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Modeling Volatility of Nigeria Stock Market Returns using Garch models An Ranking Method

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Abstract: The paper titled Modeling Volatility of Nigeria Stock Market Returns Using GARCH Models and Ranking Method studies an alternative method for comparing the performance of several GARCH models in fitting the Nigeria Stock Market Monthly Return series with particular emphasis to the period of financial boom in Nigeria. With a view to determine the effect of the ranking of several GARCH models on the performance of stock market in Nigeria. The results obtained from a known method based on the ranks of the Log Likelihood (Log L), Schwarzs Bayesian Criterion (SBC) and the Akaike Information Criterion (AIC) values. It is found that the best and the worst fit models identified by the method are not the same for the two periods i.e for Training period were CGARCH (1,1) and EGARCH (1,1) while for Testing period were ARCH (1) and GARCH (2,1). The two extreme classes of models are identified to represent the best and the worst groups respectively. The overall effect of this will tend to increase the volatility of the market returns. The paper therefore recommend that the Nigeria government should as a matter of urgency taken appropriate positive measure through the security and exchange commission to regulate the market volatility so that the provided market index could be safely be used as predictive index for measuring the performance of the firms and as a guide for investment purpose.
Keywords: GARCH Model, Returns, Fitting, Ranking.

1 Introduction

Empirical studies involving stock market return, foreign exchange rates, inflation rates are extensive. In addition, they exhibit changes in variance over time in such circumstances, the assumption of constant variance (homoscedasticity) is inappropriate. The variability in the financial data could very well due to the volatility of the financial market. More importantly, the extended financial market globalization due to the markets is known to be sensitive to factors such as rumours, political upheavals and changes in the government monetary and fiscal policies. [1] Introduced the Autoregressive Conditional Heteroscedastic (ARCH) model process to cope with the changing variance. [2], extension, the Generalized Autoregressive Conditional Heteroscedastic (GARCH) model which has a more flexible lag structure because the error variance can be modeled by an Autoregressive Moving Average (ARMA) type process. Such a model can be effective in removing the excess kurtosis. There have been a great number of empirical applications of modeling the conditional variance (volatility) of financial time series by employing different specifications of these models and their many extensions. For example, [3], [4], [5], [6] provide an extended methodological framework that can be applied to various problems in finance. [7] Proposed a class of exponential GARCH (EGARCH) model which can capture the asymmetry and skewness of the stock market return time series. However, as [8] pointed out,“ it may not be reasonable to assume that the loading best or worst fit model is constant over time.” In this research, we suggest to find the best and worst fit of the GARCH model that allows for time-varying loadings. The models are the ARCH (1), ARCH (2), GARCH (1,1), GARCH (1,2), GARCH (2,1), EGARCH (1,1), PARCH (1,1), GRJGARCH (1,1), CGARCH (1,1) and GARCH-M (1,1) and GARCH (2,2). The research proposed finding has no effect on most of the desirable properties that characterize the GARCH model. These models were designed to explicitly model and predict the time-varying conditional second order moment (variance) of a series by using past unpredictable changes in the returns of that series, and have been applied successfully in economics and finance, but more predominantly in financial market research. For

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the case of Nigeria Stock Markets (NSM) there are some studies concerned with the issue of modeling stock market volatility but to the best of the knowledge, there are no such empirical studies for the Nigeria stock market (NSM). [9], and [10]. Choose the best models for fitting time series data by comparing the ranks of the values of three goodness-of-fit statistics namely the Log Likelihood (Log L), Schwarz's Bayesian Criterion (SBC) and the Akaike Information Criterion (AIC) respectively. We notice that such a method has one weakness. Therefore, in this study an alternative method capable of overcoming such a problem is sought and used to compare the performance of potential models for fitting the return series for both periods. Then we proposed use of an ordinal scale type of measurement, which is the rank, instead of the actual values in calculating the criteria would cause some loss of information. Finally, the results from the method is studied.

2 Literature Review

There has been a large amount of literature on modeling stock market return volatility in both developed and developing countries around the world. The volatility characteristics have been investigated using econometrics models. However, no single model is superior. [11] Demonstrates that the increases in variance of stock returns can explain much of the decline in stock prices. [12] Offers empirical evidence for a positive relation between a lagged volatility measure and future expected returns. For Asian stock markets return, [13] and [14] found that the conditional variance is an asymmetric function of past innovations. The idea of using factor models with GARCH goes back to [15] who use the capital asset pricing model to show how the volatilities and fitted model between individual equities can be generated from the univariate GARCH variance of the stock market return. This model has been generalized by [16] to the case where the fitted model is time-varying. To avoid the need for a univariate GARCH parameterization and to keep the model as simple as possible, this ′dynamic conditional fitted model′ uses a GARCH (1,1) model with the same parameters for all the elements of the fitted model. [17] Examined time-series features of stock returns and volatility in four of China's stock markets. They provided strong evidence of time-varying volatility and indicated volatility is highly persistent and predictable. By employing eleven competing time series models for fitting the rate of returns data to evaluate the performance of these models, [18] predict volatility of some stock markets returns. However, when asymmetric loss functions are applied ARCH-type models provide the best fitted model.

The univariate generalized autoregressive conditional heteroscedasticity (GARCH) models that were introduced by [1] and [2] have been very successful for short and medium term volatility forecasting in financial markets. An alternative univariate GARCH models, were used in different financial markets. Many of these are being successfully applied to generating convergent term structure volatility forecasts, and in stochastic volatility models for option pricing and hedging. Various time series methods are employed by [19], including the simple GARCH model, the GARCH-in-Mean model and the exponential GARCH to investigate the Risk-Return Trade-off on the Romanian stock market. Results of the study confirm that E-GARCH is the best fitting model for the Bucharest Stock Exchange composite index volatility in terms of sample-fit. The Autoregressive Conditional Heteroscedastic (ARCH) model proposed by Engle [1] its extension, the Generalized Autoregressive Conditional Heteroscedastic (GARCH) model which has a more flexible lag structure because the error variance can be modeled by an Autoregressive Moving Average (ARMA) type process developed independently by [2], have been the first models introduced into the literature and have become very popular. However, as [8] pointed out, it may not be reasonable to assume that the loading best or worst fit model is constant over time. They suggest to find the best and worst fit of the OGARCH model that allows for time-varying loadings.

[20] Used both symmetric and asymmetric ARCH-type models to derive volatility expectations. The outcome showed that there has a positive effect of expected volatility on weekly and monthly stock returns of both Philippines and Thailand markets according to ARCH model. The result is not clear if using the other models such as GARCH, GJR-GARCH and EGARCH. For emerging African markets, [21] investigate the market volatility using Nigeria and Kenya stock return series. Results of the exponential GARCH model indicate that asymmetric volatility found in the U.S. and other developed markets is also present in Nigerian stock market (NSM), but Kenya shows evidence of significant and positive asymmetric volatility. Also, they show that while the Nairobi Stock market return series indicate negative and insignificant risk-premium parameters, the NSM returns series exhibit a significant and positive time-varying premium. [22], attempts to fit the generalized Autoregressive conditional Heteroscedastic (GARCH) model for All Share Index (ASI) of Nigerian Stock Market (NSM) returns. The data used in this paper are the daily All Share Index (ASI) of Nigerian stock market from January 2007 to December 2011 covering 1231 data points including business days and excluding public holidays. A research is made on various GARCH variants specified on the assumptions of stationary and asymmetry.

[23] studied the impacts of Inflation dynamics and global financial crises on stock market returns and volatility in

Nigeria. The data sets on monthly All Shares Index Prices of NSE and consumers 'price index (CPI) cover the period of January, 1985 to December, 2010 were used. The GARCH (1,1) model with multivariate regresses were adopted and the result shows that in the conditional mean equation; inflation exerts insignificant positive impact on stock market returns and during the global financial crises, inflation exerts significant negative effect on stock market returns. [24], explore exchange rate volatility of Nigerian Naira against some major currencies in the world using multivariate GARCH models. Their study uses daily data over the period January, 1999 to February, 2014 consisting of 3950 observation. [25] Investigate the volatility of Naira/Dollar exchange rates in Nigeria using GARCH (1,1), GJR-GARCH (1,1), EGARCH (1,1), APARCH (1,1), IGARCH (1,1) and TS-GARCH (1,1) models. Using monthly data over the period January 1970 to December 2007, volatility persistence and asymmetric properties are investigated for the Nigerian foreign exchange. The results from all the models show that volatility is persistent and the results from all the asymmetry models rejected the hypothesis of leverage effect. TSGARCH and APARCH models are found to be the best models. [26],studied the application of asymmetric GARCH models of Nigeria stock market volatility in comparison with some countries. Their data sets using daily all share index of Nigeria, Kenya, United states, Germany, South Africa and China spanning from February i4,2000 to February 14, 2013. The results reveal that volatility of Nigeria and Kenya stock returns react to market shock faster than as other countries do. The results also suggest the absence of leverage effect in Nigeria and Kenya stock returns, but confirm its existence in others. [27], studied measuring volatility effects on daily stock market returns in Nigeria. The study adapted the ex-post facto research design and data were obtained from daily reports of the Nigerian stock exchange from 2nd January, 2001 to 31st December, 2015. The results also revealed that, there is a significant ARCH/GARCH (volatility) effect on stock market returns of the Nigerian stock market. [28], studied the finametric analysis of Nigeria stock market and volatility of returns. Data used was extracted from CBN statistical bulletin 2014. The test result revealed that stock returns is volatile in an efficient market due to announcement of relevant information and that the prices of security in the market is on the downward trend. Several researchers such as [9], [10] and [29] had shown that models with a small lag like GARCH (1,1) is sufficient to cope with the changing variance. Nevertheless, due to the high volatility of the rate of returns of the NSM, higher order lag models such as the GARCH (1,2), GARCH (2,1) and GARCH (2,2). In all, the study shall compare the performance of eleven competing time series models for fitting the rate of returns data. The models are the ARCH (1), ARCH (2), GARCH (1,1), GARCH (1,2), GARCH (2,1), EGARCH (1,1), PARCH (1,1), GRJGARCH (1,1), CGARCH (1,1) and GARCH-M (1,1) and GARCH (2,2).

3 Methodologies

Autoregressive conditional heteroscedasticity (ARCH) and its generalization (GARCH) models represent the main methodologies that have been applied in modeling stock market volatility in finance time series. These models can be effective in removing the excess kurtosis. In this research different univariate GARCH specifications are employed to model stock returns volatility in Nigeria Stock Market Returns these models to be used for testing symmetric volatility are GARCH (1,1), GARCH-M (1,1), and EGARCH(1,1), CGARCH(1,1) and GRJ-GARCH (1,1). However, due to the high volatility of the rate of returns of the NSM higher order lag models such as the GARCH (1,2), GARCH (2,1) and GARCH (2,2). In this research the performance of eleven competing time series models for fitting the rate of returns data will be compared. The models are the ARCH (1), ARCH (2), GARCH (1,1), GARCH (1,2), GARCH (2,1), EGARCH (1,1), PARCH (1,1), GRJ-GARCH (1,1), CGARCH (1,1) and GARCH-M (1,1) and GARCH (2,2).

3.1 Data Description

The data used in this research is the monthly rate of returns of the (Nigeria Stock Market) (NSM), registered from January 1996 to December 2015. In the fourth quarter of 2006, political crisis which hit the Asian region had badly hurt the performance of most of the Oil Market in the world including the NSM (Nigeria Stock Market). The data was divided in to two periods Training Period from January 1996 to December 2006 and Testing Period from January 2007 to December 2015.

3.2 Model

Before looking at GARCH models, we study some general principles about modeling non constant conditional variance. Consider regression modeling with a constant conditional variance, Var(Yt\X1,t,..., Xp,t) = σ2. Then the general form for the regression of Yt on X1.t,...,Xp,tis

$$Y_t = f(X_{1,t},...,X_{p,t}) + \varepsilon_t, \quad (1)$$

whereε_t is independent of $X_{1,t},...,X_{p,t}$and has expectation equal to 0 and a constant conditional variance σ_ε^2. The function f is the conditional expectation of Y_t given $X_{1,t},...,X_{p,t}$. Moreover, the conditional variance of Y_t is σ_ε^2.

Equation (1) can be modified to allow conditional heteroskedasticity.

Let $\sigma^2(X_{1,t},...,X_{p,t})$ be the conditional variance of Y_t given $X_{1,t},..., X_{p,t}$. Then the model

$$Y_t = f(X_{1,t},...,X_{p,t}) + \sigma(X_{1,t},...,X_{p,t})\, \varepsilon_t \quad , \tag{2}$$

whereε_t has conditional (given $X_{1,t},...,X_{p,t}$) mean equal to 0 and conditional variance equal to 1, gives the correct conditional mean and variance of Y_t.

The function $\sigma(X_{1,t},...,X_{p,t})$ should be nonnegative since it is a standard deviation. If the function σ(•) is linear, then its coefficients must be constrained to ensure nonnegativity. Such constraints are cumbersome to implement, so nonlinear nonnegative functions are usually used instead. Models for conditional variances are often called variance function models. The GARCH models of this research are an important class of variance function models.

The monthly rate of returns $r_i$of the NSM are calculated using the following formula:

$$r_t = \log\left(\frac{I_t}{I_{t-1}}\right), t = 1,2,\cdots,T \tag{3}$$

WhereI_t denotes the reading on the composite index at the close oft^{th} trading day. As noted earlier, the rate of monthly returns of the NSM displays a changing variance over time. There are many ways to describe the changes in variance and one of them is by considering the Autoregressive Conditional Heteroscedasticity (ARCH) model.

3.3 ARCH(p) Models

As before, let $\varepsilon_t$be Gaussian white noise with unit variance. Then a_t is an ARCH(q) process if

$$a_t = \sigma_t\varepsilon_t, \tag{4}$$

where

$$\sigma_t = \sqrt{\omega + \sum_{i=1}^{p} \alpha_i a_{t-i}^2} \tag{5}$$

is the conditional standard deviation of a_t given the past values $a_{t-1}, a_{t-2},...$ of this process. Like an ARCH(1) process, an ARCH(q) process is uncorrelated and has a constant mean (both conditional and unconditional) and a constant unconditional variance, but its conditional variance is non constant. In fact, the ACF of a^2_t is the same as the ACF of an AR(q) process. The ARCH regression model for the series a_t can be written as $\varphi_m(B)a_t = \mu + \varepsilon_t$ for the model with intercept and$\varphi_m(B)_t = a_t\varepsilon_t$, for the non-intercept model, with

$$\varphi_m(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_m B_m \tag{6}$$

where B is the backward shift operator defined by $B^k X_t = X_{t-k}$. The parameter μ reflects a constant term (intercept) which in practice is typically estimated to be close or equal to zero. The order m is usually 0 or small, indicating that there are usually no opportunities to forecast $a_t$from its own past. In other words, there is never an autoregressive process in a_t.

The conditional distribution of the series of disturbances which follows the ARCH process can be written as

$$\varepsilon \backslash \Phi\tau \sim N(0,h_t) \tag{7}$$

where Φ_τ denotes all available information at time $\tau < t$. The conditional variance h_t is

$$ht = \omega + \sum_{i=1}^{q} \alpha i \varepsilon_{t-1}^{2} \tag{8}$$

$\varepsilon_t = \sqrt{h_t} e_t$, $e_t \sim N(0,1)$.

3.4 GARCH(1,1) Processes

The GARCH(1,1) is the most widely used GARCH process, so it is worthwhile to study it in some detail. If a_t is GARCH(1,1), then as we have just seen, a^2_t is ARMA(1,1).

$$\rho_{a^2}(1) = \frac{\alpha_1(1-\alpha_1\beta_1-\beta_1^2)}{1-2\alpha_1\beta_1-\beta_1^2} \tag{9}$$

and

$$\rho_a 2(k) = (\alpha_1+\beta_1)^{k-1}\rho_a 2(1),\ k \geq 2. \tag{10}$$

By (8), there are infinitely many values of (α_1,β_1) with the same value of $\rho_a{}^2(1)$. By (9), a higher value of $\alpha_1 + \beta_1$ means a slower decay of $\rho_a{}^2$ after the first lag. This behavior which contains the ACF of a^2_t for three GARCH (1,1) processes with a lag-1 autocorrelation of 0.5. The solid curve has the highest value of $\alpha_1 + \beta_1$ and the ACF decays very slowly.

[2] introduced a Generalized ARCH (p,q) or GARCH(p,q) model where the conditional variance ht is given by

$$h_t = \omega + \sum_{i-1}^{q} \alpha i \varepsilon_{t-1}^2 + \sum_{j-1}^{p} \beta_j h_{t-1},\ p \geq q, q > 0 and \omega > 0, \alpha_i > 0, \beta_j \geq 0 \tag{11}$$

If the parameters are constrained such that

[4] proposed a class of exponential GARCH or EGARCH models. In this model ht is defined by

$$In(h_t) = \omega + \sum_{i-1}^{q} \alpha i g(e_{t-1}^2) + \sum_{j-1}^{p} \beta_j In(h_{t-1})$$

where

$$g(e_t) = \theta e_t + \gamma |e_t| - \gamma E|e_t|$$

The coefficient of the second term in $g(e_t)$ is set to be $1(\gamma = 1)$ in this formulation. Unlike the linear GARCH model there are no restrictions on the parameters to ensure non-negativity of the conditional variances. The conditional variance (h_t) follows equation (10) and we write the model as EGARCH(p,q).

In the GARCH-in-Mean or GARCH-M model, the GARCH effects appear in the mean of the process, given by $\varepsilon_t = \sqrt{h_t e_t}$ where $e_t \sim N(0,1)$ and $r_t = \mu + \delta\sqrt{h_t + \varepsilon_t}$ for the model with intercept and $r_t = \delta\sqrt{h_t + \varepsilon_t}$ for the non-intercept model. [30] Reported there is a significant test statistics for ARCH model especially for stock returns. The Component GARCH (CGARCH) Model. It allows mean reversion to a varying level μ_t

$$\sigma_t^2 - m_t = \varpi + \alpha(u_{t-1}^2 - \varpi) + \beta(\sigma_{t-1}^2 - \varpi) \tag{12}$$

$$m_t = \omega + \rho(m_{t-1} - \omega) + \phi(u_{t-1}^2 - \sigma_{t-1}^2) \quad (13)$$

σ_{t-1}^2 is still the volatility, while m_t takes the place of ω and is the time varying long-run volatility. The first equation describes the transitory component, $\sigma_t^2 - m_t$, which converges to zero with powers of $(\alpha + \beta)$. The second equation describes the long run component m_t, which converges to ω with powers of ρ. (Glosten, JagannathanandRunkleGARCH)TheGJR-GARCH, orjust GJR, model of Glosten, JagannathanandRunkle (1993) allows the conditional variancetorespond differentlytothepast negative and positiveinnovations. TheGJR(1,1)model maybe expressed as:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I(\varepsilon_{t-1} < 0) + \beta\sigma_{t-1}^2, \quad (14)$$

where*I*denotestheindicator function. Themodel is also sometimes referred to as aSign- GARCH model. TheGJRformulation is closelyrelated to theThreshold GARCH, orTGARCH, model proposed independentlybyZakoian(1994) (seeTGARCH), and theAsymmetric GARCH, orAGARCH, model ofEngle (1990) (seeAGARCH).

3.5 The Ranking Method

The parameters of the models considered in this study are estimated using the maximum likelihood method. The likelihood function for the ARCH and GARCH models can be written as follows:

$$L = -\frac{T}{2}\log(2\pi) - \frac{1}{2}\log\sum_{t=1}^{T}\log(h_t) - \frac{1}{2}\sum_{t=1}^{T}\frac{\varepsilon_t^2}{h_t} \quad (15)$$

Where

T = total number of monthly rate of returns $\varepsilon_t = r_t$

Andh_t is the conditional variance. However, when estimating GARCH-M(p,q) model, we take

$$\varepsilon_t = r_t - \delta\sqrt{h_t} \quad .(16)$$

The procedures for performing the ranking. In this method, the values of the three goodness-of-fit statistics, namely the Log Likelihood (Log L), Schwarzs Bayesian Criterion (SBC) and the Akaikes Information Criterion (AIC) are first calculated for each rival models. The values of AIC and SBC are computed as follows;

$$AIC = -2ln(L) + 2k \quad (17)$$

$$SBC = -2ln(L) + ln(T)k \quad (18)$$

where k is the number of free parameters and T is the number of residuals that can be computed for the time series. The ranks of the models based on the calculated values are then determined for each statistic. Finally, the ranks of the models are averaged across the statistics and the models with the smallest and the largest averages are taken to be the best and the worst fit models respectively.

4 Results and Discussion

Some descriptive statistics for the monthly return of the Nigeria Stock Market are presented in Table 1.

Table 1. Summary statistics of the rate of monthly returns of the Nigeria Stock Market.

PERIOD	N	MEAN	STANDARD DEVIATION	VARIANCE	SKEWNESS	KURTOSIS
TRAINING PERIOD	132	-0.063207	0.992520	0.985096	0.274531	3.462173
TESTING PERIOD	108	-0.024417	1.006990	1.014029	0.312870	3.485325

From the results presented in Table 1, the distribution of the rate of monthly returns in Training Period is positively skewed and leptokurtic. However, for Testing Period, the standard deviation of the data is large as that in Training Period. This result, indicates the rate of returns in Testing Period is more volatile than in Training Period.

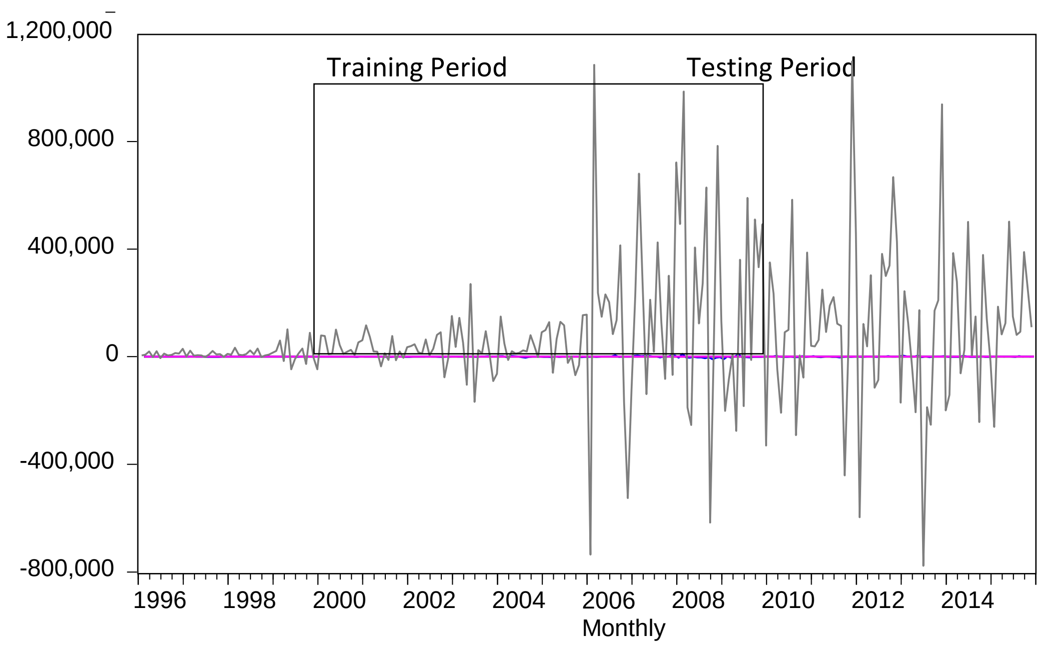

Figure 1. Monthly Rate of the Nigeria stock Market Returns from January 1996 to December 2015

The graph in figure1 shows how volatile the two periods are and it shows that from 2006 to 2012 there is a high variation in financial boom in Nigeria.

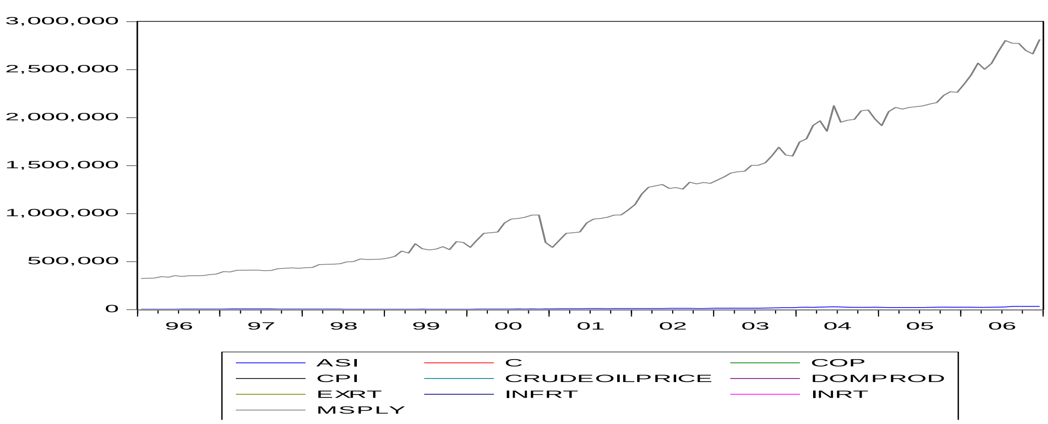

Figure 2. Graphical Representation of Training Period on Nigeria Stock Market Returns.

Figure 2 indicates that the series is not stationary as it contains a trend components which should be remove before modeling.

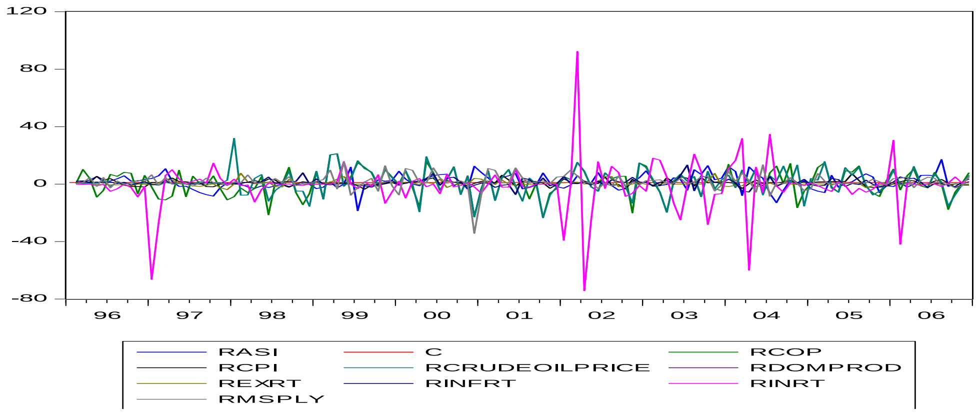

Figure 3. Graphical Representation of Returns Logarithms of Training Period on Nigeria Stock Market.

Table 2. The Criteria Value of the ARCH and GARCH Models of Training Period on Nigeria Stock Market Returns.

Model	LOGL	SBC	AIC
ARCH (1)	-386.6639	6.312633	6.071205
ARCH (2)	-386.1990	6.342750	6.079373
PARCH (1,1)	-384.5735	6.466795	6.115626
GARCH (1,1)	-386.2125	6.342958	6.079581
GARCH (1,2)	-382.5851	6.324792	6.039467
GARCH (2,1)	-380.4210	6.291753	6.006428
EGARCH (1,1)	-380.1429	6.287507	6.002182
GJR-GARCH (1,1)	-389.1248	6.424635	6.139310
CGARCH (1,1)	-389.5262	6.579624	6.206507
GARCH-M (1,1)	-382.2043	6.356194	6.048921
GARCH (2,2)	-382.1420	6.355243	6.047970

The result obtain in table 2 shows the results of the three criteria values which are Log Likelihood (Log L), SchwarzsBayesian Criterion (SBC) and the Akaike Information Criterion (AIC) values of the ARCH and GARCH models that is used in choosing the best fit model from Training period of Nigeria stock market returns.

Table 3. Performance by ranking the average rank of the goodness-of-fit statistics values for Training Period

Model	LOGL	SBC	AIC	Rank LOGL	Rank SBC	Rank AIC	Avg Rank	Rank Avg
ARCH (1)	-386.6639	6.312633	6.071205	3	9	6	6	6
ARCH (2)	-386.1990	6.342750	6.079373	5	7	5	6	6
PARCH (1,1)	-384.5735	6.466795	6.115626	6	2	3	4	3
GARCH (1,1)	-386.2125	6.342958	6.079581	4	6	4	5	4
GARCH (1,2)	-382.5851	6.324792	6.039467	7	8	9	8	9
GARCH (2,1)	-380.4210	6.291753	6.006428	10	10	10	10	10
EGARCH (1,1)	-380.1429	6.287507	6.002182	11	11	11	11	11
GJR-GARCH (1,1)	-389.1248	6.424635	6.139310	2	3	2	2	2
CGARCH (1,1)	-389.5262	6.579624	6.206507	1	1	1	1	1
GARCH-M (1,1)	-382.2043	6.356194	6.048921	8	4	7	6	6
GARCH (2,2)	-382.1420	6.355243	6.047970	9	5	8	7	8

The result obtained in Table 3:shows the Ranking method results of the goodness-of-fit test are clearlysuggested that CGARCH(1,1) is the best fit models whilst EGARCH(1,1) is the worst fit models for methods.

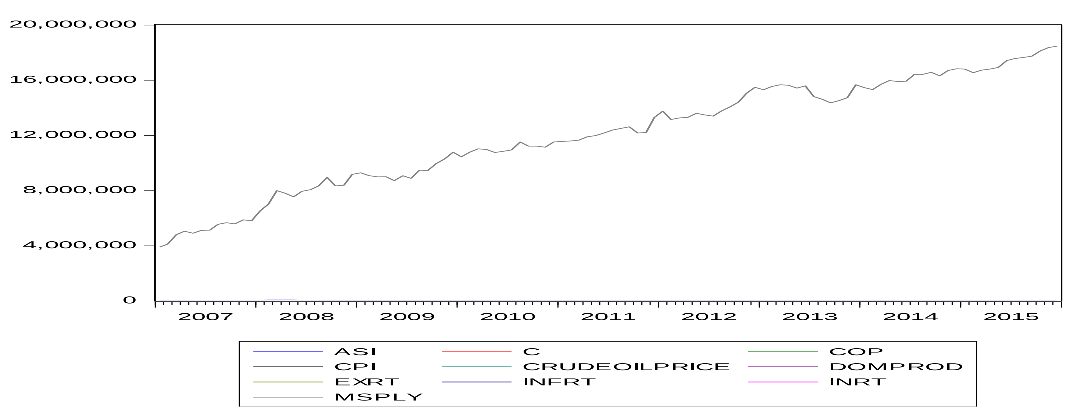

Figure 4. Graphical Representation of Testing Period on Nigeria Stock Market Returns.

From figure 4 it indicates that the series is not stationary as it contain a trend components which should be remove before modeling.

Table 4. Estimation results of the monthly rate of returns for Training Period.

MODEL	ω X10^{-5}	t-ratio	α_1	t-ratio	β_1	t-ratio	α_2	t-ratio	β_2	t-ratio	δ	t-ratio	θ	t-ratio
ARCH(1)	10.0	3.3	0.80	3.11										
ARCH(2)	10.6	3.1	0.79	3.08			-0.02	-0.42						
PARCH (1,1)	2.4	1.2	0.32	2.14	0.36	1.8	0.08	0.92			0.81	0.56		
GARCH (1,1)	10.9	2.9	0.79	3.07	-0.03	-0.41								
GARCH(1,2)	10.2	2.4	0.62	2.47	-0.14	-1.51	0.23	2.19						
GARCH (2,1)	1.9	2.8	0.78	3.44	-0.74	-3.68			0.9	22.8				
EGARCH (1,1)	3.1	4.8	1.17	4.45	0.01	0.05							-0.37	-2.3
GJRGARCH(1,1)	11.1	0.9	-0.04	-0.79	-0.08	-2.51					0.60	1.19		
CGARCH (1,1)	23.1	5.1	0.02	0.02	0.07	0.02	0.05	0.02	-.02	-0.36			0.01	0.01
GARCH-M(1,1)	15.3	3.9	0.35	2.06	0.39	1.07					-0.12	-1.12		
GARCH (2,2)	3.9	2.9	0.87	3.37	-0.67	-4.04	0.74	4.09	-.03	-1.01				

The result obtained in Table 4 shows the parameter estimates and the values of t-ratio. All parameter estimates, with the exception of α_1 for GJR-GARCH (1,1), β_1 for GARCH (1,1) and EGARCH(1,1), α_2 for ARCH (2), β_2 for CGARCH(1,1) and GARCH (2,2) and θ for CGARCH (1,1) are significant at 5% level.

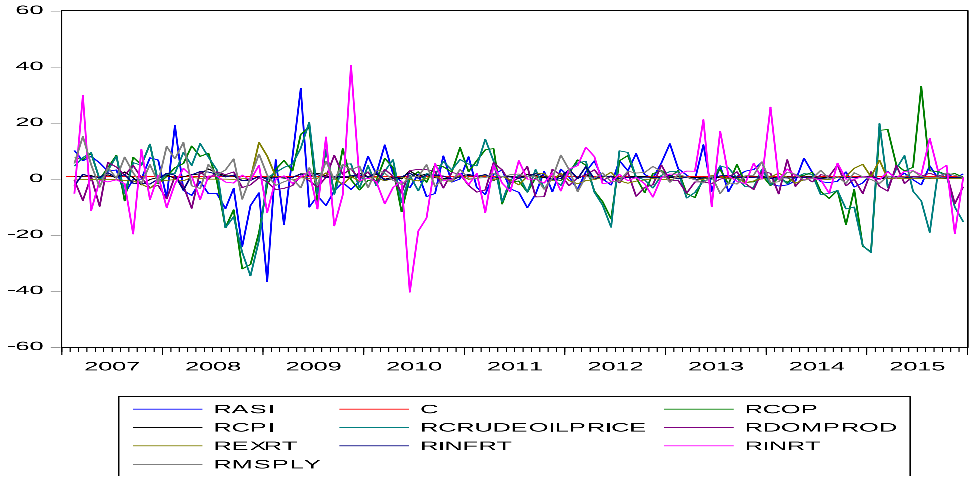

Figure 5. Graphical Representation of Returns Logarithms of Testing Period on Nigeria Stock Market.

Figure 5 shows that the trend component has been taken care of as explained above which can be seen in figure 4.

Table 5. The Criteria Values of the ARCH and GARCH Models of Testing Period on Nigeria Stock Market Returns.

Model	LOGL	SBC	AIC
ARCH (1)	-354.5865	7.108170	6.833393
ARCH (2)	-339.1416	6.863150	6.563394
PARCH (1,1)	-329.9103	6.821617	6.446921
GARCH (1,1)	-335.0621	6.786899	6.487142
GARCH (1,2)	-329.8165	6.732520	6.407784
GARCH (2,1)	-331.6776	6.767307	6.442571
EGARCH (1,1)	-351.1336	7.130971	6.806235
GJRGARCH (1,1)	-333.9890	6.810512	6.485776
CGARCH (1,1)	-335.1591	7.007068	6.582413
GARCH-M (1,1)	-332.9424	6.834621	6.484905
GARCH (2,2)	-330.8776	6.796026	6.446310

The result obtain in table 5 show the result of the three criteria values which are Log Likelihood (Log L), Schwarzs Bayesian Criterion (SBC) and the Akaike Information Criterion (AIC) values of the ARCH and GARCH models that is used in choosing the best fit model from Testing period of Nigeria stock market returns.

Table 6. Performance by ranking the average rank of the goodness-of-fit statistics values for Testing Period

Model	LOGL	SBC	AIC	Rank LOGL	Rank SBC	Rank AIC	Avg Rank	Rank Avg
ARCH (1)	-354.5865	7.108170	6.833393	1	2	1	1	1
ARCH (2)	-339.1416	6.863150	6.563394	3	4	4	4	4
PARCH (1,1)	-329.9103	6.821617	6.446921	10	6	8	8	8
GARCH (1,1)	-335.0621	6.786899	6.487142	5	9	5	6	6
GARCH (1,2)	-329.8165	6.732520	6.407784	11	11	11	11	11
GARCH (2,1)	-331.6776	6.767307	6.442571	8	10	10	9	9.5
EGARCH (1,1)	-351.1336	7.130971	6.806235	2	1	2	2	2
GJR-GARCH (1,1)	-333.9890	6.810512	6.485776	6	7	6	6	6
CGARCH (1,1)	-335.1591	7.007068	6.582413	4	3	3	3	3
GARCH-M (1,1)	-332.9424	6.834621	6.484905	7	5	7	6	6
GARCH (2,2)	-330.8776	6.796026	6.446310	9	8	9	9	9.5

The result obtained in Table 6: shows the Ranking method results of the goodness-of-fit test are clearly suggested that ARCH (1) is the best fit models whilst GARCH (1,2) is the worst fit models for methods.

5 Conclusions

This come out with an alternative method for selecting the best model from a set of competing GARCH models for fitting the Nigeria Stock Market Return series. The ranking method identified exactly the best and worst fit models as for the two periods. However, as a whole, the models occupying the intermediate positions differ in the method. The proposed method is seen to be superior and should be preferred because ranking the actual values of the three goodness-of-fit statistics and hence the inability to exactly specify the relative position of each of the competing models as faced by the criteria values may be avoided. Another advantage is this method also enables models to be classified in to several distinct groups ordered in such a way that each group is made up of models with about the same level of fitting ability. The two extreme classes of models are identified to represent the best and the worst groups respectively.

Table 7: Estimation results of the monthly rate of returns for Training Period.

MODEL	ω X10^{-5}	t-ratio	α_1	t-ratio	β_1	t-ratio	α_2	t-ratio	β_2	t-ratio	δ	t-ratio	θ	t-ratio
ARCH (1)	20.5	3.4	0.99	2.8										
ARCH (2)	12.9	3.0	0.06	0.5			0.8	3.4						
PARCH (1,1)	0.4	0.14	0.3	0.9	0.3	2.9	0.5	1.8	5.6	1.4				
GARCH (1,1)	-0.02	-0.06	0.39	2.3	0.6	5.9								
GARCH (1,2)	-0.6	-4.1	0.41	2.4	0.33	1.1	.33	1.3						
GARCH (2,1)	-0.9	-1.7	0.45	2.0	-0.2	-1.0			0.8	9.6				
EGARCH (1,1)	4.6	5.7	0.13	0.5	0.5	3.3							-0.2	-1.2
GJRGARCH(1,1)	0.01	0.02	0.2	2.0	0.3	1.4					0.6	6.9		
CGARCH (1,1)	42.0	0.8	0.9	7.7	0.16	0.32	-0.01	-0.03	0.2	0.8			0.5	1.5
GARCH-M(1,1)	1.8	0.7	-0.01	0.19	0.7	2.2					0.7	5.3		
GARCH (2,2)	-0.6	-1.34	0.42	1.9	-0.04	-.03	0.5	0.6	0.3	0.5				

References

[1] Engle, R.F. (1982). Autoregressive conditional heteroscedasticity with estimates of variance of United Kingdom Inflation, Journal Econometrica, 50(4) 987–1008.

[2] Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroscedasticity.Journal of Econometrics, 31, 307-327.

[3] Chou, R.Y. (1988). Volatility Persistence and Stock Valuations: Some Empirical Evidence Using GARCH. Journal of Applied Economics, 3, 279-294.

[4] Nelson, D.B. (1991). Conditional heteroscedasticity in asset returns: A new approach, Econometrics 52(2), 347–70.

[5] Bollerslev, T.Y.R., Chou, P. and Kroner, F.K. (1992). ARCH modeling in finance, Journal of Econometrics, 52, 5–59

[6] Engle, R.F. and Patton, A.J. (2001). What good is a volatility model? Quantitative Finance, 1, 237-245. http://dx.doi.org/10.1088/1469-7688/1/2/305.

[7] Nelson, D.B. (1999). Conditional Heteroscedasticity in Asset Returns: A New Approach. Econometrica, 59(2), 347-370. http://dx.doi.org/10.2307/2938260.

[8] Ding, Z. and Engle, R. F. (2001). Large Scale Conditional Covariance Matrix Modeling, Estimation and Testing, Academia Economic Papers, 29, 157–184.

[9] Franses, P.H. and Van Dijk, R. (1996). Forecasting stock market volatility using (non-linear) Garch models, Journal of Forecasting, 15, 229–35.

[10] Choo, C.W.C. (1999), Performance of GARCH Models in Forecasting Stock Market Volatility. Journal of Forecasting, 18, 333–334.

[11] Pindyck, R. (1984). Risk, inflation and the stock market.American Economic Review,74, 335-351.

[12] Whitelaw, R. (1994). Time variations and covariations in the expectation and volatility of stock market returns.Journal of Finance, 49, 515-541.

[13] Koutmos, G.F. (1999). Asymmetric price and volatility adjustments in emerging Asian stock market.Journal of Business Finance and Accounting, 26, 83-101. http://dx.doi.org/10.1111/1468-5957.00249

[14] Koutmos, G. and Saidi, R. (1995). The leverage effect in individual stocks and the debt to equity ratio.Journal of Business Finance and Accounting, 7, 1063-1073. http://dx.doi.org/10.1111/j.1468-5957.1995.tb00894.x

[15] Engle, R.F., Ngand, V.K. and Rothschild, M. (1990). Asset Pricing with a Factor-ARCH Covariance Structure: Empirical Estimates for Treasury Bills,Journal of Econometrics, 45, 213-238.

[16]Engle, R.F. (2000). Dynamic conditional correlation. A simple class of multivariate GARCH models" pdf version available from http://weber.ucsd.edu/~mbacci/engle/cv.html

[17] Lee, C.F., Chen, G.M. and Rui, O.M. (2001). Stock returns and volatility on China stock markets. Journal of Financial Research, 24, 523-543.

[18] Balaban E., Bayar, A. and Faff, R. (2003). Forecasting Stock Market Volatility: Evidence from 14 Countries. 10th Global Finance Conference, Frankfur 15-17.

[19] Tudor, C. (2008). An Empirical Study on Risk-Return Tradeoff Using GARCH-Class Models: Evidence from Bucharest Stock Exchange. International Conference on Business and Economy ICBE Constanta - Romania, November 6-8.

[20] Balaban, E., Bayar, A. and Faff, R. (2005). Forecasting Stock Market Volatility: Further International Evidence.ASAC, Quebec, Canada.

[21] Ogum, G., Beer, F. and Nouyrigat, G. (2005). Emerging Equity Market Volatility: An Empirical Investigation of Markets in Kenya and Nigeria.Journal of Africa Business, 6(1), 139-154.

[22] Yaya, O.S., (2013). Nigerian Stock Index: A Search for Optimal GARCH, Central Bank of Nigeria Journal of Applied Statistics, 4, 69-85

[23] Amaefula, C.G., and Asare, B.K. (2014). The Impacts of Inflation Dynamics and Global Financial Crises on Stock Market Returns and Volatility. Evidence from Nigeria, Asian Economic and Financial Review, 4(5):641-650.

[24] Musa, Y., Tasi'u, M. and Abubakar B. (2014). Forecasting of Exchange Rate Volatility between Naira and US Dollar Using GARCH Models. International Journal of Academic Research in Business and Social Sciences, 4(7), 369-381.

[25] Olowe, R.A. (2009). Modelling Naira/Dollar Exchange Rate Volatility: Evidence from GARCH and Asymmetric Models.International Review of Business Research Papers, 5(3), 377-398.

[26] Stephen, O.U. (2015). Nigeria Stock Market Volatility in Comparison with some Countries: Application of Asymmetric GARCH Models". Central Bank of Nigeria Journal of Applied Statistics.6(2), 2016.

[27] John, O.O. (2016). Measuring Volatility Effects on Daily Stock Market Returns in Nigeria.International Journal of Economics and Business Management, 2(6).

[28] Egbeonu O.C. and Isidore, I.I. (2016). Finametric Analysis of Nigeria Stock Market and Volatility of Returns".International Journal of Accounting Research (IJAR).2(10).

[29] Gokcan S., (2000). Forecasting volatility of emerging stock markets: Linear versus Non-Linear GARCH models, Journal of Forecasting, 19, 499–504.

[30] Engle, R.F. and Mustafa, C. (1992). Implied GARCH models from options prices, Journal of Econometrics, 52, 289–311.

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