APPLICATION OF QGARCH MODELS TO NIGERIA INSURANCE STOCKS

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ABSTRACT

This study used QGARCH model to analyze insurance stock in Nigeria. The data used in the study are daily insurance stocks obtained from Nigeria Stock Exchange for a period of 1961 – 2019. The analysis done in this study were conducted in R-environment using Rugarch package by Ghalanos and E-view. Four competing QGARCH models such as QGARCH (1,1), QGARCH (1,2), QGARCH (2,1) and QGARCH (2,2) with student t's distribution were considered. However, the model made used of necessary parameters, half-life and persistence to undertake the study. Model selection was based on Akaike information – criterion (AIC). Although all the models were fit because their respective values of persistence do not exceed one. In terms of performance for the distributions QGARCH (1,1) supersedes the rest models with all the parameters significant. It becomes pertinent that in modeling financial time series of insurance stocks QGARCH Models should be adopted to be able to obtain an optimum result.

Keywords: QGARCH, Akaike Information Criterion, Insurance Stocks, persistence, half-life.

INTRODUCTION

Insurance is a scheme used to guide against the effects of misfortune through provision of financial compensation from the pool of accumulated contributions or premium by all persons participating in the scheme. In developed economy, insurance does contributes a lot to the well-being of the citizens and the economy at large. Here in Nigeria, an emerging economy in Africa, there is crisis of confidence towards the industry. Nigerians developed strong apathy towards insurance and this made the industry not to be reckon with in Nigeria. The distrust was deeply bred so much that the performance of insurance stocks on the Nigerian Stock Exchange (NSE) has been negatively affected. Many of the stocks could not go beyond the minimum price per share of 50 kobo in the market and very few investors do trade on them. This scenario has refused to change with time. As a result it is generally believed that insurance inclusion is very low in Nigeria. Due to the negative attitude of people toward insurance, the ability of the Nigeria insurance industries to contribute significantly to the economic growth of the country has been in doubt.

An increase or decrease in the value of stock tends to have a corresponding effect on the economy, mostly through the money market. An increase in stock prices stimulates investment and increases the demand for credit, which eventually leads to higher interest rates in the overall economy (Spiro, 1990). High interest rate is a potential danger to the economy since the variance of inflation positively responds to the volatility of interest rate. Such development could impose challenges to monetary policy formulation and consequently undermine the price stability objective of monetary authorities. Thus, the specification of appropriate volatility model for capturing variations in stock returns is of significant policy relevance to economic managers. More so, reliable volatility model of asset returns aids investors in their risk management decisions and portfolio adjustments.

The first model that assumed that the volatility is not constant is ARCH (autoregressive conditional heteroscedasticity model) by Engle in 1982, for which he was awarded the Nobel prize in Economic Sciences in 2003. Engel's basic model has been transformed and developed too more sophisticated models, such as GARCH, IGARCH, TGARCH, EGARCH and GARCH-M (Grek, 2014). It is expected that these models should make the forecast accuracy of the original ARCH model better, but in most cases this has failed to be the case.

GARCH Model

Generalized autoregressive conditional heteroscedasticity (GARCH), which is an extension of ARCH model with autoregressive moving average (ARMA) formulation, was however proposed by Bollerslev (1986) and Tylor (1986) in order to model in a parsimonious way, and to solve some discovered disadvantages of ARCH model, such as the definition and modelling of the persistence of shocks and the problem of modelling asymmetries, (Rossi, 2004; Ragnarsson, 2011, and Kelkay& G/Yohannes, 2014). GARCH(p, q) adds p lags of past conditional variance into the equation. A GARCH(0, 1) will simply be the first-order ARCH model. But GARCH(1, 1) is the most popular model in the empirical literature, (Rossi, 2004).

However, in spite of the usefulness of GARCH model in capturing symmetric effect of volatility, it is not without some limitations, such as the violation of non- negativity constraints imposed on the parameters to be estimated.

Quadratic GARCH Model

The sophisticated analysis used by the financial industry has lent increasing importance to time series modelling. Recently, there has been growing interest in the use of non-linear time series models in finance and economics. Many financial series, such as returns on stocks and foreign exchange rates, exhibit leptokurtosis and volatility varying in time, These two features have been the subject of extensive studies ever since Nicholls and Quinn (1982), Engle (1982) reported them.

Recently, the literature emphasized the importance of moments higher than the second in several applicative contexts, as for instance portfolio choice, asset pricing and option valuation models. In fact, the third and fourth moments are connected with skewness and kurtosis which can be thought of as further risk measures. Kurtosis measured by the moment ratio $K = \frac{\mu_4}{\mu_2^2}$, gives an estimate of the peakedness of unimodal curves. Leptokurtic curves have $K > 3$. Kurtosis of GARCH model plays an important role in option pricing applications with real data. Random coefficient autoregressive (RCA) models, Nicholls and Quinn (1982), the autoregressive conditional heteroscedastic (ARCH) models, Engle (1982) and its generalization, the GARCH model, Bollerslev (1986) provide a convenient framework to study time-varying volatility in financial markets. Financial time series models for intra-day trading are typical examples of random coefficient models with GARCH errors. Appadoo et al. (2006) derive the kurtosis of the correlated RCA model as well as the normal GARCH model under the assumption that the errors are correlated. In particular, the Quadratic GARCH (QGARCH) models are used to model asymmetric effects of positive and negative shocks. The QGARCH models are used to describe the negative skewness in stock market indices. In fact, the distribution of returns can be skewed. Naturally then the symmetric GARCH models cannot cope with skewness and hence the forecasts and forecast error variances from a GARCH model may be biased for skewed time series. In fact, it is found that the QGARCH model is the best when the sample does not contain extreme observations such as the stock market crash for an alternative model that can generate skewed time series patterns.

This paper is focused on the study of Quadratic GARCH Models of insurance stocks in Nigeria which is a segment of financial time series.

MATERIALS AND METHODS

Research Design

Relevant data that was employed for this research work is daily insurance stock for relative good number of years (1961 – 2019).

Method of Data Analysis

The techniques for data analysis in this study consists of prices of daily insurance stocks and using quadratic models in the presence of different levels of autocorrelation, different levels of outliers and at different structural break. Several models of financial time series have been developed in modelling financial time series data. Notable among these models are the quadratic, exponential Bayesian, to mention but a few. This research work is the analysis of insurance stocks of Nigeria using quadratic GARCH models.

Quadratic GARCH Models

Many financial series, such as return on stocks and foreign exchange rates, exhibit leptokurtosis and volatility varying in time.

The Quadratic GARCH models are used to describe the negative skewness in stock market indices. In fact, the distribution of return can be skewed. Naturally the symmetric GARCH models cannot cope with skewness which may result to the forecast and forecast error variances thereby making the GARCH model to be biased for skewed time series. Therefore, the Quadratic GARCH models is the best, when the sample does not contain extreme observations such as the stock market crash.

The Q GARCH model differs from the classical GARCH model by

$$Y = \sqrt{h_t z_t}$$

$$H_t = \delta_0 + \delta_1 h_{t-1} + \delta_2 (y_{t-1} + \delta_3$$

$$= (\delta_0 + \delta_2 \delta_3^2) + \delta_1 h_{t-1} + 2\delta 2_2 \delta_3 y_{t-1} + \delta_2 y^2{}_{t-1} \quad (1)$$

This model reduces to the GARCH (1,1) model when the shift parameters $\delta_3 = 0$. The Q GARCH model can improve upon the standard GARCH since they can cope with positive (or negative) skewness.

Half-Life Volatility

Half-life volatility measures the mean time of a stock price or returns. The mathematical expression of half-life volatility is given as:

$$\text{Half} - \text{Life} = \frac{In(0.5)}{In(\alpha_1 + \beta_1)} \quad (2)$$

It can be noted that the value of $\alpha_1 + \beta_1$ influences the mean reverting speed (Ahmed et al., 2018), which means that if the value of $\alpha_1 + \beta_1$ is closer to one (1), then the volatility shocks of the half-life will be longer.

Distributions of Quadratic GARCH Model

This investigation employed normal and student t innovations in assessing model performance for insurance stocks in Nigeria. The study employed student's t innovations for the assessment of model performance. The student's t's distributions can account for excess kurtosis and non-normality in financial returns (Heracleous, 2003; Wilhelmsson, 2006; Kuhe, 2018).

The student t distribution is given as

$$f(y) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{v\pi\Gamma\left(\frac{v}{2}\right)}} \left(1 + \frac{y^2}{v}\right)^{-\frac{(v+1)}{2}}; -\infty < y < \infty, \quad (3)$$

While the normal (or Guassian) distribution is given as

$$f(y) = \frac{1}{\sqrt{2\pi}} exp - \frac{(y-\mu)^2}{2\sigma^2}; -\infty < y < \infty, (4)$$

Where,
μ and $\sigma$are the mean and the standard deviation of the distribution which must satisfy the conditions - $\infty < \mu < \infty$, and $\sigma > 0$.

RESULTS

Data Analysis using Rugarch Package

The analysis done in this study were carried out in R-environment using Rugarch package by Ghalanos and package by E-view. Figure 1 presents the daily prices of insurance stock in Nigeria. The data used comprises of daily prices of insurance stocks in Nigeria for the period (1961-2019). From the graph it is quite clear that there was a slight increase and decrease in the movement of stochastic linear trend of prices with outliers.
The graph exhibited a financial times series data showing instability of the respective prices of insurance stocks.

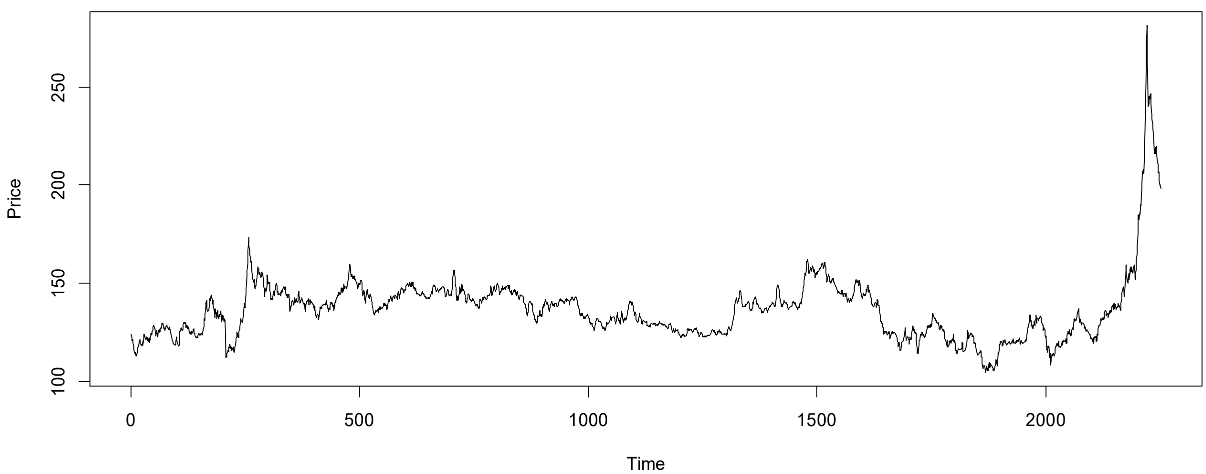

Figure 1: Time Series Plot of the daily prices of insurance stocks in Nigeria

Figure 2 presents the log transform of daily prices of insurance stocks in Nigeria. From the graph, it is evident that there was slight increase and decrease of the movement of time series data of the log transform of prices of daily insurance stocks with few outliers. The graph of the log transform equally exhibited instability of the series as exemplified in the graph.
Figure 3 presents the daily returns of insurance stocks in Nigeria for the period 1961 – 2019. After first differencing was conducted, the effects of possible outliers in the financial time series were removed to enable the series to become stable.
Table 1, showing the estimation of the unit root test indicates that both price and lnprice of stocks are not stationary at levels but stationary at first difference. On the other hand, ADF test for Returns shows that it is stationary at levels. This result agrees with the results of Adenomon and Ojo [2019].

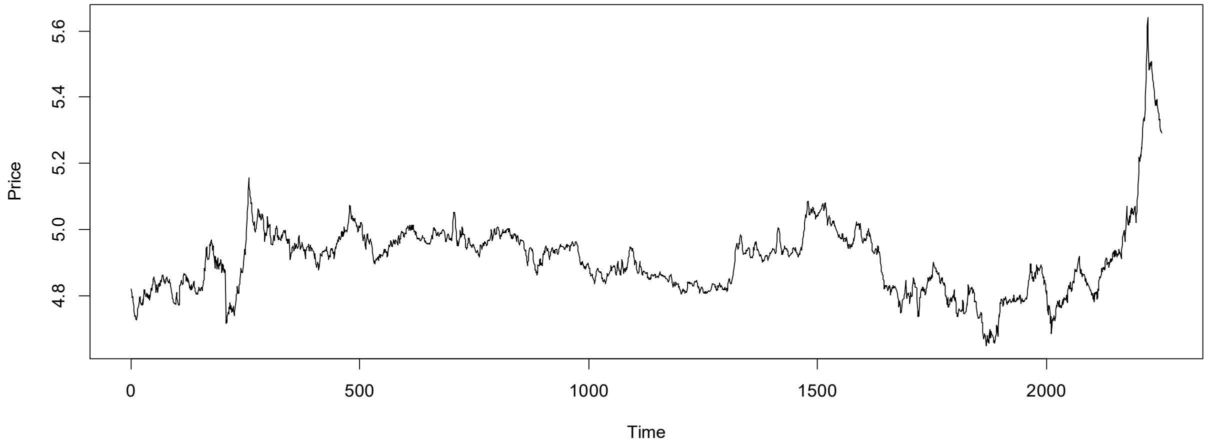

Figure 2: Time Series Plot of the Log transform of insurance stocks in Nigeria

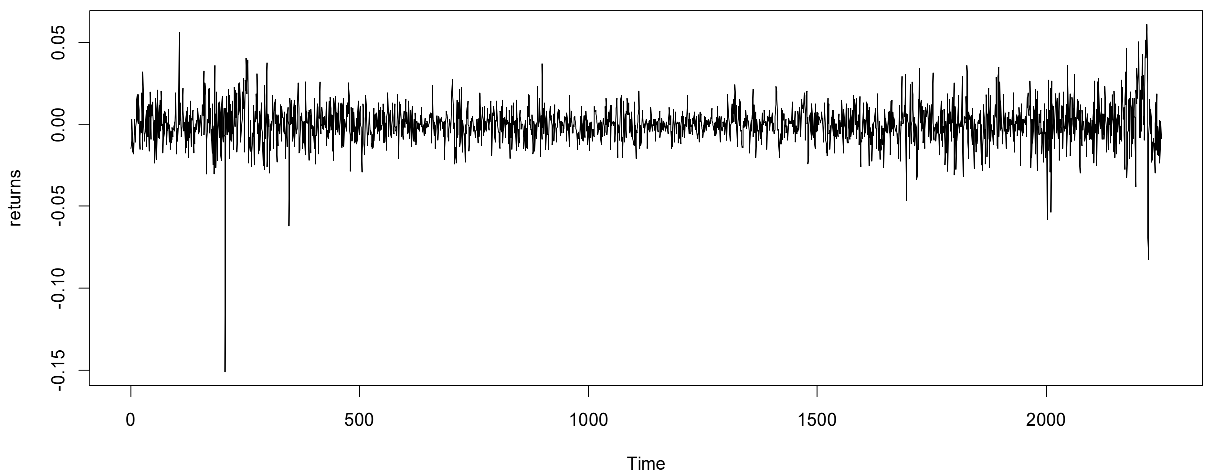

Figure 3: Time series plot of the daily returns of insurance stock in Nigeria

Table 1: Estimation of Price, lnprice and Returns with Respect to Student t Distribution

Variables	**Levels**		**First difference**		**Remark**
	t- statistic	**p-value**	**t- statistic**	**p-value**	
Price	-2.7869	0.0603	-13.7021	0.0000	I(1)
Inprice	-2.1464	0.2266	-29.8171	0.0000	I(1)
Returns	-29.8171	0.0000			I(0)

Source: Authors Computation, 2021.

Table 2 examined the characteristics of financial time series used in this research work. The price, lnprice and returns of insurance stocks exhibited the characteristics of a financial time series. The series exhibited a small standard deviation, skewness and kurtosis. In addition, the minimum value of Lnprice and returns is small compare to average value of price.

Table 2: Summary statistics of insurance stocks of Lnprice, Price and Returns

Statistics	Ln price	Price	Returns
Mean	4.909571	136.5127	0.000209
Median	4.914675	136.2750	0.000160
Maximum	5.640100	281.4900	0.061040
Minimum	4.649470	104.5300	-0.151080
Std. Dev.	0.113057	17.36503	0.012029
Skewness	1.683046	2.938870	-0.881363
Kurtosis	10.22755	18.74766	17.24093
Jarque-bera	5964.803	26511.36	19312.75
Probability	0.000000	0.000000	0.000000
Sum	11056.35	307426.6	0.471350
Sum sq. dev	28.77220	678776.0	0.325565
Number of observations	2252	2252	2251

Source: Authors Computation, 2021

Data Analysis

The analysis done in this study were carried out to obtain necessary results. Descriptive statistics of the daily insurance stocks of prices and returns in Nigeria were obtained. The respective tables below were used to carryout the analysis of the study. The distribution employed to carry out the modeling of Nigeria insurance stocks using competing QGARCH models was student T-distribution. Four Competing models of QGARCH were considered, the result in Table 3 indicates that with the use of information criterion of Akaike, QGARCH (2,2) has the smallest values; nevertheless based on the principle of parsimony, QGARCH (2,1) and QGARCH (2,2) are not fit because their respective persistence values exceed One (1).

Table 3: Analysis of QGARCH model under student t distribution

Models	Distribution	Information Criteria	Omega (ω)	Alpha(α)	Beta(β)	Gamma(γ)	Half life	Persistence
Qgarch (1,1)	Std	-6.3017	2.55E-06*	α_1= 0.1028*	β_1 =0.8838*	0.0004*	51.3800	0.9866
Qgarch (1,2)	Std	-6.3023	3.06E-06*	0.1313*	β_1 =0.5192* β_2 =0.3338	0.0005*	1.6119	0.6505
Qgarch (1,1)	Std	-6.3057	1.25E-06*	0.2063*	β_1 =0.9298	0.0003	-5.4321	1.1361
Qgarch (1,1)	Std	-6.3095	7.02E-08	α_1= 0.1823* α_2= -0.1751*	β_1 =1.5950* β_2 =-0.6025*	3.66E-05	-1.2053	1.7773

Source: Authors Computation, 2021

In addition, the values of half-life is negative which made the two models to be unfit. However, considering model QGARCH (1,1) and QGARCH (1,2) the respective values of persistence of the models are less than one, which made them to be fit.

Consequently, with the examination of QGARCH (1,1) and QGARCH (1,2); the QGARCH (1,1) is preferable because it has less parameters than QGARCH (1,2).

Result of Analysis of Life Data for Daily Prices of Insurance Stocks

The analysis started with the descriptive statistics of the daily insurance stocks of Nigeria. Figure 3.1, 3.2 and 3.3 presents the daily insurance stocks of Nigeria obtained from Nigeria Stock Exchange (NSE). The figure 3.1 and 3.2 shows the level of instabilities except in few cases. The figure 3.3 shows the descriptive statistics of returns indicating relatively stability but with few outliers.The prices and returns exhibited the characteristics of financial time series and variables that were not normally distributed.

CONCLUSION

This study has successfully modelled the Quadratic GARCH models suitable for use at different time series lengths, and at different autocorrelation coefficients and different sizes of outliers. However, it investigated the volatility of the Nigerian insurance stocks using the four competing selected QGARCH models. It also investigated the half life as well as persistence of the models. The analysis seek to obtain the best competing models that is more robust, to this effect, QGARCH (1,1) is the best model among the four selected models of QGARCH models. Based on the result giving in table 3.3, 3.4 it becomes pertinent that in modelling insurance stocks QGARCH (1,1) is superior in performance in comparison with the other models of QGARCH. three different QGARCH models were examined. The result of this study show that quadratic GARCH models were more robust models interms of insurance stocks.

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