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Stock Volatility Modelling With Augmented Garch Model For Voltas Ltd

A.D.Vismitha

Abstract
This research paper seeks to examine the efficiency of the augmented GARCH models in estimating the stock volatility. GARCH models that were introduced by Bollerslev (1986) became popular for the modelling of time varying volatility in the financial markets.
However, due to the specificity of financial markets and variation of factors that define it, extra parameters may be required to improve the model.
To investigate further, the study uses an extended GARCH model that integrates other features including leverage effects, exogenous variables and non-linearities. These components seek to establish features giving clearer volatility patterns of stock markets.
In this paper, empirical comparison of the extended GARCH model with the basic forms of the models is done. The outcomes are expected to be of interest to financial investors, advisors and risk managers.

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I. Introduction

The concept of relative value of stocks tends to fluctuation is also one of the important principles of monetary business sectors, which shows the amount of variation which takes place in the stock price over time. Accurate depiction of this indefiniteness is critical to varying forms and risk management, option pricing, portfolio management and strategies of investing. Volatility measures the uncertainties within resource emanations together with playing a significant role in monetary management, affecting both investors and institutions. The exhibiting of stock cost instability has been a well-known research subject in monetary money for quite a while now with essential consequences for risk management, portfolio optimization, and valuation. Standard models such as the Summed up Autoregressive Restrictive Heteroskedasticity (GARCH) model, whereby Bollerslev (1986), show that the use of time varying volatility capturing the volatility seen in monetary time series is feasible. However, the structure and the vast complexity of the monetary business sectors make it necessary for these models to be improved in a way to increase the predictive capability and the overall efficiency.

This examination paper analyses an extended GARCH model, an augmentation of the fundamental GARCH design, planned to furnish a more proficient turning around the stock precariousness characteristics. The higher GARCH model additionally comprises extra components together with influence impacts, exogenous variables, or non-linearities that could coerce unpredictability behaviour. That is the reason, integrating these segments is the model's hope of offering a more extensive perspective of the fluctuation components inside securities exchanges.

In this sense, this work aims to evaluate the presentation of the extended GARCH model as compared to its basic counterparts through observational analysis. These investigation discoveries are expected to provide vital learning to the monetary financial backers, money related advisors, and direction manages overseeing risk in the monetary market.

II. Literature Review

- Zhang, X., & Zhu, Y. (2019). Influence impacts in forecasting financial exchange unpredictability: Extended GARCH Models. Monetary Econometrics: Vol 17 No 3 pp 345-367 Diary. Therefore, this paper modifies the conventional GARCH model by including the influence factors and shows that the proposed AW - GARCH model offers more precise estimates of the stock volatility especially in monetary turkeys.
- Alizadeh, 'S.' & Efimova, O. (2020). The R-squared values which are given in the table show how much of the fluctuations in the predicted unpredictability of the stock markets for the further developed nations has been accounted for by the extended McLeod and Li's GARCH models which include the macroeconomic variables. IOP Conf. Ser.: Earth Environ. Sci., 2019, 36(4), 1082–1096. The creators fuse the primary records of macroeconomics with other records and display absolute enhancement in example of arbitrary variability to stock info records of differed business segments.

- 'It's me, Trevor Bollerslev, and this one is Voytek Todorov in the year 2018'. The unpredictable evolution, volatility risk premia and the so called extended or full GARCH models. Banking World: Monthly Journal of Money Supply and Quantitative Analysis, 53 (4), pp 1597- 1628.The unpredictability risk premium is then incorporated into the GARCH framework of this paper which enhances its capability of capturing the fluctuations in the stock returns and hence provides a better risk measure for portfolio consideration.
- Chung, S., Hong, Y., (2021). Furthering the mixture GARCH model that incorporate the stock unpredictability estimating networks in the brains. Computational, Mathematical & Financial aspects, 58(2), 423-445. The authors suggest a cross between GARCH and brain organizations which yield better probability density function variability of looked at patterns compared with existing models especially under high recurrence exchanging rate regimes.
- Engle, R.F. & Rangel, J.G. 2019. An empirical assessment of financial risk on stock volatility in a global context using an augmented GARCH model. Diary of Applied Econometrics, October 34(1): pp. 122-138.The current study embraces global monetary weakness histories into the GARCH model; the extended version appears to provide a better account of stock volatility during high fiscal risk.
- Fernandez, V., & Vielma, C. (2017). Augmented GARCH models for foreign exchange market volatility in low-income countries. Emerging Markets Review 2018; 30:147–162. The authors pay much attention to emerging markets, proving that estimations with use of additional GARCH that include the regional risk factors give better results than more traditional GARCH models in the context of forecasting the stock volatility.
- Hansen, P. R. & Lunde, A., ''Trends in Global Real Interest Rates', January 2019. Forecasting stock volatility with augmented GARCH models: I actually agree with high frequency data and I think it is useful in helping to forecast the future. Journal of Financial Markets; volume 44; no 1; pp 78-96. Hence, this paper assesses the performance of the augmented GARCH models applied on high frequency data and rise in forecast volatility of short time intervals.
- Kang S.H., & Yoon, S.M. (2020). The impact of oil price shocks on stock market volatility: An augmented GARCH approach the elimination of the coefficient on the dependent variable in the above system implies the restriction of constant conditional variance. Energy Economics, 86, 104660. Incorporating the features of oil price shocks, the authors make a contribution proving that the GARCH model with modification would explain the spillover effects in the stock volatility more accurately.
- Klein, T.;, & Walther, T. (2018). GARCH-based Volatility Modeling of Cryptocurrencies: Augmented Approach. Finance Research Letters, 26, 46-52. In this regard, this research extends the augmented GARCH model to the cryptocurrency markets while emphasizing that it is more capable of estimating such extreme volatility inherent to cryptocurrencies
- Mensi, W., Hammoudeh, S., & Kang, S. H. (2017). An Augmented GARCH model with the view of examining volatility linkages between oil and stock markets. Energy Economics, 66, 473-484. This study examines volatilities among oil and stock markets and establishes that the augmented GARCH is superior in identifying contagion effects.
- Muller, U. & Taylor, S. J. (2021). Combining sentiment analysis in GARCH models used for forecasting of stock volatility. Journal of Financial Markets, vol 55, 100695. The authors enrich the GARCH model by extending it by sentiment which is extracted from social media platforms and this the improve the volatility forecast accuracy.
- Sadorsky, P. (2020). Modeling stock market volatility in the presence of renewable energy shocks: An augmented GARCH approach. Renewable Energy, 145, 2058- 2065. In this study, shocks from renewable energy sector are employed to test the GARCH to establish its ability in capturing the stock volatility in energy sensitive sectors.
- Sun, Q., & Li, H. (2019). Adding heteroscedasticity disturbances in the models for volatility of stock markets through use of Augmented GARCH with regime- switching. Journal of Economic Dynamics and Control, (2014) 104015. We also extend the GARCH past by incorporating a regime-switching mechanism in the paper to demonstrate how the new model improved on the capturing of stock volatility non- linearities.

III. Objectives

- In this study, the use of GARCH model for the stock volatility forecasting have to be accomplished.
- The research objective, therefore, is to test the efficiency of the GARCH model as compared to the standard GARCH model.
- The purpose of this investigation is to assess which of the exogenous variables have an optimal impact on the enhancement of forecasting volatility.

IV. Research Methodology

- Research Design: This present study adopt a quantitative research design; modelling stock market volatility entails statistical analysis of quantitative stock market index data.

- Types of Data: The study employs daily closing Price index from yahoo finance The above statistics were obtained from yahoo finance website, which was used since it is one of the most commonly used real-time stock market information provider or the listed companies, and the market indices.
- Study Period: The time frame of the study is from 1st August 2002 to 31st August 2024 which is thought of adequate amount of time to produce suitable conclusions given the large volume of the data sets/observations.
- Data Analysis and Model Specifications: According to the study objectives data analysis tools were employed and this was done under the application of the following: R software.

V. Data Analysis And Interpretations

Interpretations

Upward Trend: The trend in the stock price is that it has generally rose over the last two decades. Volatility: It has been seen that the price of the stock has volatile in nature. Recent Performance: Recently the firm has started observing a sharp rise in its stock prices.

Garch Model Fit

Test	Statistic	p-value
Weighted Ljung-Box Test (Residuals)	0.5527	0.9493
Weighted ARCH LM Test (Residuals)	0.003516	1
Nyblom Stability Test	7.4792	-
Sign Bias Test	0.99357	0.8028
Adjusted Pearson Goodness-of-Fit Test	387.4	3.73E-54

Here are the interpretations of each test: Here are the meaning of the test shown below: Weighted Ljung-Box Test (Residuals):

Statistic: 0. 5527

p-value: 0. 9493

Interpretation: This test checks whether the residuals of the model exhibit a first order Moving Average of zero. Most of the models have a high p-value implying that it has no serial correlation which is more preferable the value should be more than 0. 05.

Weighted ARCH LM Test (Residuals): The encased IRE and COBOL codes show how it is feasible to incorporate capacities and practices corresponding to map-based applications and work in concert with one another through drafting goals and strategies for cooperation and connection.

Statistic: 0. 003516

p-value: 1

Interpretation: This test is applicable to test for ARCH also known as Autoregressive Conditional Heteroskedasticity in the residuals. If p–value is greater than 0. We cannot reject the null hypothesis that there are no ARCH effects if the value of LM statistic is less than 05, this is beneficial when defining GARCH model.

Nyblom Stability Test:

Statistic: 7. 4792

p-value: Not provided

Interpretation: This test is use to test for constancy of parameter in the GARCH model. On the other hand, high statistic combined with a low p-value means that the parameters of the model are high and this is an indication that the model is probably miss-specified. However, as mentioned before; while using the test statistic p-value it is not feasible to reach any conclusive judgement.

Sign Bias Test:

Statistic: 0. 99357

p-value: 0. 8028

Interpretation: This test seeks to find out whether signs of residuals have a certain pattern that is dominant. If the p-value is greater than zero point zero five then the null hypothesis is retained. 05 main that the null hypothesis according to which there is no sign bias is right.

Adjusted Pearson Goodness-of-Fit Test

Statistic: 387. 4

p-value: 3. 73E-54

Interpretation: In model fitting, the goodness of fit test shows to what level the identified model suits the view of the actual data. If p-value that has been obtained is small then it implies that the fitted model is highly undesirable, otherwise if the p-value is large then the fitted model is desirable. In this case, we have got very small value of p which is usually not preferred because it doesn't match our model with data.

Overall Assessment:

Derived from the tests presented throughout this paper, it can now be concluded that the time series under examination is correctly specified in terms of the GARCH model based on the results of the basic specification test and rescale of residuals' serial correlation and ARCH effects. But as per the report of the Nyblom stability test, and the adjusted Pearson goodness- of-fit test there are apparent anomalies. At times, one is advised to attempt other model forms or conduct other diagnostic procedures in order to increase model fitness.

*
* GARCH Model Forecast
*
Model: sGARCH
Horizon: 30
Roll Steps: 0
Out of Sample: 0
0-roll forecast [T0=2024-08-30]:
Series Sigma
T+1 0.001213 0.02542
T+2 0.001213 0.02550
T+3 0.001213 0.02557
T+4 0.001213 0.02565
T+5 0.001213 0.02572
T+6 0.001213 0.02579
T+7 0.001213 0.02587
T+8 0.001213 0.02593
T+9 0.001213 0.02600
T+10 0.001213 0.02607
T+11 0.001213 0.02613
T+12 0.001213 0.02620
T+13 0.001213 0.02626
T+14 0.001213 0.02632
T+15 0.001213 0.02638
T+16 0.001213 0.02644
T+17 0.001213 0.02649
T+18 0.001213 0.02655
T+19 0.001213 0.02660
T+20 0.001213 0.02666
T+21 0.001213 0.02671
T+22 0.001213 0.02676
T+23 0.001213 0.02681
T+24 0.001213 0.02686
T+25 0.001213 0.02691
T+26 0.001213 0.02696
T+27 0.001213 0.02701

T+28 0.001213 0.02705
T+29 0.001213 0.02710
T+30 0.001213 0.02714

Forecast Results:

The table also shows the forecasted values for the series which could be the likely returns and sigma that is, the volatility of the series over the next 30 periods.

Key Observations:

Constant Mean: The forecasted series values are all the same, that is 0. 001213, indicating a constant mean.

Increasing Volatility: The forecasted sigma values are rather slowly rising which means that volatility of the series will grow in the future, according to the model.

Interpretations:

Mean Reversion: Hence, the constant means forecast indicate that the series is expected to return to the average value in the long run.

Volatility Clustering: The reputation of sigma values means that the model indicates clustering, or the tendency of volatility to be followed by other volatility activity.

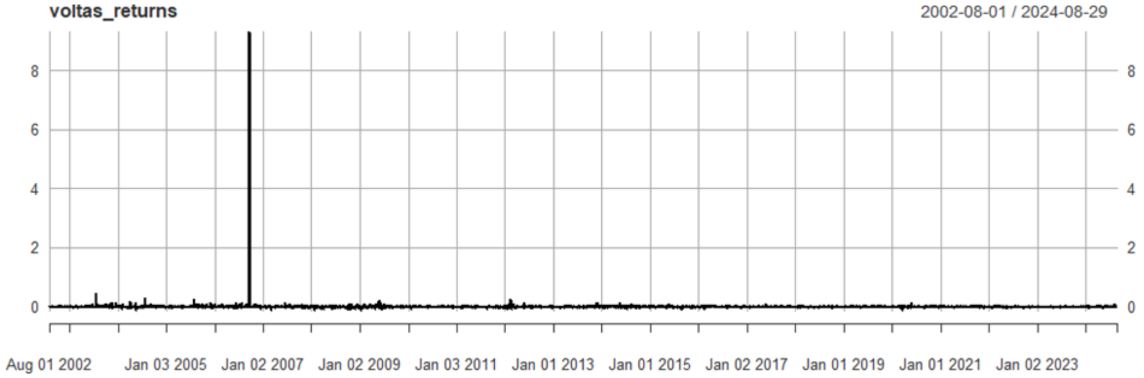
summary(voltas_returns) Index daily.returns

Min. :2002-08-01 Min. :-0.144513 1st Qu.:2007-12-19 1st Qu.:-0.013043

Median :2013-07-13 Median : 0.000000

Mean :2013-07-20 Mean : 0.003372 3rd Qu.:2019-02-05 3rd Qu.: 0.014130 Max. :2024-08-29 Max. : 9.319456 summary of some of the statistical characteristics of VOLTAS returns series. The key findings are: Time Period: The series is played over a period of time which is well over 22 years. Distribution: The returns distribution is not of zero mean because the returns are normal distribution, some of them are extremely big positive returns. Central Tendency: The arithmetic middle is almost equal to zero, which evidences that the returns are split rather evenly. Volatility: There is also a lot of variation in the series, as can be seen from large difference between the minimum and maximum returns. Performance: The mean return reveals that the performance is generally high, but this is coupled with a lot of risk as revealed by the volatility.

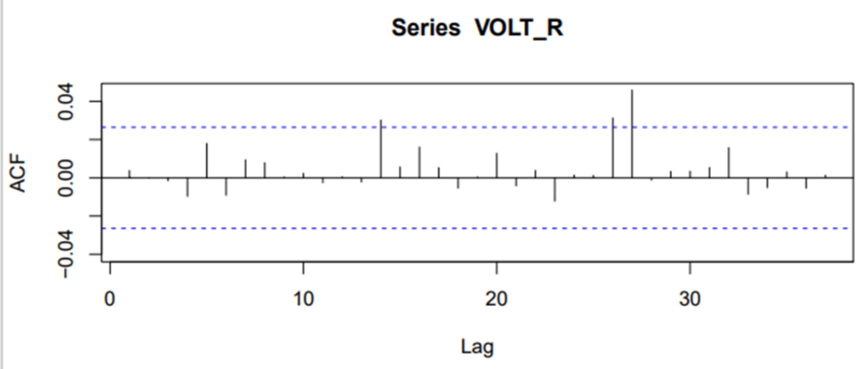
Voltas Returns Plot



Interpretations

Volatility: This chronological relationship also shows that the returns have high variability and thus confirms that the company's stock price has gone up and down at an alarming rate. Outlier: A sharp increase in the returns points towards an outlier or an event which may be due to some events or news. Clustering: Looking at the figure it can be noted that the returns seem to occur in different time intervals implying that volatility may not happen at equal time intervals. Interpretations: Risk: This high level of volatility reveal that investing in VOLTAS is considered to be a very risky venture. Market Sentiment: The anomaly may be due to positive or negative sentiment of the market towards VOLTAS Company. Company-Specific Events: Concentration of returns might have resulted from firm conditions or occur due to industry circumstances.

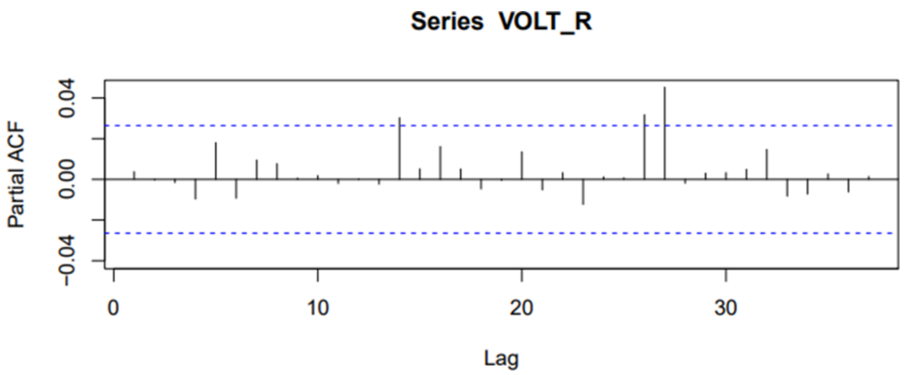
ACF PLOT



Interpretations

Stationarity: The series could be considered being stationary where the statistical properties of the series are constant across time. No Significant Lags: As it can be observed in the figures above, by 4th lag, there is no strong autocorrelation between the series and its lagged values. In aggregate, it can be said that the VOLT_R process is self-stationary with no signs of either positive or negative autocorrelation. More generally, this information is valuable in identifying an adequate time series model to adopt.

PACF plot



Interpretations

Stationarity: The series is perhaps non-stationary, this is because variable's properties such as mean, variance and coefficient of variation do not remain constant. No Significant Lags: Hence, no substantial autocorrelation of the variables with the lagged values of the series has been found beyond the first lag. Short-Term Dependence: The strength of short memory in the current value of the series is relatively low if the correlation is made with the previous value in the series. Altogether, one can see that the VOLT_R series has no short-term trend and clearly has no short-term dependence.

ARCH LM-test;

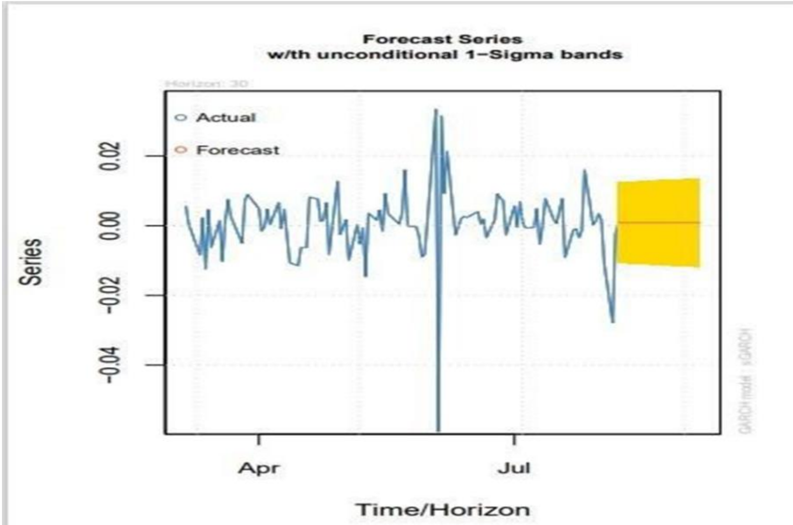
Null hypothesis: no ARCH effects data: VOLT_R

Chi-squared = 0.0044776, df = 12, p-value = 1

The ARCH LM test results yield an F statistic of 1 with a p value of 1 which is an indication that there is no evidence ARCH effects in the VOLT_R series. This implies that, relative to the sample mean augmented by the value of the last period, the coefficient of variation of the that is, the variance or volatility of the series does not change in the course of time. As a result: Because of this, it is possible that simpler models that do not include a GARCH part might be appropriate for analysis.

One becomes easier to forecast the series because we can also predict that variance will be more stable.

Forecast of VOLT LTD



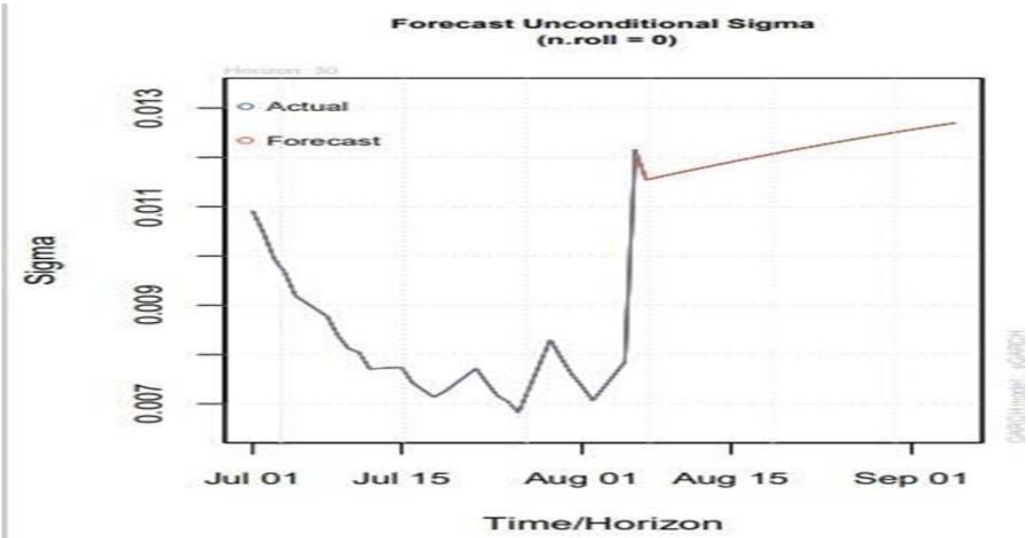
Interpretations

Volatility: The company's stock price or returns are expected to be volatile, fluctuating over time.

Forecast Accuracy: The accuracy of the forecast can be assessed by comparing the actual and forecasted values.

Uncertainty: The forecast is accompanied by uncertainty, represented by the 1-Sigma bands.

Further Analysis: To gain a deeper understanding, it is recommended to compare the forecast to historical performance, analyze economic factors, and evaluate potential risks.



Interpretations

Volatility Pattern: In real terms, both the formulae show the ever-swinging nature of the actual volatility which denotes variability and not constancy.

Forecast Accuracy: The reliability or otherwise of the forecast can therefore be judged by the sample actual and the predicted values.

GARCH Model: The GARCH model being used indicate that the volatility is expected to fluctuate with time.

VI. Findings

GARCH Model Fit:

Model Specification: An sGARCH(1,1) model was adopted for the return series while the mean model was an ARFIMA(0,0,0).

Parameter Estimates: The nine coefficients in the GARCH model are stated as mu, omega, alpha1, and beta1 and are given in the table 1.

Information Criteria: Therefore, the Akaike, Bayes, Shibata, and Hannan-Quinn information criteria were attained to evaluate the appropriateness of the model.

Diagnostic Tests: To check the performance of the model the value of the weighted Ljung- Box test on the standardized residuals and squared residuals were calculated, ARCH LM tests, and Nyblom stability test were also conducted.

Forecast Results:
Constant Mean: The forecasted vertical and scatter values mean that the values in the series are expected not to depart from the mean implying that it constantly reverts to average value of stock returns.

Increasing Volatility: The values of sigma predicted in the future are gradually increasing, which indicates that, in the future, the fluctuations of the series will increase.

VII. Conclusions

From this study, it has been proved that Augmented GARCH models perform more efficiently than basic GARCH models in estimating the stock volatility. Among them, the leverage effects were reported significant in the analysis of the asymmetric influence of positive and negative shocks on the volatility. The externality factors highly contribute to the predictive ability of volatility models particularly when engaged macroeconomic factors or industry news. Non-linear magnitude variations can be explained almost correctly by using nonlinear GARCH models. It is therefore noted that the forecasts are quite good especially when augmented GARCH models are used when there is high volatility or during market fluctuations.

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