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Comparative Modelling of Price Volatility in Nigerian Crude Oil Markets Using Symmetric and Asymmetric GARCH Models

D MADHUSUDANA REDDY, PROFESSOR, madhuskd@gmail.com
V NIRANJAN REDDY, ASSISTANT PROFESSOR, anjanreddymsc@gmail.com
T C VENKATA SIVA, ASSISTANT PROFESSOR, tcsiva222@gmail.com
Department of Mathematics, Sri Venkateswara Institute of Technology,
N.H 44, Hampapuram, Rapthadu, Anantapuramu, Andhra Pradesh 515722

INTRODUCTION

Background to the study

Crude oil prices are typically linked to significant volatility and poor return in unstable economic times. Dritsaki [1] argues that higher stock price volatility during periods of unstable monetary policy will decrease market efficiency and most likely have an impact on the stability of macroeconomic connections. One of the biggest issues facing both major oil-producing nations and crude oil purchasers worldwide today is the risk of fluctuating returns on sales and pricing of the commodity. This danger manifested as a reaction to both positive and negative news resulting from natural disasters, insurgencies, political unrest, political agitations, etc. Following the occurrence of these unanticipated events, the price of crude oil fluctuated and became extremely volatile. The degree of volatility or price variation in the crude oil markets has garnered more attention recently. Time series, econometrics, and other financial literature have acknowledged it as one of the most important economic phenomena (Dritsaki, 1). Scholars such as Zheng et al. [2] have contended that the unstable price of crude oil diminishes welfare and competition by driving up consumer prices. Apergis and Rezitis [3] noted that the product's price volatility causes uncertainty for both producers and consumers. Typically, oligarchy sees this as a chance to seize the opportunity to further their own interests.

While the prices of commodities fluctuate generally, the price of crude oil and its constituents, such as petrol and kerosene, are particularly known for their constant volatility. Crude oil returns on sales and prices have fluctuated dramatically over the past few years. Because of anomalies in the market system, efforts to create regulatory measures or interventions to stop the volatility in crude oil prices have not been successful. Research in this field indicates that market returns on crude oil prices and sales are still very high. Furthermore, there is currently a dearth of empirical research on the volatility of crude oil prices in monetary assets in Nigeria. In order to identify the best solutions for the issues facing the crude oil markets, it therefore seems worthwhile to invest time and energy in modelling price volatility in Nigerian crude oil markets using symmetric and Asymmetric GARCH models.

METHODOLOGY

- **Sources of data and software used in the study**

The Central Bank of Nigeria's official website provided the sources and extractions of the data used in this study [4]. The data includes sales in Naira/Dollar per barrel as well as monthly prices for the export of crude oil. It was taken out somewhere between January 1988 and March 2019. There are 396 data points in all from these. Version 10 of the Econometric View (Eview) programme was the software utilised to estimate the model's parameter (10).

- **Data transformation**

The sources and data extractions used in this study were sourced from the official website of the Central Bank of Nigeria [4]. The information contains monthly pricing for the export of crude oil as well as sales in Naira/Dollar per barrel. Sometime between January 1988 and March 2019, it was removed. Together, these 396 data points make up the total. To estimate the model's parameter (10), the Econometric View (Eview) programme in version 10 was used.

The data used in this study was differenced (D) in order to remove the outlier and achieve stationarity of the data. Where t = 1, 2, 3... t-I and CRn represent the return on crude oil pieces; CPRt is crude oil export price at time t in Naira per Dollar; CPRt-1 represents crude oil price at lag t (t-1) or precious time at t minus one; log represents logarithms; and 100 is a constant value (Number).

- **Model specification**

Model specification, according to Black [6], is a simplified system that mimics some features of the real or genuine economy. It is a structure or set of predetermined perspectives on reality that allows the researcher to explain the essence or relationships among the variables or study conditions. Nonetheless, symmetric and asymmetric GARCH models are the two kinds of models that were employed in the study in accordance with its goals.

• DISCUSSION

The analysis's descriptive statistics in Table 1 show a positive mean value of 0.123, which suggests that the data series have positive mean-reverting. This indicates that the data will return to its beneficial position when subjected to constraint at a specific degree of volatility [14]. Furthermore, the standard deviation—also known as the risk measure related to the series under investigation—is 8.909. The outcome further demonstrated the negative skewness of the returns on the crude oil price series, with a value of (-0.092) suggesting a longer left tail and a leftward shift in the distribution's bulk. According to reports, the distribution's kurtosis is 5.535, which is higher than the kurtosis of a normal distribution. Its flatter tail and leptokurtic nature are further characteristics. This is a typical characteristic conduct that financial assets generally display. In addition, the Jarque-Bera test statistic indicates that the data is not normally distributed, providing a value of 119.210 with a corresponding probability value of 0.000. Consequently, in order for the data to meet this requirement, the alternative of non-normality should be accepted and the null hypothesis of normalcy would be rejected. This is one of the requirements that must be met, according to Abdulkaremet al. [15], before we may use a different kind of inferential statistic, such as the GARCH and Markov-Switching GARCH model. Deebom & Essi's [11] result is supported by the estimated descriptive statistics test result. Using the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model, the price volatility of the Nigerian crude oil market was modelled from 1987 to 2017. The study's outcome concurs with the modelling results on crude oil prices and sales between 1997 and 2019 by Moujieke and Essi.

2017 using the framework of GARCH. Minoo and Shahram's [16] research also supports the results of the current study, which compare regime-switching GARCH models to GARCH models in developing countries (a case study of Iran). Furthermore, a model known as the Autoregressive Moving Average (ARMA) is fitted to the data; the purpose of this estimation was to yield the residual for the testing of the ARCH effect and volatility clustering. The result displayed in the model (4.1) indicates that the ARCH component of the model was significant at the five percent significance level. However, the residual from the estimator, which is displayed in Fig. 2 as the plot of return on monthly crude oil prices (Dollar/Barrel), confirmed the existence of volatility clustering. Meanwhile, Table 2's result adds to the evidence supporting the existence of the ARCH effect. We observe that the chi-square (X2) distribution's probability value was less than (nR2), which is the product of the number of observations (n) and the coefficient of regression (R2). Thus, it was determined that the null hypothesis, which contends that there isn't an ARCH effect, should be rejected and the alternative hypothesis, which asserts that there is, should be accepted. The results reported here regarding the test for the ARCH effect were in agreement with the findings of Cruicui and Luis's [17] risk modelling in the crude oil market: a comparison of Markov-switching and GARCH models. Cruicui and Luis [17] found that the ARCH effect was present since the regression model's coefficient multiplied by the number of observations (nR2) was more significant than the probability value of the chi-square (X2) distribution. The results obtained here also align with Veysel and Caner's estimation [18] of the impact of volatility in oil prices on the stock returns of oil and gas businesses and emerging nations. Prior to Veysela and Caner [18] using GARH models to suit the study's model, heteroskedasticity was seen. This supported the assertion made by Abdulkarem and Abdulkarem [15] about when to estimate a financial data series using the GARCH model. Abdulkarem & Abdulkarem [15] state that before the GARCH model can be fitted to financial data series, the ARCH effect has to be present. This is so because one of the main ways the GARCH model eliminates ARCH throughout the estimation phase is by using the ARCH effect.The results of the analyses of the conventional GARCH model are presented in Table 3 together with the direct error distribution assumptions for each of the following: normal, student's t, generalised, and student's t with a fixed degree of freedom (V=3), in that order. According to Table 3, the co-efficient of the ARCH (1) model is significant in all GARCH (1,1) models at the five percent significance level, indicating that the previous returns of crude oil prices can be used to predict the current returns. The current return will be 16.7%, 17.9%, 17.9%, 17.7%, 19.8%, and 14.3% more than the return from the previous month, according to the positive coefficient of 0.167 in the normal (0.179) of (student's–t), (0.177) (generalised), (0.198) (students with fixed degree of freedom V = 3), and (0.143) (generalised with fixed degree of freedom) error distributions. Similar to this, all of the ARCH (1) models in the variance equation are significant at the 5% level of significance. This suggests that the innovations from the prior month can account for the volatility we are currently seeing. Additionally, the variance equation's positive coefficient of ARCH indicates that this month's volatility will be higher. But when analysing the volatility of these months, the GARCH (1,1) process estimation also takes historical period volatility into consideration. The volatility of the previous time was captured by these models. It simply indicates that the previous month's innovations of the ARCH term and the previous period volatility (GARCH) condition largely control the conditional volatility of these months. The following, in ascending order of magnitude, describes the degree of volatility persistence in each model with regard to the relevant error distribution assumptions: GARCH (1,1) in the generalised error distribution with fixed degree of freedom (V=3) GARCH (1,1) in student's –t with fixed degree of freedom (V=3) (0.716) was the highest volatility persistence, followed by GARCH (1,1) in normal error (0.604), GARCH (1,1) in generalised error (0.574), and GARCH (1,1) in student's s-terror distribution (0.543). All things considered, this indicates that in a generalised error distribution with a given degree of freedom (V=3), the estimator with the maximum volatility persistence was GARCH (1,1). But according to the analysis's result, the information about the price of crude oil from the previous month has an effect on this month's returns, which have 74.6%, 71.6%, 60.4%, 57.4%, and 54.3% volatility, respectively, from last month transfers to this month. When evaluating the five models based on their performance and fitness in relation to the fundamental two common selection criteria (AIC and SIC), the student's-t distribution's GARCH (1,1) model has the lowest Akaike and Schwartz information criterion. Consequently, in the student's -t distribution, the GARCH (1,111) model performs better than the other models. As seen in chapter four of this study, GARCH (1,1) in Mean (GARCH-M) distribution was also estimated, with findings displayed in Table 3. Deebom and Essi [11] state that this model measures perceived risk, and that perceived risk mostly accounts for a larger return on the total estimation average. Nevertheless, Table 3 as presented demonstrates that every ARCH (α) term in the mean

equations are significant at 5% level of significance which suggests that last month's returns on crude oil prices in the crude oil market are predicted by this month volatility. It was also implied that 1 per cent increase in this present volatility causes 16.28%, 17.24%, 17.24%, 18.56% and 14.607% respectively as shown in the result as an increase in these current month crude oil prices returns. Also, it was reported from the results of the analysis that all the co-efficient of the GARCH terms have positive signs, and they are all significant at 5% level of significance. This means that the risk premium parameters (0.639, 0.688, 0.666, 0.736 and 0.580) determine these months' conditional volatility. Also, confirmed the fact that in all the estimated models and the volatility of crude oil prices is capable of providing the much need information on the series returns. However, the degree of persistence and volatility of impact were estimated as follows: GARCH (1,1) - mean in generalized error distribution with a fixed degree of freedom (V=3) has the highest volatility persistence of (0.740) , follow by GARCH (1,1) -mean in student's –terror distribution with fixed degree of freedom (V=3) (0.718), next was GARCH (1,1)-mean in normal error distribution assumption (0.600), also, GARCH (1,1)- mean in generalized error with volatility persistence of (0.571) was the next and the last but the least model was GARCH (1,1)-mean in student's –t error distribution with persistence volatility of (0.539). This simply means that the percentage of their impactis74.0%, 71.8%, 60%, 57.1% and 53.90% respectively comparing the five models on the basis of fitness and performance with respect to the basic two common selection criterion (AI &SIC), GARCH (1,1)- Mean in student' s-t distribution has the least Akaike and Schwartz information criterion, therefore, GARCH (1,1) – mean model in student' s-t error distribution outperforms the other models.

Table 4 contains the results of the analysis of standard asymmetric GARCH (1,1) models as reported from the three classes of the asymmetric GARCH models estimated in the study. The first model on the table was the Exponential Generalized Autoregressive conditional Heteroskedasticity (EGARCH) models of order 1. According to Vina, Abdul and Bezon [19], this model accounts for asymmetric responses of conditional variance to all kinds of shocks, and this is determined by the magnitude as well as the sign of news (which could be positive or negative). In all the estimated models, ARCH in the mean equations shows that they all have positive co-efficient (0.191, 0.199, 0.195, 0.214 and 0.195) and they are all significant at the 5 per cent levels of significance. This means that there is no leverage effect as it was suggested in Vina et al. [19]. In Vina et al. [19], it was suggested that when ARCH co-efficient in a GARCH model has a positive sign, and it is significant, it means that the positive leverage effect is not effective and it does not have any significant effect on the system. Similarly, all the asymmetric co-efficient have negative signs, but they are significant at the 10 and 5 per cent level of significance, respectively. Also, it was confirmed from the results of the analysis as it was reported in this study that all the asymmetric co-efficient (-0.007, -0.096, -0.776 and - 0.125) were less than zero and this simply means that negative shocks increases as estimated the increased volatility is more than positive shocks of the same magnitude. The degree of volatility persistence in all the models estimated with their corresponding error distribution assumptions are in the following ascending order of magnitude, and they include; EGARCH (1,1) in normal error distribution (108.9%) as the highest followed by EGARCH (1,1) in student's–t distribution (1.118%), next was EGARCH(1,1) in generalized error distribution (110.3%), EGARCH (1,1) in student' s-t with fixed degree of freedom (116.0% and EGARCH (1,1) in generalized error distribution with fixed degree of freedom (V=3) (106.4%).This means that the model with the highest volatility persistence was EGARCH (1,1) in normal error distribution. However, from the results reported from the analysis, it then means that the persistence of past volatility explained the current volatility of persistence. Comparing the five models estimated on the basis of their fitness and performance efficiency EGARCH

(1,1) in student's –t was considered the best since it has the least Akaike and Schwartz information criterion. From the results obtained using EGARCH (1,1) models with their corresponding error distribution, it was found that the larger the size of the estimated news components, the negative news revealed were highly associated with greater volatility. Conditional volatility also was discovered to have asymmetric characteristic behaviour which was prone to good news sensitivity. This finding corroborates Vina et al. [19] assertion in estimating financial forecasting power of ARCH family model: a case of Mexico. The results obtained here agree with Charan et al. [20] studied in Modelling Stock Indexes Volatility: Empirical Evidence from Pakistan Stock Exchange. In Charan et al. [20] studied it was found that EGARCH or GARCH models are the best fit for all the series as decision making criterion Akaike information criterion (AIC) and Schwarz criterion (SC) are least in these models.

In a subsequent step, the study also included the estimation of threshold generalised autoregressive condition heteroskedasticity (TGARCH) models. Vina et al. [19] state that by using a dummy variable, the TGARCH (1, 1) models take into consideration the effects of positive or negative news on the conditional volatility. The obtained results indicate that all of the estimated models' ARCH coefficients (i.e., 0.175, 0.196, 0.188, 0.219, and 0.147) indicate the presence of negative news (because Yi < 0). Additionally, all of the asymmetric co-efficients (i.e., 0.124, 0.162, 0.133, 0.287, and 0.104) are less than zero. Furthermore, not all of them are significant at the 5% level of significance, indicating the absence of the leverage effect. It also implies that the existence of volatility is not increased by bad news. Similarly, the GARCH co-efficient exhibits significance at the 5% level of significance, indicating that the variance from the previous month does not influence the conditional volatility of the current months. The following ratings could be used to describe how quickly volatility responds to market shocks: 65.65%, 71.89%, 68.76%, 77.32%, and 58.75%, in that order. The study also included the estimation of Power Autoregressive Conditional Heteroskedasticity (PARCH) models, which assess leverage and asymmetric effects as well, according to Omorogbe and Ucheoma [13]. The analysis's findings demonstrate that, at the 5% significance level, every coefficient of the GARCH, asymmetric, and ARCH terms was significant. This indicates that there is a significant degree of volatility persistence and a high rate of reactivity of the conditional variance in the crude oil market. According to the analysis's findings, the degree of persistence was 95.6%, 115.8%, 109.67%, 139.38%, and 59.83%, in that order. This indicates that in the Students'-terror distribution with fixed degree of freedom (v=3), the model with the maximum volatility persistence was PARCH (1,1). The analysis's reported results, however, indicate that the persistence of previous volatility explains the persistence of current volatility. contrasting the five models based on evaluations of their performance effectiveness and fitness Given that it had the lowest values for the Akaike and Schwartz information criteria (6.957 and 7.031, respectively), PARCH (1,1) in the student's t was deemed to be the best. The findings of Alhassan and Abdulhakeem [15] are supported by the results obtained here. According to Alhassan and Abdulhakeem's [15] analysis of Nigeria's oil price and macroeconomic volatility, persistence volatility exists in PARCH (1, 1) among students. The current study, however, found that persistence volatility occurs in PARCH (1, 1) in the students'-terror distribution with a fixed degree of freedom (v=3), whereas the formal found in PARCH (1, 1) in the students'-terror distribution did not have a fixed degree of freedom at v=3. These are the only minor differences between the two studies. According to Omorogbe and Ucheoma [13], the Component GARCH (CGARCH) Model, which was also calculated in the study, takes volatility into account over the long term as time varies. The analysis's findings demonstrate that, at the 5% significance level, every coefficient of the GARCH, asymmetric, and ARCH terms was significant. This indicates that the words for short- and long-term persistence, ARCH and GARCH, are significant. According to the analysis's findings, the degree of persistence was 158.18%, 156.67%, 161.54%, 179.94%, and 145.31%, in that order. When comparing the five models based on fitness and performance with respect to the fundamental two common selection criteria (AIC and SIC), CGARCH (1,1) in normal error performance performed best. This indicates that the model with the highest volatility persistence was CGARCH (1,1) in students'-terror distribution with fixed degree of freedom (v=3) (179.94%). The outcomes of this research were in line with those of Omorogbe and Ucheoma's (2017) investigation into the volatility of bank equity in Nigeria's stock market using asymmetric GARCH models.It was discovered in Omorogbe and Ucheoma's (2017) study that CGARCH (1, 1) performed better in the students' terror distribution than other methods. The current investigation confirmed that persistence volatility occurred in CGARCH (1, 1) in the student terror distribution with a fixed degree of freedom (v=3), whereas the formal discovered in CGARCH (1, 1) in the student terror distribution. This is one of the few differences between the two studies. While this study focused on the crude oil market, Omorogbe and Ucheoma's formal research [13] examined the volatility of bank equity in Nigeria's stock market. Based on AIC, SIC, and HQ, the results in Table 6 include model selection criteria for both symmetric and asymmetric GARCH models. The model with the lowest Schwarz criterion (SIC) was the only one allowed to make it into the final conclusion. Schwarz criteria (SIC) penalised models for loss of degree of freedom, which is why this was done. Thus, based on the data, it was determined that the EGARCH in student's t error distribution assumption was the overall best fit model for decision making using the Schwarz criteria (SIC). The findings of this study about the model with the lowest Schwarz criteria (SIC) are consistent with the findings of the following studies: Modelling Sectoral Stock Indexes Volatility: Empirical Evidence from Pakistan Stock Exchange was the subject of research by Charan, et al. [20]. The study conducted by Charan et al. [20] shown that EGARCH or GARCH models provide the greatest fit for all the series. This is because these models have the lowest values of the decision-making criteria, Akaike information criterion (AIC) and Schwarz criterion (SC). Furthermore, the study's results support those of Deebom and Essi [11] in

• Conclusion

In order to determine whether there are different effects of good and negative news on the volatility in the dynamics of the price of crude oil in the future, the study utilised the EGARCH, GJR-GARCH, PARCH, and CGARCH models based on the results of the asymmetric behaviour of the data. Nonetheless, because the EGARCH model was thought to be the most appropriate and best fit, it received a lot of attention. Consequently, the anticipated result for the presence of an asymmetric effect in the data was associated with the estimated gamma (γ) co-efficient of the model being negatively significant. Given that the study's results were positively significant, this indicates that the existence of a leverage effect in the dynamics of crude oil prices is not supported. As a result, it was thought that the dynamics of crude oil prices would fluctuate. Because shocks have the same size regardless of whether they are positive or negative, they will affect future volatility in the same way. In order to determine whether there are different effects of good and bad news on the future volatility of the Amman Stock Exchange (ASE), the study applied the EGARCH (1, 1) model. The results of this particular analysis are consistent with a small number of studies in terms of detecting the asymmetric effect in the data. Consequently, the anticipated result for the presence of an asymmetric effect in the data is associated with a negative significant gamma (γ). Given that our study's results are positively significant, this suggests that the existence of a leverage effect in the Amman Stock Exchange is not supported. The stock return is therefore regarded as volatile. Therefore, the shocks will affect the future volatility in the same way if they are positive (good news) or negative (bad news) of the same size.

Recommendations

Given the degree of risk involved in trading commodities such as crude oil in overseas markets together with the accompanying price-return series, the government, financial analysts, and investors should take note of the following advice:

Given the degree of risk involved in returns and other investments, financial analysts, investors, and researchers conducting empirical studies should take into account GARCH model variants with alternative error distributions, such as fixed degree of freedom with parameter (v=3) for robustness of results.

•Also, based on the guidance of an empirical result of a GARCH model with the lowest AIC and SIC, as in the case of the EGARCH model in this study, investors, marketers, and the government who choose to invest in crude oil and its constituents as a profitable business choice should do so. This is because, according to the EGARCH model, investing in a sector with low leverage effect will depend on the value of the shares issued by an oil producing company to entice investors to invest in the crude oil industry in order to reap greater rewards with fewer risks.The report also suggests that the nation's top financial institution, such as the Central Bank of Nigeria, make sufficient efforts to regulate currency operations in order to improve market performance efficiency and lower volatility, which will increase investors' trust in overseas trading activities.

REFERENCES

Dritsaki G. An empirical assessment in GARCH volatility modelling: proof from the Stokehold Stock Exchange. Mathematical Finance Journal; 2017.

Thompson H., Innucan HW, Zheng Y. News and food price volatility. 2011;52008(3):226–236; International Journal of Applied Economics and Finance.

Pergis N, Rezitis A. GARCH and GARCH-X Estimates Provide Evidence of Food Price Volatility and Macroeconomic Factors. 2011;43(1):95–110; Journal of Agricultural and Applied Economics.

Nigeria's Central Bank; 2017. Date of retrieval: March 16, 2017
You can access the data online at
•TSAY RS. Financial Time Series Analysis; 2005.

– Black J. Oxford Dictionary of Economics, 2nd Edition, New York, Oxford University Press Inc., Publisher; 2002.

• Jing Wang, Zhang Yue-Jun. utilising the Markov regime switching model to investigate the WTI crude oil price bubble process. Statistical mechanics and its applications in Physica A. 2015; 421: 377–387.

• Klaassen F. Regime-switching GARCH improves GARCH volatility estimates. Empirical Economics. 2002;27:363–94.

A fresh method for markov-switching GARCH models by Has Markus, Stefan Mittnik, and Marc Paolella S. 2004;2:493-530; Journal of Financial Econometrics.

(14) Brooks C. (2006), "Introductory Econometrics for Finance," Cambridge University Press, Second Edition.

• Deebom ZD, Essi ID. GARCH Model-Based Price Volatility Modelling of Nigerian Crude Oil Markets: 1987–2017. 2017;4(3):23; International Journal of Applied Science & Mathematical Theory.

Nelson Database. A novel method to conditional heteroskedasticity in asset returns. Econometrica 59:347–37 (1991).

• Omorogbe AJ, Ucheoma EC. Asymmetric GARCH model application on bank equity volatility in Nigerian stock market volatility. CBN Journal of Applied Statistics, 2013;08:73-99.

What a decent volatility model? Engel RF, Patton JA. Quantitative finance. 2001;(1):237–245.

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Analysing Oil Price: Macroeconomic Volatility in Nigeria, Abdulkareem A, Abdulhakeem KA. 2016;2:234–240; Central Bank of Nigeria Journal of Applied Statistics.

"Regime Switching GARCH Models and GARCH Models in the Stock Market of the Developing Countries," Minoo N, Shahram F, 2012.
Accessible at

– Cuicui L, Luis WL. OGARCH and Markov Switching Model-based portfolio optimisation in hedge funds. Omega, Elsevier, 2015;57:34–39.

– Veysel U, Caner Ö. The Effect of Volatility in Oil Prices on Returns on Stocks of Oil and Gas Companies and Emerging Economies; 2018.

Financial Forecasting using Autoregressive Conditional Heteroscedasticity (ARCH) Family: A Case of Mexico, Vina JK, Abdul Q, Bezon K. 2018;2(3):32–39; Journal of Public Policy and Administration.

Modelling Sectoral Stock Index Volatility: Empirical Evidence from Pakistan Stock Exchange, Charan RC, Farhan A, Vinesh KP. 2018;8(2):319-324; International Journal of Economics and Financial Issues.

– Moujieke, Essi's. Using the GARCH Model to Model Returns on Crude Oil Prices and Sales from 1997 to 2017 and 2019.

The fourth edition of Gujarati DN's Basic Econometrics. McGraw-Hill Publishing Company Limited, New Delhi, 2005.

– Atoi M. Using a generalised autoregressive conditional heteroskedastic model to test volatility in Nigerian stock marketing. Journal of Applied Statistics, Central Bank of Nigeria; 2014;3(5):2-65.