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Application of EGARCH Models to Nigeria Insurance Stocks

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ABSTRACT

This study used EGARCH 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. Four competing EGARCH models such as EGARCH (1,1), EGARCH (1,2), EGARCH (2,1) and EGARCH (2,2) with student t's distribution and student skewed 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 EGARCH (1,1) supercede the rest models with all the parameters significant. It becomes pertinent that in modeling financial time series of insurance stocks EGARCH Models should be adopted to be able to obtain an optimum result.

Key words: EGARCH, Akaike Information Criterion Insurance Stocks, Persistence, Half life.

INTRODUCTION

As we rightly know, insurance is a scheme used to prevent 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 economies, 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 dislikeness towards insurance and this made the industry an industry that is not properly 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.

According to Hamadu and Mojekwu (2010), historically, insurance stocks business behavior in Nigeria can be traced to the actions of British merchants in 1874. These British merchants commenced their insurance business activities as agents for insurance companies in Britain, the major area of business being marine insurance. These agents operating in Nigeria packaged and organized insurance covers for imported and exported products. The modern insurance business was introduced into West Africa during the early 20th century by European traders to provide financial and economic protection for their business (Ngwuta, 2007).

GARCH Model

Generalized autoregressive conditional heteroskedasticity (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.

Exponential GARCH Model

The exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model was proposed by Nelson (1991) to overcome some weaknesses of the GARCH model in handling financial time series. In particular, t allow for asymmetric effects between positive and negative asset returns. The log of the conditional variance in EGARCH signifies that the leverage effect is exponential and not quadratic. And the transformation of volatility by its logarithm removes the restriction on the parameter to guarantee the positivity of the variance, (Tsay, 2005; Majose, 2010 and Atoi, 2014).

Christie (1982) and Nelson (1991) have showed evidence of asymmetric responses, indicating the leverage effect and differential financial risk relying on the direction of movements in price change. In responding to the weakness of symmetric assumption, Nelson (1991) introduced the exponential GARCH (EGARCH) models with a conditional variance formulation that adequately captured asymmetric response in the conditional variance. EGARCH models had been demonstrated to be superior compared to other competing asymmetric conditional variance in many studies (Alexander, 2009). Hojatallah and Ramanarayanan (2010) examined the volatility of Indian stock exchange and its stylized facts using ARCH models. Their results revealed that, GARCH (1, 1) model explains volatility of the Indian stock market and its stylized facts such as fat tails, mean reverting and volatility clustering. Hansen and Lunde (2005), compared volatility models using daily exchange rate data and IBM (International Business Machines) Stock prices. Their results showed that, there was no winner among the models studied and that non of the models gave significantly better prediction than the GARCH (1, 1). Neokosmidis (2009) asserted that financial data have some key features like leverage effects and volatility clustering which cannot be captured by models such as the ARMA model. He proposed the use of ARCH family of models to estimate financial time series. According to Giovanis (2008) the GARCH model was able to capture volatility clustering successfully making it an appropriate model for volatility forecasting. Bera and Higgins (1993), provided an informal details of some of the essential developments and their effect on applied work in the ARCH model since its origination by Engle in a seminar paper in 1982. They complement its usefulness in its ability to capture some stylised facts as well as its applicability to numerous and diverse areas such as in, asset pricing, interest rates, optimal dynamic hedging strategies, option pricing and risk modelling among others. They began with a short study on the rate of return on the U.S dollar/British pound exchange rate on weekly bases, changes in the three month growth rate and the Treasury bill rate of the New York Stock Exchange (NYSE) monthly composite index. This investigation is focused on the study of Exponential GARCH Models of insurance stocks in Nigeria which a segment of financial time series

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MATERIALS AND METHODS

Research Design

Relevant data that was employed for this research work is on 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 Exponential 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 this models are the quadratic, exponential Bayesian, to mention but a few. This research work is the modelling of insurance stocks of Nigeria using exponential GARCH models.

EGARCH model

The EGARCH model was proposed by Nelson (1991) to overcome some weaknesses of the GARCH model in handling financial time series pointed out by Enocksson and Skoog (2012), In particular, to allow for asymmetric effects between positive and negative asset returns, he considered the weighted innovation.

$$g(\varepsilon_t) = \theta\varepsilon_t + \gamma[|\varepsilon_t| - E(|\varepsilon_t|] \quad 1$$

Where,

θ and γ are real constants. Both ε_t and $|\varepsilon_t| - E(|\varepsilon_t|$are zero-mean iid sequences with continuous distributions. Therefore, E[$g(\varepsilon_t)$] = 0. The asymmetry of g(ε_t) can easily be seen by rewriting it as

$$g(\varepsilon_t) = \begin{cases} (\theta+\gamma)\varepsilon_t - \gamma E(|\varepsilon_t|) \text{ if } \varepsilon_t \geq 0, \\ (\theta-\gamma)\varepsilon_t - \gamma E(|\varepsilon_t|) \text{ if } \varepsilon_t < 0. \end{cases} \quad 2$$

An EGARCH(m, s) model, according to Tsay (2005), Dhamija and Bhalla (2010), Jiang (2012), Au (2013) and Grek (2014), can be written as

$$a_t = \sigma_t\varepsilon_t, \qquad \ln(\sigma_t^2) = \omega + \sum_{i=1}^{s}\alpha_i \frac{|a_{t-i}| + \theta_i a_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{m}\beta_j \ln(\sigma_{t-i}^2), \quad 3$$

Which specifically results in EGARCH (1,1) been written as

$\alpha_t = \sigma_t\varepsilon_t$

$$\ln(\sigma_t^2) = \omega + \alpha(\left[|a_{t-1}| - E(|a_{t-1}|)\right]) + \theta a_{t-1} + \beta\ln(\sigma_{t-1}^2) \quad 4$$

Where:

$|a_{t-1}| - E(|a_{t-1}|)$ are iid and have mean zero. When the EGARCH model has a Gaussian distribution of error term, then E($|\varepsilon_t|$) = $\sqrt{2/\pi}$, which gives:

$$\ln(\sigma_t^2) = \omega + \alpha(\left[|a_{t-1}| - \sqrt{2/\pi}\right]) + \theta a_{t-1} + \beta\ln(\sigma_{t-1}^2) \quad 5$$

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:

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$$\text{Half} - \text{Life} = \frac{In(0.5)}{In(\alpha_1+\beta_1)} \quad 6$$

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 exponential 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 and skewed student's t innovations for the assessment of model performance. The student't and the skewed student's t 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

$$f(y) = \frac{\Gamma(\frac{v+1}{2})}{\sqrt{v\pi}\Gamma(\frac{v}{2})}(1+\frac{y^2}{v})^{-\frac{(v+1)}{2}}; -\infty < y < \infty, \quad 7$$

The Skewed student t distribution is given as

$$f(y;\mu,\sigma,v,\lambda) = \begin{cases} bc\left(1+\frac{1}{v-2}\left(\frac{b(\frac{y-\mu}{\sigma})+a}{1-\lambda}\right)^2\right)^{-\frac{v+1}{2}}, if\ y < -\frac{a}{b} \\ bc\left(1+\frac{1}{v-2}\left(\frac{b(\frac{y-\mu}{\sigma})+a}{1+\lambda}\right)^2\right)^{-\frac{v+1}{2}}, if\ y \geq -\frac{a}{b} \end{cases} \quad 8$$

Where, v is the shape parameter with $2 < v < \infty$ and λ is the skewness parameter with $-1 < \lambda < 1$, μ and σ are the mean and the standard deviation respectively, of the skewed student t distribution, while the constants a, b and c are given as

$$a = 4\lambda c\left(\frac{v-2}{v-1}\right); b = 1+3(\lambda)^2 - a^2; c = \frac{\Gamma(\frac{v+1}{2})}{\sqrt{\pi(v-2)\Gamma(\frac{v}{2})}}. \quad 9$$

While the normal (or Guassian) distribution is given as

$$f(y) = \frac{1}{\sqrt{2\pi}}\exp-\frac{(y-\mu)^2}{2\sigma^2}; -\infty < y < \infty, \quad 10$$

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

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DATA PRESENTATION AND ANALYSIS

Data Presentation

The data for this study are presented in the figures below. 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.

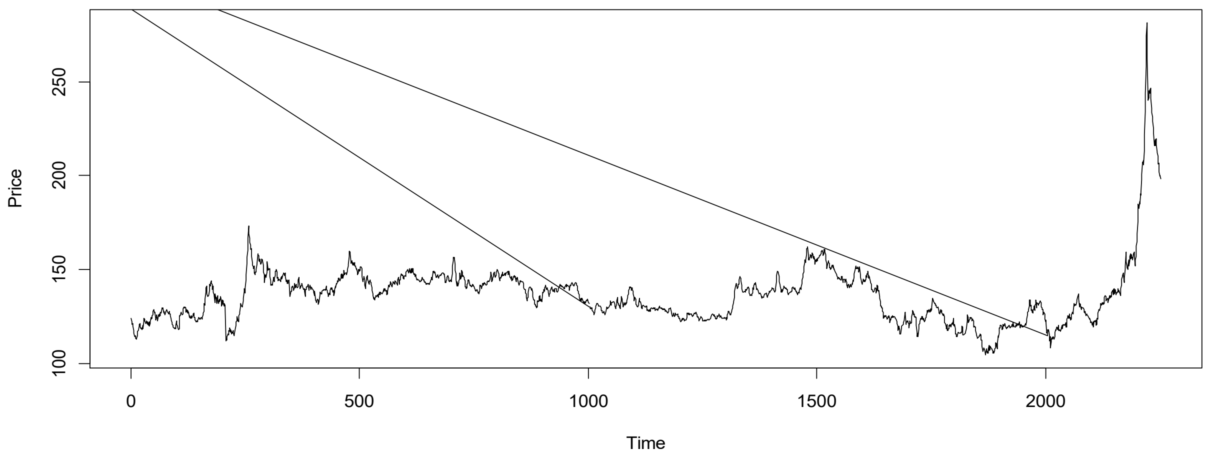

Figure 1: Time Series Plot of the daily prices of insurance stocks in Nigeria

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.

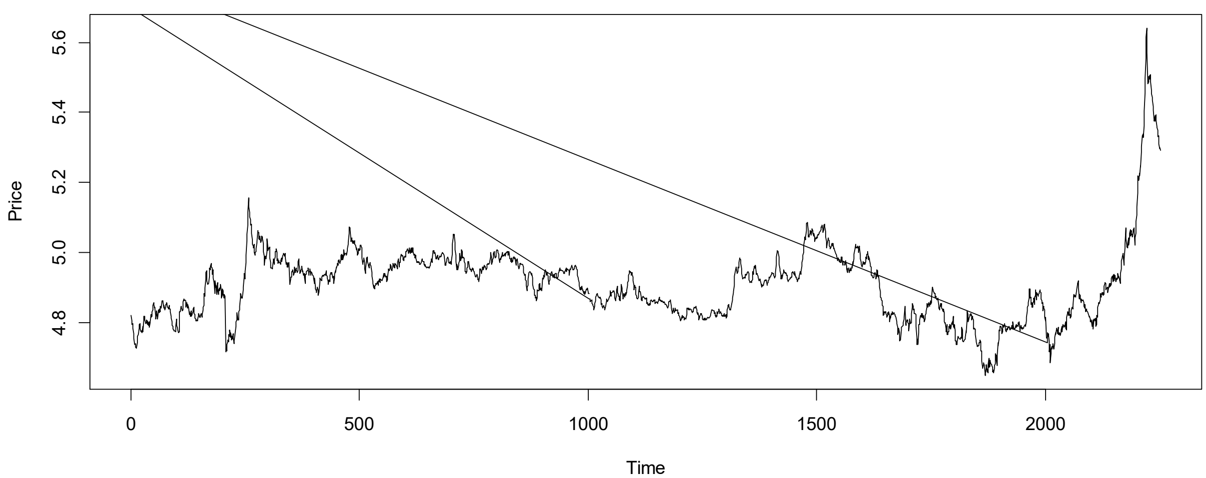

Figure 2: Time Series Plot of the Log transform of insurance stocks in Nigeria

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.

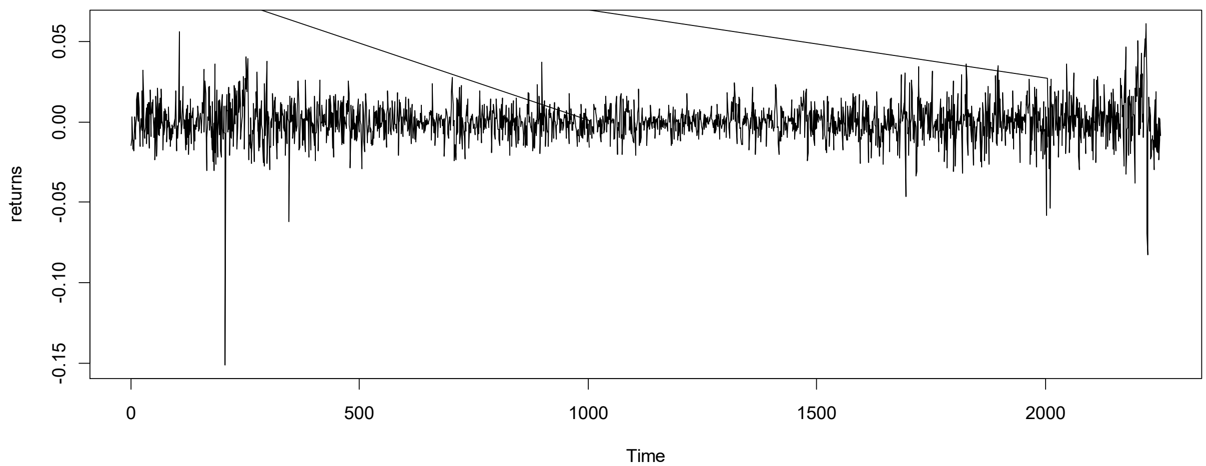

Figure 3: Time series plot of the daily returns of insurance stock in Nigeria

Table 1 is 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].

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.

The 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

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Data Analysis and Result

The analysis done in this study were carried in R-environment using Rugarch package by Ghalanosand package by E-view. 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 used to conduct the modeling of Nigeria Insurance stocks using competing E GARCH models was student skewed t's distribution (SStd).

Four competing models were examined, the result from Table 3 indicates that with the use of information criterion of Akaike, EGARCH (2,2) has the smallest information criterion, followed by EGARCH (1,2) and EGARCH (1,1).

However, viewing the models as regard the number of parameters examined under this competing models, EGARCH (1,1) had the least parameter which show that it is preferable to other models. In addition all the parameters of EGARCH (1,1) are all significant. All the models are fit because their persistence is less than one.

Table 3: Analysis of EGARCH model under student skewed t's distribution

Models	**Distribution**	**Information criteria**	**Omega (ω)**	**Alpha(α)**	**Beta(β)**	**Gamma (γ)**	**Half life**	**Persistence**
Egarch (1,1)	Sstd	-6.3089	-0.2503*	-0.0442*	0.9725*	0.2004*	24.8100	0.9724
Egarch (2,1)	Sstd	-6.3105	-0.1657*	α_1=0.0745* α_2=-0.0381	0.9818*	γ_1= 0.3131* γ_2 = -0.1529	37.6394	0.9818
Egarch (1,2)	Sstd	-6.3094	-0.2944	α_1=0.0556	β_1= 0.6573* β_2= 0.3103*	γ_1= 0.2496	21.0378	0.9676
Egarch (2,2)	Sstd	-6.3097	-0.1637*	α_1= 0.0749* α_2= -0.0392	β_1 = 1.0000* β_2= -0.0180*	γ_1= 0.3153* γ_2 = -0.1582*	38.0927	0.9820

Source: Authors Computation, 2021
* indicates significant

The distribution used to conduct the modeling of insurance stocks employing competing EGARCH Models was the student t's distribution. Four competing models were conducted, the result of analysis revealed from table 4 shows that with the use of information criterion of Akaike; EGARCH (2,1) has the smallest information criterion among the competing models.

Nevertheless, EGARCH (1,1) is preferable to other competing models simply because it considered less parameters than the other model. However, based on the principle of parsimony the respective models are fit because their values do not exceed one.

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Table 4: Analysis of E GARCH Model under the student t-distribution

Models	Distribution	Information Criteria	Omega (ω)	Alpha (α)	Beta (β)
Egarch (1,1)	Std	-6.3096	-0.2463*	0.0433*	0.9728*
Egarc(2,1)	Std	-6.3110	-0.1652*	α_1 = 0.07150 α_2= 0.0356	0.9818
Egarc(1,2)	Std	-6.3100	-0.2910	α = 0.0546	β_1= 0.6557* β_2= 0.3123*
Egarch(2,2)	Std	-6.3102	-0.1632	α_1=0.0719 α_2=-0.0366	β_1= 1.0000* β_2= -0.3123*

Source: Authors Computation, 2021.

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 1, 2 and 3 presents the daily insurance stocks of Nigeria obtained from Nigeria Stock Exchange (NSE). The figure 1 and 2 shows the level of instabilities except in few cases. The figure 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 were not normally distributed.

CONCLUSION

This study has successfully modelled the Exponential 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 three selected GARCH 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, EGARCH (1,1) is the best model among the four selected models of EGARCH models. Based on the result giving in table 3.3, 3.4 it becomes pertinent that in modelling insurance stocks egarch (1,1) is superior in performance in comparison with the other models of EGARCH. three different GARCH models were examined. The result of this study show that quadratic and exponential GARCH models were more robust than Bayesian GARCH models in terms of insurance stocks.

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