0.0011	β	0.987179***	0.0000
Summary Statistics					
Log-Likelihood					182.6198
AIC					-0.8239
R^2					0.1287
ARCH-LM Test					0.2492 [0.6179]

Note: *** refers to significance at 1%, ** refers to significance at 5% and * refers to significance at 10%.

Table 5 – RBSI EGARCH (1,1,1) MA (2) Estimation Results

Variable	Coefficient	P-value	Variable	Coefficient	P-value
C	-0.002360	0.5556	MA(2)	0.352344***	0.0000
MA(1)	0.866387***	0.0000			
		Variance Equation			
ω	-1.155077***	0.0002	γ	-0.155961***	0.0010
α	0.211461***	0.0004	β	0.847791***	0.0000
		Summary Statistics			
Log-Likelihood					778.4526
AIC					-3.6823
R^2					0.5000
ARCH-LM Test					0.9391 [0.3331]

Note: *** refers to significance at 1%, ** refers to significance at 5% and * refers to significance at 10%.

Table 6 – RBPI EGARCH (1,1,1) MA (1) Estimation Results

Variable	Coefficient	P-value	Variable	Coefficient	P-value
C	-0.003604	0.5960	MA(1)	0.509791***	0.0000
		Variance Equation			
ω	-0.862029**	0.0196	γ	-0.114770***	0.0026
α	0.227164**	0.0127	β	0.857575***	0.0000
		Summary Statistics			
Log-Likelihood					411.1627
AIC					-1.9339
R^2					0.2101
ARCH-LM Test					0.5252 [0.4690]

Note: *** refers to significance at 1%, ** refers to significance at 5% and * refers to significance at 10%.

As described before the parameter β is the measurement of volatility persistence which also known as the GARCH effect. If the β value is large, longer periods of time is required for volatility to disperse and effects of a shock to be removed. The large number also implies greater fluctuations. For both RBSI and RBPI the parameter is about at 0.85 range, which is expected at most financial time series. For the RBCI the parameter value is 0.98, which is a

very high volatility persistence level. The high value of lag coefficient means that returns of all BDI sub-indices require very long times to get rid of the effects of external shocks and fluctuate wildly during innovation periods. The results suggest that shocks in return of BCI, BSI, and BPI only disperse 1.3%, 15.2% and 14.2% each week. The parameter α is the return coefficient of the model, which is also known as the ARCH effect. The larger the α value becomes, the quicker it shows the movements in the markets and fluctuate longer. When the estimation results are examined it can be said that RBPI, only with a 0.01 margin from RBSI, reflects the movements of its segment of the dry bulk freight market quicker and more sensitively than the other two indices. Also α values of RBCI, RBSI, and RBPI are larger than 0.1, which means volatility of both indices are very sensitive to happenings of the market. We can speculate that due to the large size difference and extreme fluctuations of Capesize market compared to Supramax and Panamax markets, there might be different mechanisms effecting the reaction time of the index to the movements in the markets. The significance of this parameter proves the existence of volatility clustering in all three indices. And finally the parameter γ is the magnitude of models asymmetric volatility, which also known as the leverage effect parameter. When γ results in zero, it means that the volatility is symmetric for the series. If the parameter results in positive or negative value and becomes significant then it means the leverage effect is undeniable for the series. The sign of the γ value determines the properties of leverage effect. If γ results in a negative value, that means negative shocks or bad news generates more volatility than positive shocks or good news. If γ results in a positive value it can be said that positive shocks destabilize the series more than the negative shocks. According to the estimation results all three indices possess leverage effect with a negative γ value, RBSI and RBPI having slightly more effect at better confidence level than the RBCI. Which means bad news generate more volatility for all of the BDI sub-indices than the good ones. One possible reason for that because shipping is such a capital intensive industry. When a negative development occurs in the market stakeholders might react more harshly than they react in the positive developments. Because when considering the properties of the market a negative investment and even a false investment can lead to bankruptcy, while reacting to positive happenings of the market is usually a win more decision.

The estimation results indicate that both volatility persistence and leverage effect are obvious for all three freight index returns. According to the estimations the dry bulk freight market for all three vessel types has negative leverage, in other words bad news generate more volatility for the BDI sub-indices than the good ones. In addition to this, it can be said that dry bulk freight market, especially the Capesize segment, requires a long time for the effects of the shocks to be disappear on their own. The volatility generated for return of BCI, BSI, and BPI by those shocks persist through approximately 50 weeks, 43 weeks, and 45 weeks in order.

Also all three indices have very high sensitivity ratios, which means that these indices, especially BSI and BPI, will reflect quickly to the happenings of the shipping and economy in general. This also proves the phenomenon of shipping industry being one of the quickest and harshest reflecting sectors to the developments in the global economy. Modeling procedure based on AIC, significance of variables, and log-likelihood criteria have ended up with functional models with appealing statistical diagnostics.

4. Conclusion

This study focused on modelling the volatility of sub-indices of BDI, namely BCI, BSI, and BPI via EGARCH type models. The weekly index returns of BCI, BSI, and BPI between 02 January 2011 – 03 February 2019, each consisting of 419 observations. The examined return values showed leptokurtosis and volatility clustering, both being fore signs of heteroscedasticity. For the next stage autoregressive structures of both series were determined by estimating with an OLS estimator. After determining the AR and MA operators for series residuals of the series were tested against heteroscedasticity via ARCH-LM test. According to the heteroscedasticity test results residuals of the index return series which were estimated with OLS, are under considerable ARCH effect. Therefore, with the aim of the study in mind return of the BCI found to be most suitable for ARMA(2,3)-EGARCH(1,1,1) model, return of the BSI found to fit best to MA(2)-EGARCH(1,1,1) model and return of the BPI is found to be fit best to MA(1)-EGARCH(1,1,1) model after various testing and post estimation diagnostics. These models can serve as a reliable analytical tool for decision makers in dry bulk shipping business. When looking at the estimation results as an investor's perspective the leverage effect emerges as a core function of the freight mechanism of the dry bulk market. With the high sensitivity, high shock persistence and negative leverage effect properties considered, shipping industry which is already infamous with its knifes edge position on the stability, will surely has to stay on alert for any crisis situation at the global economy and will be tested harshly as it has been throughout the recent history.

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