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Modelling and Forecasting Yield Volatility of Baltic Exchange Dry Index

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ABSTRACT

Purpose – Baltic Dry Index (BDI) is shipping freight-cost index which is reported daily by Baltic Exchange. The index is a benchmark for the prices of ship chartering contracts which is a proxy for the maritime economy, BDI is heavily used by financial traders to predict the world economy, the volatility forecast has an important implication for all the investors and hence in this paper the daily forecast performance of different models is evaluated.
Research methodology – The daily forecast performance of conditional and unconditional volatility of 12 long memory GARCH-type models based on the root-mean-square error (RMSE) is evaluated. Because all return series were skewed and fat-tailed, each conditional volatility model was estimated under a skewed Student distribution.
Findings – According to the idea that the accuracy of Value-at-Risk (VaR) estimates was sensitive to the adequacy of the volatility model used, the result showed that the 250-day moving average models, exponential smoothing, and (component GARCH) CGARCH function better than other models based on RMSE standard. The results of hybrid models such as Dibold-Mariano statistics showed that there was no significant difference between the predictive power of 250 days moving average (MA250) and CGARCH.
Practical implications – BDI was widely regarded as a benchmark for the world economy by traders and hedge fund managers.
Originality/Value – we examine the science of volatility prediction in BDI which has not been performed before.

1 Introduction

The volatility of the financial market is one of the important variables in investment decisions, securities and derivatives prices, risk management, regulation, and policy regulation. The prediction of volatility has attracted the attention of many researchers [1]. Infact, the fluctuation of financial markets has an important impact on the country's economy through the creation or reduction of public confidence and credibility[2]. The shipping business is the engine of the world economy as over 90% of global trade, raw commodities, and finished goods are carried across by the sea-going ships. Dry bulk ships cover 40% of sea transport compared with 38% for tankers and 22% for container ships [3]. Dry bulk freight rates which are reported daily by Baltic Exchange in London is called the Baltic Dry Index (BDI). Investors, bankers, and hedge fund managers widely regard the BDI as a benchmark for the world economy and as an indicator for the future wellbeing of financial and commodities. No research has been done on the yield volatilities of BDI, so the identification of the yield volatilities pattern in BDI could be an appropriate step to take investment and policy decisions for both direct participants of the shipping market and stock markets traders throughout the world.

So far, various models and techniques have been proposed for volatility modeling, autoregressive conditional heteroscedasticity (ARCH), originally introduced by [4] and later developed by [5] that were now known as the most important model for high-frequency financial time series data [6, 7]. Several studies have been accomplished by using these models in the context of exchange rate fluctuations and their predictions. For example, with GARCH models' reception availability from ARCH models, exponential movement evaluated average & historical average models have had a better performance in forecasting volatility of the US monthly stock index [8]. Pagan & Schwert (1990) have compared the ability of GARCH, EGARCH model, Markov state transition, and three non-parametric models in predicting monthly volatility of the US stock returns [9]. The results showed that conditional models performed better. Bhowmik and Wang, (2020) found that the GJR and GARCH models performed better than other models in predicting Australia's monthly volatility index [10]. Pourkermani (2023) has applied several types of forecasting in shipping variables [11], Pourkermani (2022) has modelled the relation between Baltic Exchange Indexes [12], generally the results showed that the GARCH model with normal hybrid distribution (1, 1) was a suitable model. Zhu et al. (2019) used linear and GARCH models to predict two stock indices in the Chinese stock market. The results showed that the predictive power of these models varies depending on the evaluation criteria, but the performance of the random walk model was generally worse than all other models [13].

In this study, unlike most accomplished studies, a range of models was compared together, and ultimately, we would check the performance of autoregressive conditional volatility models and alternative models in predicting BDI Price Index.

2 Research data & variables

The data used to test the assumptions of the BDI index time series were observed from 1/9/2012 to 12/29/2020. The logarithm of the initial data ratio was obtained before each analysis and the main time series of this article were as such:

$$r_t = l_n\left(\frac{BDI_t}{BDI_{T-l}}\right) \quad (1)$$

However, the 1984 daily return data of r would have been obtained and utilized the squared daily returns as a measure of daily volatility.

The statistical features observed had an inverse-zero without conditional mean index, and they appeared to be automatically correlated. This was not a broad-spectrum histogram index and was less likely to deviate from the mean. This was shown in Figure 1, which included the time-series r, the histogram, and the normal distribution curve. The standard deviation of the index was approximately 0.04; these maximum and minimum sample variations were generally between 5 or 6 mean standard deviations of each sample. The sample stretch was also larger than the normal distribution, and there was also evidence of skewness to the right (rows 3, 4). The value of the root test of the ADF statistical unit in the yield of r was equal to -8.01. Therefore, the unit root hypothesis at the 99% confidence level would be rejected. As the results showed, the series had more skewness than the normal distribution, the Jarque-Bera statistical results also showed that the hypothesis of normality of the series would be rejected [14].

Table 1: Descriptive statistics

	e_t	e_t^2		e_t	e_t^2
1 Mean	0/0013 (0/000)	-	7 Median	0/001	
2 Standard Deviation	0/0041	-	8 Maximum	0/0232	
3 Skewness	0/53	-	9 Minimum	-0/0214	
4 Kurtosis	7/33	-	10 Total	0/033	
5 Q (5)	952/7 (0/000)	952/07 (0/000)	11 Total deviation of squares	1647/378 (0/000)	
6 Q (15)	1703/6 (0/000)	1563/2 (0/000)	12 Jarque–Bera test		

1) In row 1, the numbers in parentheses indicate the probability that the series mean is assumed to be zero.
2) In rows 5 and 6, the numbers in parentheses indicate the probability of assuming the absence of autocorrelation.
3) In row 12, the numbers in parentheses indicate the assumption that the series is normal.

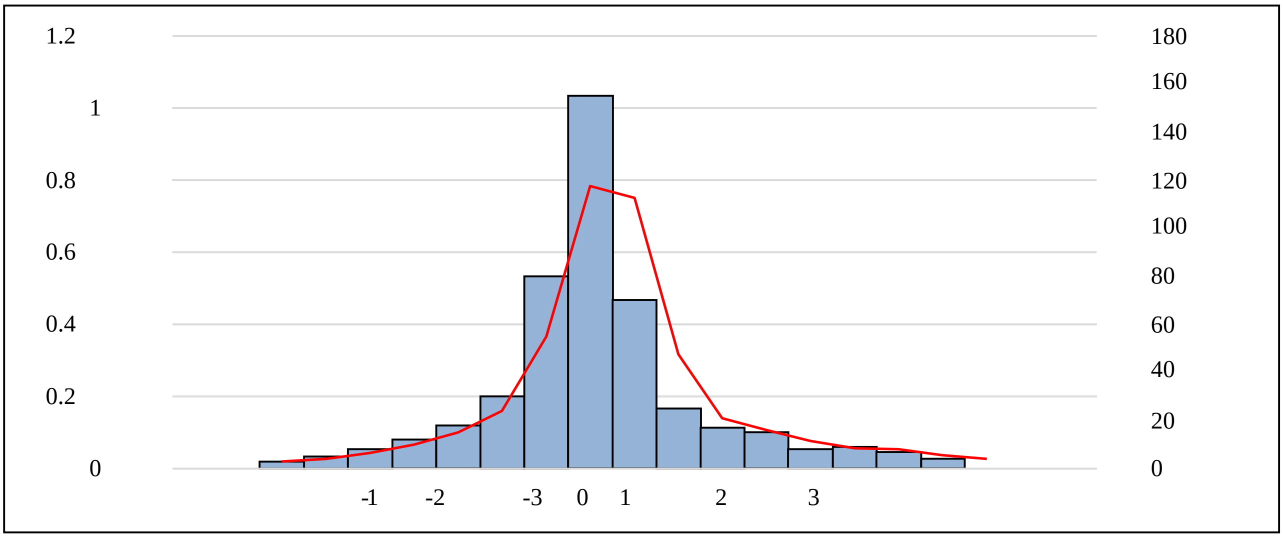

Chart 1: histogram and the normal distribution curve

Here, it could be considered more appropriate methods for volatilities prediction from root-mean square error (RMSE), related to each of the methods that had smaller RMSE criteria. RMSE anticipated criteria would be defined as: First;

$$RMSE = \sqrt{\frac{1}{N}\sum(\sigma_{t,f}^2 - \sigma_t^2)^2} \qquad (2)$$

In the above statistics, n was the number of forecasts, and $\sigma_{t,f}^2$ was used to forecast volatility and σ_t^2 was the real volatility. Diebold-Mariano test statistic was used to perform a statistical test for two desired models' predictive power. Suppose that two competing models existed for prediction and e_{1i}, e_{2i} were the forecasting error. Furthermore, assume that the loss of i forecasting error was equal to $g(e_i)$. We showed the difference between the loss of using these two models as $d_i = g(e_{1i}) - g(e_{2i})$. If $\bar{d}$ & γ_i...were the mean and variance of the sample sequence$\{d_i\}$ respectively, then, by uncorrelating$\{d_i\}$the sequence of the components, the Diebold –Marnce of the statistic would be defined as below:

$$DM = \frac{\bar{d}}{\sqrt{\frac{\gamma_0}{(H-1)}}} \qquad (3)$$

H was equal to the number of forecasting courses in the above statistic. This statistic had the value of the t distribution with the degree of freedom H-1.But if there were a correlation between the elements of sequence$\{d_i\}$, with being nonzero and q of initial value γ_i (covariance), the above-mentioned statistic would be adjusted as such:

$$DM = \frac{\bar{d}}{\sqrt{\frac{(\gamma_0+2\gamma_1+...+2\gamma_q)}{(H-1)}}} \qquad (4)$$

Here, the statistic included t distribution with the degree of freedom H-1. In the following sections, we would introduce different models and present why and how it was addressed in this study.

3 Variance measurement models

The prediction models introduced in this paper were classified as models which their performances were based on historical information. Therefore, the moving average model, exponential smoothing model, ARMA model, neural network (as unconditional models), and GARCH models include GARCH, TGARCH, EGARCH, and PGARCH (as conditional models) had been used to test the hypothesis. Since there was not enough opportunity to announce all the models in this section, we would explain only the models that had the lowest RMSE among the conditional and non-conditional models. The 120-day moving average models and the exponential smoothing models through unconditional models, CGARCH (1,1) and HARCH (1,1) had the lowest RMSE values among the conditional models, respectively. On the other hand, for global comparison between selected conditional and unconditional models, the combined forecasting method was used, which would be examined later. The descriptions of these models were as such:

4 Moving average model:

In this model, the arithmetic mean of past data was used for forecasting. The most important parameter in the model was the time period used to calculate the mean [15]. Based on the findings of technical studies, most researchers often used periods of 20, 60, 120 and 250 days (from one month to one year).

$$\sigma_{T,f}^2 = \frac{1}{M}\sum_{i=1}^{M}\sigma_{T-i}^2 \quad \& \quad T = 1920,\dots,1984 \quad \& \quad M = 20,60,120,250 \qquad (5)$$

4.1 Exponential smoothing models (ES):

It was given greater weight to more recent data and less weight to old information in this model with reduced geometric weight to the observations contained one series time- interval (Smyl, 2020):

σ_(T,f)^2=(1-λ) σ_(T-1)^2+λσ_(T-1,f)^2 & T=1920,...,1984 (6)

In which 0<λ<1 (smoothness constant) should be chosen to have the best fit to decrease the total error of the sample squares. In this article, the λ was estimated at 0.14.

4.2 GARCH model:

This model considered the conditional variance dependent on its interruptions. This version was defined as following *[16*]:

$$\sigma_i^2 = \omega + \alpha_1\varepsilon_{i-1}^2 + \beta_1\sigma_{i-1}^2 \qquad (7)$$

Where α_1 and β_1 and $\omega > 0$ and α_1 and β_1 amounts were estimated 0.32 & 0.55 respectively

4.3 CGARCH model:

The volatility model consisted of two components: one for short-term and another for long-term volatilities *[17*]:

$$\sigma_2^1 - m = \varpi + \alpha(\varepsilon_{t-1}^2 - \varpi) + \beta(\sigma_{t-1}^2 - \varpi)$$

$$m_t = \omega + \rho(m_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \qquad (8)$$

The first equation described the relation of the temporary element, which reached zero with power $\alpha + \beta$. The second equation also showed the long-run element along with power ρ to ω and power ρ. The values of α, β, ρ were 0.3, 0.4, 0.9, respectively.

4.4 The combination of predictions:

When we reached different predictions using different models and methods, methods such as regression could be used to compare these models in general. The dependent variable for specific time periods should be determined in the regression method considering these values; the predicted values and its accuracy should be analyzed [18].

$$A_{T+j} = \beta P_{1,T+j} + (1-\beta)P_{2,T+j} + \varepsilon_{T+j} \qquad (9)$$

Where AT + j is the real-time value, P1, T + j, T + j was the predicted value of the first method, and P2, T + j was the predicted value using the second method. To estimate β, the following could be done:

$$A_{T+j} - p_{2,T+j} = \beta(P_{1,T+j} - p_{2,T+j}) + \varepsilon_{c,T+j} \qquad (10)$$

In fact, it was possible to achieve an optimal prediction combination with estimating parameter (β). The reason for this simplification was that the sum of the prediction coefficients in combinational prediction should be $1\alpha = 1-\beta, \alpha+\beta = 1..(21)$.To generalize the method related to a few predictions, obtained based on different methods or models, we could write:

$$A_{T+j} = \beta_1 P_{1,T+j} + \beta_2 P_{2,T+j} + \cdots + \beta_k P_{k,T+j} + \varepsilon_{C,T+j} \qquad (11)$$

Since the sum of the coefficients should be equal to 1, β could be written by imposing constraint:

$$\beta_1 + \beta_2 + \ldots + \beta_k = 1$$

$$\beta_k = 1 - \beta_1 - \beta_2 + \ldots$$

$$A_{T+j} - p_{k,T+j} = \beta_1\left(P_{1,T+j} - P_{2,T+j}\right) + \beta_2(P_{2,T+j} - P_{k,T+j}) + \ldots + \beta_k(P_{k-1,T+j} - P_{k,T+j}) + \varepsilon_{c,T+j} \qquad (12)$$

Or briefly

$$A^*_{T+j} = \beta_1 P^*_{1\,T+j} + \beta_2 P^*_{2\,T+j} + \ldots + \beta_k P^*_{k-1,T+j} + \varepsilon_{c,T+j} \qquad (13)$$

Where in the said model, all the predictions and the actual amount were expressed as ak deviation predicted. The 120-day moving average and exponential smoothing models had had the minimum value of RMSE among non-conditional models, CGARCH, GARCH across conditional models; therefore, we could obtain a general prediction with the combination of these models forecasting for the first category (non-conditional models) and for second models category (conditional models). A general prediction by a combination of mentioned premium forecasting models, according to the method described, compared the power of the two combined models with the evaluation criteria.

5 The experimental results and their interpretation

According to the evaluation criteria shown in Table 2, the results of the predictions of the superior conditional variance and unconditional variance models were represented, along with the rank of each existing model. According to this table, non-conditional models (except the ARMA model) had completely better predictions than conditional models. Based on this table, the evaluated average model had generally made good predictions. The exponential smoothing model also performed well in relation to the RMSE criteria. Therefore, it could be said that the use of past was considered a good model to predict returns by giving appropriate weight.

CGARCH Conditional variance models did not perform well except in the GARCH component model (CGARCH) and the GARCH model (Conrad, & Kleen, 2020). The GARCH component model led to a separate focus on short-term and long-term fluctuations. It could be considered that the good performance of this model was due to the diversity in the nature of short-term and long-term fluctuations.

Table 2. The result of the different prediction models

CN	CNHO	GARCH	CGARCH	ES	MA250	
1.00E-03	3.9944E-05	4.025E-05	4.005E-05	4.004E-05	3.9945E-05	RMSE
0.523 (1.67)[a]					Diebold- Mariano test	

A= t-stat for 95% confidence interval, degree of freedom 63

Due to the uncertainty of the better performance of conditional and non-conditional models, the following was a comparison of hybrid models. The statistical values of RMSE in each unconditional hybrid model CNHO and conditional model CHO were 0.000039944 and 0.001, respectively. Therefore, it seemed that the performance of the hybrid unconditional model was better than other models, but the combination of the conditional model prediction has not led to a better result.

To evaluate the similarity of RMSE values better, in the next step, we have discussed the similarity test of these values between different models. Line 3 in Table 1 showed the Diebold-Mariano statistical value with

the critical value of the t-statistic at the 95% confidence level for the following hypothesis:
H: Equality of the best conditional variance model (CGARCH), predictive power and the best non-conditional variance model (MA250) (equality of their RMSE values).
The above hypothesis has been examined due to the great emphasis that often existed on the differences between conditional variance and similar variance model and the component GARCH model since there were no significant difference between the numbers related to RMSE values. Therefore, the test accepted the above hypothesis zero, it does not seem very unrealistic. As such, the result obtained showed that the approximate similarity of the RMSE point was not so misleading

6 Conclusions

Regarding the importance of fluctuations in the stock market, in this article, we tried to provide a suitable model for predicting price fluctuations in shipping indices. The results showed that the performance of unconditional smoothing models and exponential moving average of 250 days was acceptable;

models in predicting fluctuations. Therefore, a significant or non-significant test of the RMSE difference between the two models was discussed in this hypothesis. In addition, the {di {sequences obtained by the study showed that there was no automatic correlation. According to this table, it was clear that there was no significant difference between the predictive power of the 250-day moving average

according to the results of hybrid models, unconditioned models had better performance than conditional models. Therefore, the use of past data achieves a better prediction. On the other hand, as observed, there was no significant difference between the 250-day moving average and the predictive power of GARCH models due to Diebold-Mariano test statistics, as the root difference was the mean of the square. The error of these two models was not so great. Thus, unlike many recent studies, the prediction of conditional models was not significantly different from other models, and even their point estimation was worse than some unconditional oscillation models.

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