**Cover page**

# MODELLING ABRUPT SHIFT IN TIME SERIES USING INDICATOR VARIABLE: EVIDENCE FROM NIGERIAN INSURANCE STOCK

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**NIGERIA**

**JULY, 2015**

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**DEPARTMENT OF MATHEMATICS**
**AHMADU BELLO UNIVERSITY, ZARIA**
**NIGERIA**

**JULY, 2015**

# DECLARATION

I declare that the work in this thesis entitled "**MODELLING ABRUPT SHIFT IN TIME SERIES USING INDICATOR VARIABLE: EVIDENCE FROM NIGERIAN INSURANCE STOCK**" has been carried out by me in the Department of Mathematics under the supervision of Dr. H.G Dikko and Prof O.E Asiribo.

The information derived from literature has been duly acknowledged in the text and a list of reference provided. No part of this thesis was previously presented for another degree or diploma at this or any other Institution.

| Samson AGBOOLA | _____ | _____ |
|---|---|---|
| Name of Student | Signature | Data |

# CERTIFICATION

The thesis titled "**MODELLING ABRUPT SHIFT IN TIME SERIES USING INDICATOR VARIABLE: EVIDENCE FROM NIGERIAN INSURANCE STOCK**" by Samson AGBOOLA (MSC/SCIE/23245/2012-2013) meets the regulations governing the award of the degree of Master of Science of Ahmadu Bello University, Zaria and is approved for its contribution to knowledge and literary presentation.

| | | |
|---|---|---|
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# DEDICATION

This Thesis is dedicated to God Almighty and Agboola Families.

# ACKNOWLEDGEMENT

Glory beto God for His mercy endures forever Amen. Father thank you for you thought toward me in this course of my study, am not better than others, thanks for making it possible for me to complete this work.

I acknowledge the work of previous authors and papers cited. Also, I sincerely appreciate the untiring efforts of my supervisors Dr. H.G Dikko and Prof O.E Asiribo who despite their busy schedules has been able to read through the work, make comments and provided me necessary guides that has made this study a huge success. May God bless you and your family (Amen).

My sincere gratitude also goes to the Head of the Department, Prof. B. Sani, and all Lecturers in the Department who have taught me in one way or other. I really appreciate you all for your contributions toward my academic pursuit.Thanks to you Dr., LawongDemian of Economic Department for your kindness and interest in the contribution toward this study, I cannot pay you enough but God will reward you. Special thanks go to my parent Mr. and Mrs. A. Agboola, my pastors and their wife, in Zaria of Salvation Assembly and Grace and truth parish, Minna, Deacon Mike .A, Deacon Femi A. and his wife and Pastor Sunday E. The Redeemed Christian Church of God and all my choir members in salvation assembly and Grace and Truth my sister Bukola, Salome, my brothers Ayodeji. May God bless you all (Amen). Also my profound gratitude goes to all my postgraduate colleagues. Thanks a lot.

## Abstract

This study models abrupt shift in time series using indicator variable: evidence from Nigeria Insurance stocks. Data on daily closing prices for some selected Nigerian Insurance stocks were collected between 2nd January, 2000 and 26th May, 2014. Daily returns were then computed from thedaily prices. To study the volatility pattern of Insurance stock, seven symmetric models and five asymmetric models with dummy variables incorporated to their variance equation were considered and these are ARCH (1), ARCH (2), ARCH (3), GARCH (1, 1), GARCH (2, 1), GARCH (1, 2), GARCH (2, 2), EGARCH (1, 1), EGARCH (1, 2), EGARCH (2, 1), EGARCH (2, 2) and TARCH (1, 1). Post estimation and performance evolution metric was evaluated using the RMSE, MAE and MAPE. The results showed that, the daily returns were stationary but not normally distributed and eight out of ten stocks considered for the study showed evidence of ARCH effect. Furthermore, the results of the post estimation revealed that most of the models were competitive and model ARCH (1) and EGARCH (1, 1) proved to be the most suitable among the twelve competing volatility models considered in some of the Insurance company. This present study findings are very crucial and informative to investors and intending investors as it will help in stock pricing strategy as volatility is the major index used to evaluate asset performance and stock pricing strategy.

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# Acronyms

| | |
|---|---|
| **AIICO**: | American International Insurance Company (AIICO) plc. |
| **GUINEAINS**: | Guinea Insurance plc. |
| **GUINNESS:** | Guinness Insurance plc. |
| **LASACO**: | Lasaco Assurance plc. |
| **LAWUNION**: | Law Union and Rock Insurance plc. |
| **NEM**: | NEM Insurance Company Nigeria plc. |
| **NIGERINS**: | Niger Insurance Company plc. |
| **PRESTIGE**: | Prestige Assurance Company plc. |
| **UNIC**: | Unic Insurance plc. |
| **WAPIC**: | Intercontinental West African Provision Insurance Company (WAPIC) Plc. |
| **NSE** | Nigeria Stock Exchange |
| **NSER** | Nigeria Stock Exchange Return |

# CHAPTER 1

# INTRODUCTION

## 1.1 Background of the study

Dummy variables are variables that can take any values. In statistics and econometrics, particularly in regression analysis, a dummy variable is one that takes the value 0 or 1 to indicate the absence or presence of some categorical effect that may be expected to shift the outcome. Dummy variables are used as devices to sort data into categories (such as stable/unstable, etc.). They may be explanatory or outcome variables; however, the focus of this study is explanatory dummy variable construction and usage. Typically, dummy variables are used in the following applications: time series analysis with seasonality or regime switching; analysis of qualitative data, such as survey responses. Some scholars have argued based on statistical analysis of time series that certain phenomena do not correspond to regime shifts, Feng. *et al.,* (2006). Outliers, level shifts, and variance changes are common place in applied time series analysis.

However, their existence is often ignored and their impact is overlooked, for the lack of simple and useful methods to detect and handle those extraordinary events. The problem of detecting level shifts, and variance changes in a univariate time series is considered. Three different types of regime shift (smooth, abrupt and discontinuous) are identified on the basis of different patterns in the relationship between the responses. The smooth regime shifts is represented by a quasi-linear relationship between the response and control variables. The abrupt regime shift exhibits a nonlinear relationship between the response and control variables, and the discontinuous regime shift is characterized by the trajectory of the response variable differing when the forcing variable increases compared to when it decreases Collie *et al.,* (2004).

In order to apply the concept to a particular problem, one has to conceptually limit its range of dynamics by fixing analytical categories in time by considering the event and categorically applying it in achieving the aim and objectives of the study.

In this study, we are going to model the abrupt shift in a time series, i.e. in event from stable and unstable economic. Therefore our indicator variable will take in the value of 0 for stable and 1 for unstable economy in order to study the abrupt shift in time series since we are considering a time series data to observe these nonlinear relationship in each of the stock with seven symmetric and five asymmetric models incorporating an indicator variable in the variance equation..

## 1.2 Statement of the problem

As the financial sector in Nigeria took a turn towards recapitalization process, first in the banks, the Insurance industry under the direction of the National Insurance Commission underwent a full recapitalization process that ended with a more robust Insurance industry characterized by players grouped into key categories according to level of capitalization.

The recapitalization of the Insurance industry in Nigeria in July 2004 boosted the number of securities listed on the Nigerian Stock Exchange (NSE) thereby increasing public awareness and the confidence about the Nigerian Stock market. However, since April, 2008, investors have been worried about the falling stock prices on the Nigerian stocks although this problem has been attributed to the global economic meltdown (Olowe, 2009a). However, despite this problem, volatility modelling and forecasting have not attracted much attention in Nigeria (Dallah and Ade, 2010). Although, several studies in volatility modelling have been carried out this include; study by Ibiwoye and Adeleke (2008) whose work centred on the analysis of price movements in Insurance stocks before and after-2005 consolidation. Olowe (2009a) wrote on

Stock Return Volatility and the Global Financial Crisis in an Emerging Market: The Nigerian Case. Onwukwe*et al.,* (2011) in their study modelled the volatility of four Nigerian Firms listed on the Nigerian Stock Exchange. Olowe (2009b) also conducted another study which focused on the impact of the 2005 re- capitalization of the banking and Insurance industry on the stock market. Also, worthy of note is another study conducted by Dallah and Ade (2010); their study was on modellng and forecasting of daily returns of the Nigerian Insurance stocks.

However, none of these studies model abrupt shift in time series using indicator variables: Evidence from Nigeria Insurance Stock. This gives room for this study as some of theInsurance stocks in the Insurance sector may not necessarily exhibit the same volatility pattern due to government regime shift from the period of 2000 to 2008 and from 2009 to 2014 during the time of study. This study is also very timely because of the fact that now that investors' confidence have been eroded as a result of the incessant downward movement in the price of Nigerian Insurance stocks. Therefore, it becomes imperative to model abrupt shift in time series using indicator variable.

## 1.3 Aim and Objectives of the study

The aim of this study is to model abrupt shift in time series using indicator variable: Evidence from the Nigerian Insurance stocks quoted on the floor of the Nigerian stock exchange using incorporated dummy variable on the volatility models. The aim of this study will be achieved using the following objectivesto:

1. examine the stationarity of the returns and test for normality of the residuals
2. to model the volatility in the return using different volatility models.
3. observe the significance of the indictor variable on the volatility of the returns.

4. compare the models in term of fitness and forecasting accuracy and recommend a suitable volatility model for volatility forecast.

## 1.4 Statement of hypothesis

The following null hypothesis were postulated to explain the modelling abrupt shift in a time series using dummy variable on Nigeria Insurance stocks.

$H_{01}$: there is no significant difference in the abrupt shift on each of the Nigeria Insurance stock

$H_{02}$: there is significant difference in the abrupt shift on each of the Nigeria Insurance stock

## 1.5 Significance of the study

Since volatility is a key parameter used in many applications, from derivatives valuation to asset management, risk management and for the fact that the main cause of stock market volatility has not been well understood. Thus, a proper understanding of its pattern will offer investors, analysts, brokers, dealers and other regulators an avenue to make a more reliable investment decision so that investors' hard earned money can be put into a viable investment.If few or more event is occurring in time, we can use this approach in observing the significant and the theoretical property of the models.In addition, information contained in this study will also be beneficial to other researchers including students who may want to research further on this topic. It will serve as a resource material for them. The study can also serve as a springboard for further study whose results can be improved on with a more updated data.

## 1.6 Scope of the study

This study considered some conditional heteroscedasticity models in modelling abrupt shift in a time series using indicator variable on the Nigerian Insurance stocks. The volatility models and the incorporating dummy variable in this study include the Autoregressive

Conditional Heteroscedastic Models (ARCH) of order one, two and three, the Generalized Autoregressive Conditional Heteroscedastic Model (GARCH), Exponential Generalized Autoregressive Conditional Heteroscedastic Model (EGARCH) and the Threshold Autoregressive Conditional Heteroscedastic Model (TARCH).Furthermore datato be considered for this study were from daily closing prices of Insurance stocks traded on the floor of the Nigerian Stock Exchange (NSE) from the period of fourteen year, 2nd January 2000 to 26th May, 2014 with ten Insurance companies such as AIICO, GUINEAINS, GUINNESS, LASACO, LAWUNION, NEM, NIGERINS, PRESTIGE, UNIC AND WAPIC.

## 1.7 Limitation of the study

More Insurances compaines would have been considered but due to the insufficient start-up date, this limit us using ten Insurancecompaines and also further work on other useful family volatility models like Multivariate GARCH models, stochastic volatility model and comparison of this research with dynamic conditional correlation models.

## 1.8 Contribution to Knowledge

The contribution to knowledge in this study is to add an additional constraint to the existing model i.e. an indicator variable to the conditional variance to capture government regime shift in stock market volatility for some of the Insurance companies in Nigeria and to find out the best models for the selected Insurance stock in term of best models estimation and forecasting models.

## 1.9 Definition of terms

### 1.9.1 Heteroscedasticity

This is a situation whereby the variances of the error term of a model are not equal that is the variance of the error term varies with time.

### 1.9.2 Insurance

Is the main way for businesses and individuals to reduce the financial impact of a risk occurring.

### 1.9.3 Investment

Is time, energy, or matter spent in the hope of future benefits actualized within a specified date or time frame.

### 1.9.4 Investor

Someone who commits capital in order to gain financial returns.

### 1.9.5 Nigeria Stock Exchange

This is the body responsible for the regulation of stock activities and other securities in Nigeria.

### 1.9.6 Stock

Refer to a security that represents partial ownership in a corporation.

### 1.9.7 Stock Exchange

Is a form of exchange which provides services for stock brokers and traders to trade stocks, bonds, and others security.

### 1.9.8 Stock Market

Is the market that people use to trade shares, which are like small pieces of the company that a person can owned. The value of the share depends on how many people want to buy it and how many people are selling it.

### 1.9.9 Risk Management

Is the process of making and carrying out decisions that will minimize the adverse effects of risk on an organization

### 1.9.10 Unit Root Test

Is a test applied to a time series variable whether the time series variable is non-stationary.

### 1.9.11 Stationary Series

Is a series which has no unit root, that is the mean and variance does not change over time.

### 1.9.12 Non-Stationary Series

Is a series which has a unit root, that is, the mean and variance changes has time progresses.

### 1.9.13 Nigerian Stock Exchange

This is the body responsible for the regulation of stock activities and other securities in Nigeria.

### 1.9.14 Dummy variable

A dummy variable also known as an indicator variable, design variable, Boolean indicator, categorical variable, binary variable, or qualitative variable is one that takes the value 0 or 1 to

indicate the absence or presence of some categorical effect that may be expected to shift the outcome. Dummy variables are used as devices to sort data into mutually exclusive categories (such as before shock/aftershock, etc.). For example, in econometric time series analysis, dummy variables may be used to indicate the occurrence of wars or major strikes. A dummy variable can thus be thought of as a truth value represented as a numerical value 0 or 1.

### 1.9.15 Incorporating a dummy independent variable

Dummy variables are used frequently in time series analysis with regime switching, seasonal analysis and qualitative data applications. Dummy variables are involved in studies for economic forecasting, bio-medical studies, credit scoring, response modelling, etc. Dummy variables may be incorporated in traditional regression methods or newly developed modeling paradigms.

Dummy variables are incorporated in the same way as quantitative variables are included (as explanatory variables) in regression models. For example, if we consider a regression model of wage determination, wherein wages are dependent on gender (qualitative) and years of education (quantitative) but in this study we are incorporating dummy variable in a time series models such ARCH, GARCH, EGARCH and TARCH.

For example

Let considered ARCH model with dummy variable incorporated with the time series model

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + ... + \alpha_q \varepsilon_{t-q}^2 + \delta_1 D_{Shift} + \varepsilon_t \qquad (1.1)$$

Where $\delta_1 D_{Shift}$ is the added dummy variable to the conditional variance model.

In this ARCH model, a dummy variable with a value of 0 will cause its coefficient to disappear from the equation. Conversely, the value of 1 causes the coefficient to function as a supplemental intercept, because of the identity property of multiplication by 1. This type of specification in an ARCH model is useful to define subsets of observations that have different intercepts without the creation of separate models.

# CHAPTER 2

# LITERATURE REVIEW

ARCH and GARCH models, which stand for autoregressive conditional heteroscedasticity and generalized autoregressive conditional heteroscedasticity, have become widespread tools for dealing with heteroscedastic time series. The goal of such models is to provide a volatility measure – like a standard deviation -- that can be used in financial decisions concerning risk analysis, portfolio selection and derivative pricing. Applications of the ARCH/GARCH approach are widespread in situations where volatility of returns is a central issue. Many banks and other financial institutions use the idea of "value at risk" as a way to measure the risks faced by their portfolios.

Engle (1982)first proposed the autoregressive conditional heteroscedasticity (ARCH) model for modeling the changing variance of a time series; Engle used an ARCH model to study inflation in the United Kingdom. Bollerslev (1986)showed that a GARCH model with a small number of terms may be more efficient than an ARCH model with many terms. Empirical studies in recent years have focused on volatility investigation on the pattern of financial assets such as ARCH effect, volatility clustering, and persistence and leverage effect. For example, (Tse and Tsui, 1997), (Pesaran and Robinson, 1993), (Yoon and Lee, 2008), (Longmore and Lee, 2004), (Taylor and Tsun1986) and many others used many extension of the GARCH model proposed by Nelson (1991) like the GARCH-in Mean, IGARCH, EGARCH, TARCH, PARCH.

The use of dummy variables requires the imposition of additional constraints on the parameters of regression equations to obtain estimates for the model. Among the possible constraints the most useful are (a) to set the constant term of the equation to zero, or (b) to omit

one of the dummy variables from the equation. In econometrics time series analysis, dummy variables may be used to indicate the occurrence of wars or major strikes. Dummy variables are used frequently in time series analysis with regime switching, seasonal analysis and qualitative data applications. Dummy variables are involved in studies for economic forecasting, bio-medical studies, credit scoring, response modelling, etc

Alabi (2014) used dummy variable to compare the year 2012 internally generated revenue (IGR) and wage bills of the six geopolitical zones in Nigeria by categorizing the geopolitical zones as dummy variables in a regression model to find out if the average internally generated revenue and wage bills of the geopolitical zone are statistically different from each other. From his analysis, he concluded that the northeast and northwest zones are statistically different.

Ajab*et al.*,(2012) investigated stock market volatilities exploiting a number of asymmetric models (EGARCH, ICSS-EGARCH, GJR-GARCH, and ICSS-GJR-GARCH). The finding supports the widely accepted view that accounting for the regime shifts detected by the iteratedcumulative sums of squares (ICSS) algorithm in the variance equations overcomes the overestimation of volatility persistence.

Moustafa (2011) model and forecast time vary stock return volatility in the Egyptian stock market using four models. The empirical results show that EGARCH is the best model between the examined models according to the usual evaluating statistical metrics (RMSE, MAE, and MAPE) and found no significance difference between the errors of competing models.

Scott (2006)used GARCH models with dummies to study the impact of U.S monetary policy on inflation. From the analysis, he concluded that the impact of U.S monetary policy on

inflation is negative but not significant on the parameter of the dummy variable the parameter. Stock return volatility represents the variability of stock price changes during a period of time. This phenomenon has attracted growing attention of academia, policy makers and other players in this sector. This is because return is a major measure of risk associated with asset instead of price because if you want an investment that gives 10% of your return you invest on it than in price i.e. it is much better to deal with return than price. Also, high volatility in stocks, bonds and foreign exchange markets usually raise from important public policy issues about stability of financial market and impact of stock volatility on the economy cannot be sub estimated.

Onwukwe*et al.,* (2011) used volatility to model four Nigerian Firms listed on the Nigerian Stock Exchange. Olowe (2009b) also conducted another study which focused on the impact of the 2005 recapitalization of the banking and Insurance industry on the stock market. (Dallah and Ade, 2010) carried out a research on modeling and forecasting daily returns of Nigerian Insurance stock using Engle(1982) proposed model and Nelson (1991) to estimate suitable models in, from the study the researcher concluded that the exponential generalized autoregressive conditional heteroscedastic (EGARCH) models is more suitable in modelling stock price returns as it outperforms the other models in goodness of fit and out of sample volatility forecasting.

The contribution to knowledge in this study is to add an additional constraint to the existing model i.e. an indicator variable to the conditional variance to capture government regime shift in stock market volatility for some of the Insurance companies in Nigeria using some heteroscedasticity mode and to find out the best models for the selected Insurance stock in term of best models selection estimate, goodness of fit models and forecasting models.

# CHAPTER 3

# METHODOLOGY

## 3.1 Data for the study

Data for this study were from daily closing prices of Insurance stocks traded on the floor of the Nigerian Stock Exchange (NSE)**.** These time series data cover almost fourteen years starting from 2nd January 2000 to 26th May, 2014. These Insurance are AIICO, GUINEAINS, GUINNESS, LASACO, LAWUNION, NEM, NIGERINS, PRESTIGE, UNIC AND WAPIC.

These makes the total number of Insurancecompainesto be considered ten. These data are available on Cash Craft website (**www.cashcraft.com).**

## 3.2 Computation of return series from price

$$\text{Let } R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{3.1}$$

where $P_t$ and $P_{t-1}$ are the present and previous closing prices and $R_t$ the continuously compounded return serieswhich is the natural logarithm of the simple gross return.

## 3.3 Steps-involve in building volatility models

Building a volatility model for an asset return series consists of principal steps namely:

(a) Compute return series from price series

(b) Test for the stationarity of the return series

(c) Specify the mean equation by building an econometric model such as AR (Autoregressive Model), MA (Moving Average), or ARMA (Autoregressive Moving Average).

(d) Use the residuals of the mean equation to test for ARCH effects.

(e) Specify volatility model if ARCH effects are statistically significant and perform a joint estimation of the mean and volatility equation.

(f) Check the fitted model carefully and refine it if necessary.

## 3.4 Stationary Test (Augmented Dickey Fuller Test)

Stationarity of the return series is one of the major assumptions in financial time series modelling. This assumption can be checked using the unit root, an **Augmented Dickey–Fuller test (ADF)** is a test for a unit root in a time series sample (Dickey and Fuller, 1997).

Let $y_t = \phi_1 y_{t-1}$ (3.2)

$y_t - y_{t-1} = \phi_1 y_t - y_{t-1}$

$\Delta y_t = (\phi_i - 1) y_{t-1}$

$\Rightarrow \phi_1 - 1 = 0 \text{ or } \phi_1 = 1$

Null hypothesis is $H_0 : \phi_1 = 1$

and alternative hypothesis is : $H_1 : \phi_1 < 1$

The Test Statistic (t-ratio): $= \dfrac{\phi_1^n - 1}{std(\phi_1)} = \dfrac{\sum_{t=1}^{T} P_{t-1} e_t}{\sigma^2 \sqrt{\sum_{t=1}^{T} P_{t-1}^2}}$ (3.3)

where $\phi_1 = \dfrac{\sum_{t=1}^{T} p_{t-1} p_t}{\sum_{t=1}^{T} p_{t-1}^2}$ and $\hat{\sigma}^2 = \dfrac{\sum_{t=1}^{T} (p_t - \hat{\phi}_1 p_{t-1})^2}{T-1}$

$P_0 = 0$, $T$ is the sample size and $\phi_1$ for each Insurance stock.

The null hypothesis is rejected if the calculated value of t is greater than t critical value.

## 3.5 Test for ARCH effect (Test for heteroscedasticity)

One of the most important issue before consider Heteroskedastic models is examine the residuals for evidence of heteroscedasticity. To test for the presence of heteroscedasticity in residuals of Nigerian Insurance stock return series, the Lagrange Multiplier (LM) test for ARCH effects proposed by Engle (1982) is applied. In summary, the test procedure is performed by first obtaining the residuals $e_t$ from the ordinary least squares regression of the conditional mean equation which might be an autoregressive (AR) process, moving average (MA) process or a

combination of AR and MA processes; (ARMA) process using EViews 7 statistical software. For example, in ARMA (1,1) process the conditional mean equation will be as:

$$r_t = \phi_1 r_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} \tag{3.4}$$

after obtaining the residuals $e_t$, the next step is regress the squared residual on a constant and itsq lags as in the following equation:

$$e_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + ... + \alpha_q e_{t-q}^2 + r_t \tag{3.5}$$

The null hypothesis, that there is no ARCH effect up to order q can be formulated as:

$$H_0 : \alpha_1 = ... = \alpha_q = 0 \tag{3.6}$$

against the alternative

$$H_a : \alpha_i \neq 0 \text{ for some i} \in \{1,..,m\} \tag{3.7}$$

The test statistic for the joint significance of the q-lagged squared residuals is the number of observations times the R-squared $(TR^2)$ from the regression. $TR^2$ is tested against $\chi^2_{(q)}$ distribution. This is asymptotically locally most powerful test.

## 3.6 Jarque-Bera Test for normality

Jarque- Bera test is the commonly used diagnostic statistic to test for normality of the residuals. It measures the difference between the skewness and kurtosis of the series with those of the normal distribution. The test statistic is computed as:

$$JB = \frac{N-k}{6}\left[S^2 + \frac{(K-3)^2}{4}\right], \tag{3.8}$$

is approximately $\chi_2^2$. S is the skewness and K is the kurtosis.

$K = \frac{\mu_4}{\mu_2^2} - 3 = \frac{\mu_4}{\sigma^4} - 3$, if K < 0, platykurtic, K > 0, excess kurtosis, leptokurtic and K= 0, mesokurtic. We reject the null hypothesis of normality if the Jarque- Bera statistic exceeds the corresponding critical value. (Lawford, 2004).

### 3.7 Stock market volatility

The volatility $\sigma$ of a stock is a measure of uncertainty about the returns provided by stock. In financial market, volatility is often referred to standard deviation σ or variance $\sigma^2$. From a number of observations in the empirical sample, the parameter is normally computed as follows:

$$\sigma^2 = \frac{1}{n-1}\sum_{i=1}^{n}\left(R_i - \mu\right)^2 \tag{3.9}$$

where $\mu$ is the mean return,

$$R_t = \ln \frac{P_t}{P_{t-1}} \tag{3.10}$$

where $R_i$ is the return series, $P_t$ and $P_{t-1}$ are the present and previous day closing prices respectively.

Using the simple present value model, Shiller (1981) finds that the level of stock market volatility is too high, relative to the variation in the underlying micro and macro fundamentals. Specifically, he finds that changes in real dividends and real interest rates cannot explain the level of market volatility.

Some other studies also concluded that standard macro factors and corporate characteristics cannot explain the time varying nature of equity volatility (Christie, 1982). Schwert (1989) added that the standard macroeconomics variables such as inflation, money

growth, and industrial production also do not sufficiently explain the variation in the market volatility. But, behavioural finance literature pointed out that information crowding, noise trading and liquidity- driven transactions as potentials reasons for the high level of market volatility relative to the volatility in the underlying information flow.

## 3.8 Volatility models

### 3.8.1 Autoregressive Conditional Heteroscedasticity model

The Autoregressive Conditional Heteroscedasticity (ARCH) model was proposed by Engle (1982). The introduction of the ARCH model was the first attempt to capture stock volatility without the assumption of constant variances which commonly exists in many conventional financial econometrics models. It is unlikely in financial time series that the error terms will be constant overtime, therefore allowing for conditional heteroscedasticity in stock return analysis is reasonable. The ARCH (q) model proposed by Engle (1982) formulates volatility as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + ... + \alpha_q \varepsilon_{t-q}^2 + r_t \qquad (3.11)$$

where $\alpha_i > 0,$ for i=0, 1, 2… q are the parameters of the models

However, ARCH model is simple but many parameters are required to estimate the volatility of stock returns. The problem of parsimony among the other problems of ARCH model such as how to specify the value of *p* and the violation of non-negativity constraints led to more general framework GARCH (p,q) proposed by Bollerslev (1986) and (Taylor and Tsun 1986).

**Theorem 1**

Assume that $z_t$ is asequenceof independent and identically distributed random variable with mean zero and unit variance. Then, for ARCH (1) model, $E(\varepsilon_t) = 0$ and $\text{var}(\varepsilon_t) = \frac{\alpha_0}{1-\alpha_1}$ , where $\varepsilon_t = z_t\sigma_t$

***ARCH model with dummy variable***

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + ... + \alpha_q\varepsilon_{t-q}^2 + \delta_1 D_{Shift} + r_t \qquad (3.12)$$

where $\alpha_i > 0,$ for i=0, 1, 2… q are the parameters of the models and $\delta_1 D_{Shift}$ is the added dummy variable to the conditional variance model.

**Theorem 2**

Assume that $z_t$ is asequenceof independent and identically distributed random variable with mean zero and unit variance and δD is the incorporated dummy parameter. Then, for ARCH (1) model, $E(\varepsilon_t) = 0$ and $\text{var}(\varepsilon_t) = \frac{\alpha_0 + \delta D}{1-\alpha_1}$, where $\varepsilon_t = z_t\sigma_t$ and D takes the value 0 or 1

### 3.8.2 Generalized Autoregressive Conditional Heteroscedasticity model

Extending the framework of Engle (1982), Bollerslev (1986) and Taylor (1986) proposed the generalized ARCH (q) model to GARCH (p, q*)* in which they added the q lags of past conditional variance into the equation. GARCH (p, q) model allows for both autoregressive and moving average components in the Heteroskedastic variance. The GARCH (p, q) model was stated as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + ... + \alpha_q\varepsilon_{t-q}^2 + \beta_1\varepsilon_{t-1}^2 + ... + \beta_p\varepsilon_{t-p}^2 + r_t \qquad (3.13)$$

where $\alpha_i > 0$ and $\beta_i > 0$ for all i and j

**Theorem 3**

The GARCH (p, q) with $z_t$ which is a discrete time stochastic process defined by:

$$\varepsilon_t = z_t\sigma_t,\ \sigma_t^2 = \alpha_0 + \sum_{i=1}^{p}\alpha_i\varepsilon_{t-i}^2 + \sum_{j=1}^{q}\beta_j\sigma_{t-j}^2$$

is weakly stationary with

$$E(\varepsilon_t) = 0 \text{ and } \operatorname{var}(\varepsilon_t) = \alpha_0\left[1-\left(\sum_{i=1}^{p}\alpha_i + \sum_{j=1}^{q}\beta_j\right)\right]^{-1}$$

$\operatorname{cov}(\varepsilon_t, \varepsilon_t) = 0$ for $t \neq s$, if and only if $\sum_{i=1}^{p}\alpha_i + \sum_{j=1}^{q}\beta_j < 1,\ (\alpha_0 > 0)$

***GARCH model with dummy variable***

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + ... + \alpha_q\varepsilon_{t-q}^2 + \beta_1\varepsilon_{t-1}^2 + ... + \beta_p\varepsilon_{t-p}^2 + \delta_1 D_{Shift} + r_t \qquad (3.14)$$

where $\delta_1 D_{Shift}$ is the added dummy variable to the conditional variance model that takes the value 0 or 1.

**Theorem 4**

The GARCH (p, q) with $z_t$ which is a discrete time stochastic process and δD which is the dummy variable is defined by:

$\varepsilon_t = z_t\sigma_t,\ \sigma_t^2 = \alpha_0 + \sum_{i=1}^{p}\alpha_i\varepsilon_{t-i}^2 + \sum_{j=1}^{q}\beta_j\sigma_{t-j}^2 + \delta D$ is weakly stationary with

$$E(\varepsilon_t) = 0 \text{ and } \operatorname{var}(\varepsilon_t) = \alpha_0 + \delta D\left[1-\left(\sum_{i=1}^{p}\alpha_i + \sum_{j=1}^{q}\beta_j\right)\right]^{-1}$$

$\text{cov}(\varepsilon_t, \varepsilon_t) = 0 \text{ for } t \neq s$, if and only if $\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j < 1, (\alpha_0 > 0)$ and D takes the value 0 or 1

(Scott, 2006)

Furthermore, empirical findings suggest that GARCH model is more parsimonious than ARCH model. Although GARCH model has been the most popular volatility model, it has three main problems. Firstly, non-negativity constraint may be violated by the estimated models. Secondly, GARCH model does not take into account the leverage effect and not allow for feedback between the conditional variance and conditional mean (Brook, 2008). Since the GARCH model was developed, a huge number of extension models have been proposed as the awareness of GARCH model's weaknesses. The differences among these models are the manner under which they evolve overtime (Tsay, 2005). The recent GARCH models try to correct the disadvantages of the previous models for their inefficiency to capture the volatility behaviours.

There are a number of other specifications of GARCH type models which capture the asymmetric response of volatility on news. The VGARCH, Asymmetric GARCH model. (AGARCH) and the NAGARCH model allow the several type of the asymmetry in the impact of news on volatility. In 1993, the concept of news impact curve was introduced by (Engleand Ng 1993). The news impact curve attempts to characterize the impact of past residual term on the volatility in different models and capture the differences between the alternative models.

### 3.8.3 Exponential Generalized Autoregressive Conditional Heteroscedasticity Model

Instead of directly performing the conditional variance, the EGARCH model is formed in logarithm of the conditional variance. Even if the GARCH models successfully capture the thick

tail returns and the volatility clustering, they are poor models if one wishes to capture the leverage effect.

The EGARCH (p, q) is given by as proposed by Nelson (1991):

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{p} \alpha_i \left[ \lambda \varepsilon_{t-i} + \gamma \left\{ \left| \varepsilon_{t-i} \right| - \sqrt{\frac{2}{\pi}} \right\} \right] + \sum_{i}^{q} \beta_j \ln(\sigma_{t-j}^2) \qquad (3.15)$$

$\alpha_0, \alpha_i, \gamma, \beta_j$ are the parameters of the model.

If p =1 and q =1, the model above reduces to EGARCH (1, 1) given as

$\varepsilon_t = z_t \sigma_t$

$$\ln(\sigma_t^2) = \alpha_0 + \beta \ln \sigma_{t-1}^2 + \left[ \alpha_1 \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \gamma \left( \frac{\left| \varepsilon_{t-1} \right|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right) \right] \qquad (3.16)$$

$\alpha_0, \alpha_1, \gamma, \beta_1$ are the parameters.

Firstly, since $\ln \sigma_t^2$ is modeled, the conditional variance is ensured to be non-negative. Hence, the non-negativity constraint is not necessary. Secondly, the standardized value of residuals $\varepsilon_t$ is employed instead of squared residuals because Nelson (1991) argued that this allows for more natural interpretation of the size and persistent of shocks. Finally, the parameter $\gamma$ can generate the leverage effect because it allows the sign of yesterday's shock enters the model.

If $\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}}$ is positive or negative, the effect of the shock on the conditional variance is $(\alpha_1 + \gamma)$ and $(\alpha_1 - \gamma)$ respectively.

***EGARCH (p, q) Model with dummy variable is given as***

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{t=1}^{q} \left( \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \gamma_i \left( \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right) \right) + \sum_{j=1}^{p} \left( \beta_j \ln \left( \sigma_{t-j}^2 \right) \right) + \delta_1 D_{Shift} \qquad (3.17)$$

where $\delta_1 D_{Shift}$ is the added dummy variable to the conditional variance model.

### 3.8.4 ThresholdGeneralized Autoregressive Conditional Heteroscedasticity model

The Threshold GARCH model is similar to GJR-GARCH of Glosten, Jagannathan&Runkle (1993) stated as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q}(\alpha_i + \gamma_i N_{t-i})\varepsilon_{t-i}^2 + \sum_{j=1}^{p}\beta_j \sigma_{t-j}^{\ 2} \qquad (3.18)$$

$\alpha_0, \alpha_i, \gamma_i, \beta_j \geq 0$

where, $N_{t-i}$ is an indicator for negative $\varepsilon_{t-i}$ that is $N_{t-i}$ is 1 if $\varepsilon_{t-i} < 0$ and 0

if $\varepsilon_{t-i} \geq 0$.

In GARCH models, the sign of lagged residuals does not play any role by squaring them in conditional variance equation. To overcome this, the Threshold GARCHmodel proposed by Glosten*et al.*, (1993) provided a dummy variable which is an indicator for sign of error terms. The TARCH model allows good news (positive return shocks) and bad news (negative return shocks) having different effect on volatility.

Shock to volatility seems to have long memory impact on the future volatility. This effect, as mentioned above, can be capture by IGARCH. But in IGARCH model, the unconditional variance does not exist and a shock impacts on future volatility over infinite horizon. This motivates the introduction of Fractionally Integrated FIGARCH (p, d, q) by Baillie *et al.*, (1996) with non-negative d. For d = 0, model reduces the standard GARCH model, but for values of 0<d<1 shocks to the volatility will decay at a slow hyperbolic rate. Asymmetries are also simply introduced to the model by allowing the impact of past positive and negative innovations as in the TARCH model.

***TARCH (p, q) with dummy variable***

$$\sigma_t^2 = \alpha_0 + \sum_{t=i}^{q}(\alpha_i \varepsilon_{t-i}^2) + \gamma \varepsilon_{t-1}^2 d_{t-1} + \sum_{j=1}^{p}(\beta_j \sigma_{t-j}^2) + \delta_1 D_{Shift} \quad (3.19)$$

where $\delta_1 D_{Shift}$ is the added dummy variable to the conditional variance model

## 3.9 Forecasting volatility

### 3.9.1 Implied volatility

One of the approaches that can be used as the market's forecast of the volatility of underlying asset returns over the lifetime of the option is the implied volatility introduced by (Latane and Rendleman, 1976). This method uses option prices observed in the market instead of historical stock price series of underlying assets to estimate volatility. A fair value of an option can be obtained by Black-Scholes pricing formula which includes price of underlying asset, option strike price, risk free rate, time to maturity and volatility parameter. All these variables except volatility parameter are observable.

The implied volatility approach bases on the idea that the option prices are revealed by the financial market and all other variables are directly measured to inversely estimate volatility parameter by a numerical procedure. For a single option, implied volatility is the parameter that makes the theoretical value of the model equal to market price (Hein, 2008). To derive the volatility by the option, Brook (2008) recommended two methods which include; the method of bisections and Newton-Raphson. Implied volatility takes into account not only historical data but also other relevant information such as complex behavior of investors, past events and anticipated events which may not be covered by other approaches. However, the implied volatility is not reliable to apply for deep-in-the-money and deep-out-the-money options due to the insensitivity of these options' prices to volatility.

## 3.10 Forecasting Evaluation

Evaluating the performance of different forecasting models plays a very important role in choosing the most accurate models. In particular, researchers and investors need to decide the evaluating criteria on which to base. Although the vast number of papers has studied the construction of modeling and forecasting volatility, a few of them focus on the volatility forecasting evaluation.

According to Bollerslev*et al.*, (1994) the economic loss function which determines the cost incurred by the investors is the most meaningful measure of forecast evaluation. It is ideal to employ the economic loss function. However, the economic loss function is normally unavailable because it requires the specific details of the investors' decision process and the cost or benefits that result from using these forecasts. Therefore, the statistical loss function is utilized in practice instead of economic loss function. The most widely used evaluation measures are Mean Square Error (MSE), Mean Absolute Error (MAE) expressed as:

$$MAE = \sum_{t=T+1}^{T+K} \frac{\left|\hat{\sigma}^2{}_t - \sigma^2{}_t\right|}{K} \qquad (3.20)$$

Root Mean Square Error (MSE) given by,

$$\text{RMSE} = \sqrt{\frac{\sum_{t=T+1}^{T+K}\left(\hat{\sigma}^2{}_t - \sigma^2{}_t\right)^2}{K}} \qquad (3.21)$$

Where, K is the number of steps ahead, T is the sample size, $\hat{\sigma}_t$ and $\sigma_t$ are the square root of the conditional forecasted volatility and the realized volatility respectively. Root Mean Square performance of alternative GARCH models in forecasting volatility is sensitive with the choice of Mean Square Error (RMSE), and Mean Absolute Percent Error (MAPE).

$$\text{MPE} = \frac{100}{K} \sum_{t=T+1}^{T+K} \left| \frac{\hat{\sigma}^2{}_t - \sigma^2{}_t}{\sigma_t} \right| \qquad (3.22)$$

Other evaluations frameworks have been introduced by a number of author such as Lopez (2001) with 'probability scoring rules'. In practice, when comparing the different models, it is rarely the case that one model dominate the other with respect to all evaluation measures. The common way to solve the problem is to carry out the average figures of some statistical measures and then compare the forecast models based on the parameter obtained (Hein, 2008).

## 3.11 Stylized facts about asset price volatility

A number of stylized facts about the volatility of financial asset prices have emerged over the years, and have been confirmed in numerous studies. The following are some of the stylized facts about asset price volatility.

### 3.11.1 Volatility exhibits persistence

The clustering of large moves and small moves (of either sign) in the price process was one of the first documented features of the volatility process of asset prices. Fame (1965) reported evidence that large changes in the price of an asset are often followed by other large changes and small changes are often followed by small changes. This behaviour has been reported by numerous other studies, such as Baillie, *et al.*, (1996), Chou (1988) and Schwert(1989). The implication of such volatility clustering is that volatility shocks today will influence the expectation of volatility many periods in the future.

## 3.12 Model Selection Criteria

Akaike Information Criteria (AIC,) and Schwarz Criteria (SIC) are the most commonly used model selection criteria

$$\text{AIC} = 2K - 2\ln(L) = 2K + \ln\left(\frac{RSS}{n}\right) \qquad (3.23)$$

where k is the number of parameters in the model and L is the maximized value of the likelihood function for the model and $RSS = \sum e^2$ is the residual sum of squares.

The main reason for preferring the use of a model selection procedure such as AIC in comparison to traditional significance tests is the fact that, a single holistic decision can be made concerning the model that is best supported by the data in contrast to what is usually a series of possibly conflicting significance test.

## 3.13 Volatility model

These models include the symmetric and asymmetric volatility models. The models are ARCH(1), ARCH(2), ARCH(3), GARCH(1, 1), GARCH(2, 1), GARCH(1, 2), GARCH(2, 2) E GARCH (1, 1), EGARCH (1, 2), EGARCH (2, 1), EGARCH (2, 2) and TARCH(1, 1). In each model we incorporated dummies variables as showed above.

## 3.14 Maximum likelihood

Under the presence of ARCH effects, the Ordinary Least Square estimation is not efficient and the estimate of covariance matrix of the parameters will be biased due to invalid‘t’ statistics. Therefore, ARCH-type models cannot be estimated by the simple technique such as OLS. The method known as the maximum-likelihood estimation is employed in ARCH models. Under the maximum-likelihood approach, a set of parameters are chosen that have most likely generated observed data, using an iterative computer algorithm like Berndt- Hall- Hall-Hausman or Marquardt algorithm in EViews 7.

Intuitively speaking, we assume that we have the correct models and obtain the distribution of error terms. From these, we can compute the probability that the observed data would actually occur as in the estimated model. The parameters, so-called maximum-likelihood parameters are chosen to maximize the probability. In Maximum likelihood estimation, each realization of $\varepsilon_t$ has the conditional variance $\sigma_t^2$, the joint likelihood of realization $\varepsilon_t$ through $\varepsilon_p$ is given as

$$L = \prod_{t=1}^{p} \left( \sqrt{\frac{1}{2\pi\sigma_t^2}} \right) \exp\left\{ -\frac{\varepsilon_t^2}{2\sigma_t^2} \right\} \qquad (3.24)$$

Taking the natural logarithm of both sides of the equation, we have the log likelihood function as:

$$\ln L = \frac{-p}{2} \ln(2\pi) - 0.5 \sum_{t=1}^{p} \sigma_t^2 - 0.5 \sum_{t=1}^{p} \left( \frac{\varepsilon_t^2}{\sigma_t^2} \right) \qquad (3.25)$$

# CHAPTER 4

# RESULTS

## 4.1 Introduction

This chapter presents a detailed analyses of the data collected. To really come out with a good model of daily return volatility of some of the Nigerian Insurance stocks, both the symmetric and asymmetric models were fitted to the return series. Various heteroscedastic models considered include ARCH (1), ARCH (2), ARCH (3), GARCH (1, 1), GARCH (2, 1), GARCH (1, 2), GARCH (2, 2), EGARCH (1, 1), EGARCH (1, 2), EGARCH (2, 1), EGARCH

(2, 2) and TARCH (1, 1) with each model incorporated with dummy variable as their independent variable to monitor the trend of the model in each of the stocks.

Furthermore, this Chapter also explains the properties of the return series, time plot for the return series, test for unit root, specification of the appropriate mean equation for return series, test for ARCH effect using Lagrange Multiplier, estimation of the parameters of the volatility models with incorporated dummy variable, selection of best of the twelve competing models and forecast performance evaluation of these models using Root Mean Square Error, Mean Absolute Error and Mean Absolute Percentage Error.

## 4.2 Properties of the data

An initial descriptive analysis of the ten Nigerian Insurance stocks were carried out and the result shown in Table 1. The obtained result as shown in Table 4.1, showed that the mean return series for some of the Insurance were negative indicating that these Insurances incurred loss during the period under study. Despite this loss, two of the Insurances still reported positive return. Also, the result of Jarque-Bera statistic revealed that the return series for all the Insurance were not normally distributed as the p-values were less than 1% and 5%.

Table 4.1: Descriptive Statistics of the return of Nigerian Insurance stocks.

| Insurance | Mean | Maximum | Minimum | Std. Dev. | Skewness | Kurtosis | Jarque-Bera | P-Value |
|---|---|---|---|---|---|---|---|---|
| AIICO | -0.000409 | 0.587787 | -0.70058 | 0.04386 | -1.65049 | 66.62714 | 558324.2 | 0.00000 |
| GUINEAINS | -0.000055 | 4.503507 | -4.50351 | 0.112138 | 0.001071 | 1577.041 | 341000000 | 0.00000 |
| GUINNESS | 0.000550 | 2.437514 | -2.36001 | 0.064577 | 1.251101 | 1158.406 | 184000000 | 0.00000 |
| LASACO | -0.000188 | 0.169076 | -0.74444 | 0.028115 | -6.43315 | 161.7233 | 3487869 | 0.00000 |
| LAWUNION | -0.000236 | 0.267204 | -0.36101 | 0.026082 | -0.75693 | 22.99468 | 55302.61 | 0.00000 |
| NEM | 0.000086 | 1.085189 | -1.08519 | 0.039406 | -0.01211 | 374.8869 | 19021994 | 0.00000 |
| NIGERINS | -0.000782 | 2.107812 | -2.10064 | 0.061868 | -0.10295 | 813.5779 | 90369905 | 0.00000 |
| PRESTIGE | -0.000517 | 1.499623 | -1.49962 | 0.050971 | -0.47472 | 468.2124 | 29767251 | 0.00000 |
| UNIC | -0.000495 | 0.300105 | -1.09861 | 0.037344 | -7.60834 | 233.1766 | 7318982 | 0.00000 |
| WAPIC | -0.000068 | 2.167385 | -2.20303 | 0.065371 | -0.72138 | 761.1758 | 79063428 | 0.00000 |

## 4.3 Stationary test (unit root test)

The stationarity of the return series were investigated by observing the time plot of the series. The figure obtained as presented in Appendix A revealed that the return series for all Insurances studied were all stationary. Also, a formal test of stationarity was also carried out using the Augmented Dickey- Fuller Test. The results obtained for each Insurance showed that the Augmented Dickey- Fuller test statistic were all less than their critical values at 1%, 5% and 10% as shown in Table 4.2. Hence, there is no unit root. The return series were all stationary. Therefore, there is no need for transformation.

Table 4.2: Augmented Dickey-Fuller Test of stationarity test (ADF) of the return series of Nigerian Insurance stocks.

| Insurances | ADF Test Statistic | Comment |
|---|---|---|
| AIICO | -59.0846 | Stationary at level without transformation |
| GUINEAINS | -21.7066 | Stationary at level without transformation |
| GUINNESS | -33.5573 | Stationary at level without transformation |
| LASACO | -26.3485 | Stationary at level without transformation |
| LAWUNION | -28.5031 | Stationary at level without transformation |
| NEM | -31.4748 | Stationary at level without transformation |
| NIGERINS | -50.2719 | Stationary at level without transformation |
| PRESTIGE | -48.5239 | Stationary at level without transformation |
| UNIC | -33.2005 | Stationary at level without transformation |
| WAPIC | -49.7348 | Stationary at level without transformation |

1% critical = -3.91, 5% critical = -3.41, 10% critical = -3.13

## 4.4 Specification of Mean Equation

Performing any of the conditional heteroscedastic models, the mean equation were specified. For the purpose, an autoregressive(AR) process, moving average process(MA) or a combination of AR and MA process(ARMA) may be specified, Suliman(2012). In order to identify the appropriate model to be fitted for the mean equation and to determine the order of the mean equation, the use of information criterion and the adoptions of principle of parsimony was used, which state that the best model is the simplest model that captures the important features of the data in order to bring out the best specification mean equation.

Hence, MA (2) was fitted for the return series of AIICO, WAPIC, MA (1) was fiited for the return series of GUINEAINS, GUINNESS, PRESTIG, MA (3) was fitted for the reurn series of LAWUNION, NEM, AR (3) was fitted for the return series of LASACO, UNIC while AR (2) was fitted for the return series of NIGERINS Insurance. The parameters of each of the ARand MA models were significant for most of the Insurance ($p<0.05$) as displayed in Table 4.3 and 4.4.

Table 4.3: Summary of the mean equation fitted for difference conditional heteroscedastic models of AIICO, GUINEAINS, GUINNESS, LASACO, and LAWUNIONInsurance.

| | | | Parameters Estimates | | | |
|---|---|---|---|---|---|---|
| Insurance | Model | Type | $\phi_0$ | $\phi_1$ | $\phi_2$ | $\phi_3$ |
| **AIICO** | **MA(2)** | ARCH(1) | -0.00296** | 0.04775** | 0.06641** | |
| | | ARCH(2) | -0.004168** | 0.17686** | 0.04424** | |
| | | ARCH(3) | -0.00254** | 0.15369** | 0.05196** | |
| | | GARCH(1, 1) | -0.00216** | 0.13964** | -0.06841** | |
| | | GARCH(1, 2) | -0.00358** | 0.11962** | 0.04799** | |
| | | GARCH(2, 1) | -0.00246* | 0.19085** | 0.05546** | |
| | | GARCH(2, 2) | -0.00255* | 0.18073** | 0.06345** | |
| | | E-GARCH(1, 1) | 1.66E-06 | 0.12425** | 0.02227 | |
| | | E-GARCH(1, 2) | 1.00E-05 | 0.09276** | 0.01670 | |
| | | E-GARCH(2, 1) | -0.00181** | 0.19730** | 0.06741** | |
| | | E-GARCH(2, 2) | -0.00135** | 0.19134** | 0.06964** | |
| | | TARCH(1, 1) | -0.00118 | 0.05632** | 0.06668** | |

| | | | | | | |
|---|---|---|---|---|---|---|
| **GUINEAINS** | **MA(1)** | ARCH(1) | -5.48E-05 | 0.03902 | | |
| | | ARCH(2) | -6.29E-05 | 0.08265 | | |
| | | ARCH(3) | -6.84E-05 | 0.07167 | | |
| | | GARCH(1, 1) | 1.04E-05 | 0.00181 | | |
| | | GARCH(1, 2) | 1.78E-05 | -0.00034 | | |
| | | GARCH(2, 1) | -0.00010 | 0.03632** | | |
| | | GARCH(2, 2) | 0.00028 | 0.02792 | | |
| | | E-GARCH(1, 1) | 3.06E-07 | 1.57E-09 | | |
| | | E-GARCH(1, 2) | 2.25E-07 | 5.00E-13 | | |
| | | E-GARCH(2, 1) | 5.30E-07 | -5.35E-05 | | |
| | | E-GARCH(2, 2) | -9.31E-07 | -3.19E-05 | | |
| | | TARCH(1, 1) | -5.42E-05 | 0.06578 | | |
| **GUINNESS** | **MA(1)** | ARCH(1) | -9.05E-05 | 0.02926** | | |
| | | ARCH(2) | -1.85E-05 | 0.06138** | | |
| | | ARCH(3) | -0.00193 | 0.03362 | | |
| | | GARCH(1, 1) | -2.15E-05 | 0.06055** | | |
| | | GARCH(1, 2) | -0.00065 | 0.12532 | | |
| | | GARCH(2, 1) | 0.01077** | 0.26974** | | |
| | | GARCH(2, 2) | 0.00040 | 0.33884** | | |
| | | E-GARCH(1, 1) | 0.00099** | 0.02877 | | |
| | | E-GARCH(1, 2) | 0.00096** | 0.01880 | | |
| | | E-GARCH(2, 1) | -0.00237** | 0.10936** | | |
| | | E-GARCH(2, 2) | -0.00298** | -0.01759** | | |
| | | TARCH(1, 1) | 0.00232** | -0.00940 | | |
| **LASACO** | **AR(3)** | ARCH(1) | -0.00149* | 0.29535** | 0.06352** | 0.03812* |
| | | ARCH(2) | -0.00134 | 0.23999** | 0.09710** | 0.04248 |
| | | ARCH(3) | -0.00138 | 0.26671** | 0.07981** | 0.05560* |
| | | GARCH(1, 1) | -7.82E-05 | 0.07503** | 0.03069 | -0.02363 |
| | | GARCH(1, 2) | -7.79E-05 | 0.03743 | 0.03813 | -0.02174 |
| | | GARCH(2, 1) | -8.92E-05 | 0.29789** | 0.06945** | 0.00457 |
| | | GARCH(2, 2) | -7.18E-05 | 0.02707 | 0.04798 | -0.02510 |
| | | E-GARCH(1, 1) | 4.39E-07** | 0.09324** | 0.44942** | -0.05885** |
| | | E-GARCH(1, 2) | 0.00023 | 0.63498** | 0.12366** | 0.24196** |
| | | E-GARCH(2, 1) | -0.00045 | 0.02378 | 0.33138** | 0.64541** |
| | | E-GARCH(2, 2) | 3.63E-07** | 0.31448** | 0.00011 | -0.00304 |
| | | TARCH(1, 1)) | -0.00129 | 0.28724** | 0.06161** | 0.04050* |
| **LAWUNION** | **MA(3)** | ARCH(1) | -0.00075 | 0.11654** | 0.11534** | 0.08697** |
| | | ARCH(2) | 0.00025 | 0.06285** | 0.30113** | 0.17806** |
| | | ARCH(3) | -0.00078** | -0.08141** | 0.11451** | 0.38124** |
| | | GARCH(1, 1) | -0.00011 | 0.07706** | 0.11279** | 0.04924* |
| | | GARCH(1, 2) | -6.57E-05 | 0.08141** | 0.09758** | 0.04947* |
| | | GARCH(2, 1) | -8/35E-05 | 0.07488** | 0.10972** | 0.04864* |
| | | GARCH(2, 2) | -7.87E-05 | 0.07651** | 0.10707** | 0.05119* |
| | | E-GARCH(1, 1) | -1.91E-07** | 0.09546** | 0.12415** | 0.10995** |
| | | E-GARCH(1, 2) | 1.91E-07** | 0.10724** | 0.12613** | 0.08243** |
| | | E-GARCH(2, 1) | -2.43E-07** | 0.12317** | 0.14196** | 0.09109** |
| | | E-GARCH(2, 2) | -2.90E-07** | 0.12074** | 0.15164** | 0.09599** |
| | | TARCH(1, 1) | -0.00076 | 0.11689** | 0.11526** | 0.08679** |

**** Significance at 1%, * Significance at 5%**

Table 4.4: Summary of the mean equation fitted for difference conditional heteroscedastic models ofNEM NIGERINS, PRESTIGE, UNIC and WAPIC Insurance.

| | | | Parameters Estimates | | | |
|---|---|---|---|---|---|---|
| Insurance | Model | Type | $\phi_0$ | $\phi_1$ | $\phi_2$ | $\phi_3$ |
| **NEM** | **MA(3)** | ARCH(1) | -0.00077 | 0.24198** | 0.12908** | 0.06401** |
| | | ARCH(2) | -0.00084 | 0.23800** | 0.11375** | 0.06015** |
| | | ARCH(3) | -0.00099 | 0.25237** | 0.11178** | 0.07782** |
| | | GARCH(1, 1) | -0.00079 | 0.25028** | 0.10299** | 0.06377** |
| | | GARCH(1, 2) | -0.00115 | 0.22782** | 0.11174** | 0.09484** |
| | | GARCH(2, 1) | -0.00254 | 0.24209** | 0.09949** | 0.03196** |
| | | GARCH(2, 2) | -0.00086 | 0.25098** | 0.10689** | 0.06262** |
| | | E-GARCH(1, 1) | -0.00140 | 0.23139** | 0.13309** | 0.06874** |
| | | E-GARCH(1, 2) | -0.00085 | 0.12065** | 0.09673** | 0.10758** |
| | | E-GARCH(2, 1) | -0.00206** | 0.23660** | 0.18504** | 0.23396** |
| | | E-GARCH(2, 2) | -0.00089 | 0.09751** | 0.10276** | 0.10180** |
| | | TARCH(1, 1) | -0.00095 | 0.24762** | 0.13576** | 0.06775** |

| | | | | | | |
|---|---|---|---|---|---|---|
| **NIGERINS** | **AR(2)** | ARCH(1) | -0.00354** | 0.43248** | -0.03428** | |
| | | ARCH(2) | 0.00055** | 0.23977** | -0.39066** | |
| | | ARCH(3) | -0.00219** | 0.23471** | 0.00617** | |
| | | GARCH(1, 1) | -0.00138* | 0.41785** | -0.02093 | |
| | | GARCH(1, 2) | -0.00157** | 0.41563** | -0.00224 | |
| | | GARCH(2, 1) | -0.00179** | 0.40597** | 0.02550 | |
| | | GARCH(2, 2) | 1.75E-08 | 0.28592** | 0.03244** | |
| | | E-GARCH(1, 1) | 6.76E-07** | 0.20235** | 0.08430** | |
| | | E-GARCH(1, 2) | 5.26E-07** | 0.13273** | 0.10810** | |
| | | E-GARCH(2, 1) | -0.00403** | 0.10548** | 0.13298** | |
| | | E-GARCH(2, 2) | -2.09E-07* | 0.17711** | 0.14773** | |
| | | TARCH(1, 1) | 0.00036** | 0.38692** | -0.03060** | |
| **PRESTIGE** | **MA(1)** | ARCH(1) | -0.00079 | 0.08691** | | |
| | | ARCH(2) | -0.00069 | 0.05360 | | |
| | | ARCH(3) | -0.00087 | 0.05200 | | |
| | | GARCH(1, 1) | -0.00055 | 0.08031* | | |
| | | GARCH(1, 2) | 0.00013 | 0.06432 | | |
| | | GARCH(2, 1) | -4.72E-05 | 0.02377 | | |
| | | GARCH(2, 2) | 0.00023 | 0.01411 | | |
| | | E-GARCH(1, 1) | -0.00251** | -0.13263** | | |
| | | E-GARCH(1, 2) | 1.88E-05 | 0.04341** | | |
| | | E-GARCH(2, 1) | -0.00064 | 0.03295* | | |
| | | E-GARCH(2, 2) | -0.00082 | 0.12827** | | |
| | | TARCH(1, 1) | -0.00055 | 0.07799** | | |
| **UNIC** | **AR(3)** | ARCH(1) | -0.00230** | 0.12945** | 0.10866** | -0.03333** |
| | | ARCH(2) | -0.00073** | 0.16153** | 0.36869** | -0.22476** |
| | | ARCH(3) | -0.00043** | 0.14448** | -0.28458** | 0.41347** |
| | | GARCH(1, 1) | -2.40E-05 | 0.06307* | 0.02836 | -0.08270** |
| | | GARCH(1, 2) | -2.43E-05 | 0.06062* | 0.03192 | -0.08020** |
| | | GARCH(2, 1) | -2.39E-05 | 0.06042* | 0.02990 | -0.07775** |
| | | GARCH(2, 2) | -2.12E-05 | 0.05996* | 0.03025 | -0.07845** |
| | | E-GARCH(1, 1) | -5.00E-07** | 0.21819** | 0.17335** | 0.04887* |
| | | E-GARCH(1, 2) | 7.67E-07 | 0.23893** | 0.28080** | 0.08707** |
| | | E-GARCH(2, 1) | 5.45E-07** | 0.23526** | 0.13045** | 0.01799 |
| | | E-GARCH(2, 2) | -4.64E-07** | 0.22636** | 0.14161** | 0.04495* |
| | | TARCH(1, 1)) | -0.00094 | 0.13209** | 0.13543** | -0.01997 |
| **WAPIC** | **MA(2)** | ARCH(1) | -0.00463** | 0.34950** | 0.07519** | |
| | | ARCH(2) | -0.00748** | 0.28677** | 0.03826** | |
| | | ARCH(3) | -0.00669** | 0.38527** | 0.07065** | |
| | | GARCH(1, 1) | -0.00495** | 0.39920** | 0.05920** | |
| | | GARCH(1, 2) | -0.00495** | 0.39828** | 0.05713** | |
| | | GARCH(2, 1) | -0.01036** | 0.17166** | 0.03754 | |
| | | GARCH(2, 2) | -0.01523** | 0.19266** | 0.01408 | |
| | | E-GARCH(1, 1) | -0.00366** | 0.16085** | 0.08415** | |
| | | E-GARCH(1, 2) | -0.00244** | 0.22270** | 0.04361* | |
| | | E-GARCH(2, 1) | 0.00102 | 0.21793** | 0.04387* | |
| | | E-GARCH(2, 2) | 0.00177** | 0.24552** | 0.02604 | |
| | | TARCH(1, 1) | 0.00136 | 0.31707** | 0.07404** | |

**** Significance at 1%, * Significance at 5%**

## 4.5 Testing for ARCH Effect

After obtaining the mean equation for different Insurance stocks as discussed above, the residuals obtained were used to test for the presence of heteroscedasticity or ARCH effect. The Lagrange Multiplier (LM) test proposed by Engle (1982) was applied. The F Statistic and the P values obtained are summarized in Table 4.5. The results of F Statistic were significant at 1% for eight Insurance stock returns while two of the Insurance does not exhibit heteroscedasticity. Therefore we cannot run the heteroscedasticity model on them because they do not fulfill the condition of ARCH effect.

Table 4.5: Lagrange Multiplier test of the presence of ARCH effect

| Insurance | F Statistic | P- values |
|---|---|---|
| AIICO | 303.61 | 0.0000 |
| GUINEAINS | 0.0013 | 0.9710 |
| GUINNESS | 1087.58 | 0.0000 |
| LASACO | 0.1642 | 0.6853 |
| LAWUNION | 183.75 | 0.0000 |
| NEM | 1092.56 | 0.0000 |
| NIGERINS | 1092.76 | 0.0000 |
| PRESTIGE | 1079.61 | 0.0000 |
| UNIC | 10.79 | 0.0000 |
| WAPIC | 1091.77 | 0.0000 |

## 4.6 Estimation of Parameters for the Heteroskedastic Models with Dummy Variable

After ascertaining the fact that there is a presence of heteroscedasticity in the series, Twelve different heteroscedastic models were fitted by adding a dummy variable to the conditional variance model to test the significance of the hypothesis of the model on each of the model. These models comprise both symmetric and asymmetric models, the different model considered were ARCH (1), ARCH (2), ARCH (3), GARCH (1, 1), GARCH (1, 2), GARCH (2, 1), GARCH (2, 2), EGARCH (1, 1), EGARCH (1, 2), EGARCH (2, 1), EGARCH (2, 2) and TARCH (1, 1). For AIICO Insurance, all heteroscedastic models fitted had all their parameters significant ($p< 0.05$) except that some of the model in the abrupt shift showed a positive values with significant level of 0.01 as showed in table 4.6 and table 4.7 below.

Moreover, NEM, PRESTIGE and UNIC the parameters estimated were significant except the leverage effect of the TARCH (1, 1) model ($p>0.05$). For PRESTIGE Insurance, the indicator variable is positive throughout the models indicating that the shift was positive. I.e. government regime shift did not affect it. Results are presented in Table 4.6 and Table 4.7 with others Insurance stocks.

Table 4.6: Parameter Estimates of the heteroscedastic models of AIICO, GUINNESS, LAWUNION and NEM

| | | Parameters Estimates | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Insurances | Model | $\alpha_0$ | $\alpha_1$ | $\alpha_2$ | $\alpha_3$ | $\beta_1$ | $\beta_2$ | $\gamma$ | $\delta_1 D_{Shift}$ |
| AIICO | ARCH(1) | 0.000861** | 0.72940** | | | | | | 0.000147** |
| | ARCH(2) | 0.000700** | 0.412316** | 0.516570** | | | | | -2.32 x $10^{-5}$* |
| | ARCH(3) | 0.000702** | 0.412557** | 0.516548** | -0.001167 | | | | -2.36 x $10^{-5}$** |
| | GARCH(1, 1) | 4.81 x $10^{-5}$** | 0.528641** | | | -0.320052** | | | -4.60 x $10^{-5}$** |
| | GARCH(1, 2) | 0.001843* | 0.310132** | | | 0.440429** | -0.110176** | | -9.25 x $10^{-5}$ |
| | GARCH(2, 1) | 0.000703** | 0.412493** | 0.517515** | | -0.002242 | | | -2.35 x $10^{-5}$* |
| | GARCH(2, 2) | 0.000704** | 0.412044** | 0.518978** | | -0.003354 | 0.00629 | | -2.29 x$10^{-5}$ |
| | E-GARCH(1, 1) | -0.214902** | 0.065416** | | | 0.016909** | | 0.972833** | -0.007654** |
| | E-GARCH(1, 2) | -0.213505** | 0.071962** | -0.002804 | | 0.031670** | 1.016937** | -0.042939 | 0.003011** |
| | E-GARCH(2, 1) | -1.035493** | 0.405694** | 0.048482** | | 0.128492** | | 0.876267** | -0.037338** |
| | E-GARCH(2, 2) | -0.448589** | 0.232128** | | | 0.069805** | 0.235766** | 0.719694** | -0.026649** |
| | TARCH(1, 1) | 0.000868** | 1.015785** | | | -0.641668** | | -0.320052** | 0.000172** |
| GUINNESS | ARCH(1) | 0.004142** | 0.176437** | | | | | | -0.003991** |
| | ARCH(2) | 0.000308** | 3.203975** | 0.028851** | | | | | -7.91 x $10^{-5}$** |
| | ARCH(3) | 0.004133** | 0.142449** | 6.57 x $10^{-5}$ | -0.000746** | | | | -0.003628** |
| | GARCH(1, 1) | 0.000363** | 5.678915** | | | -5.110868** | | | -0.000112** |
| | GARCH(1, 2) | 0.003409** | 2.854225** | | | -0.002376 | 0.001797 | | -0.003215** |
| | GARCH(2, 1) | 0.004080 | 0.138673** | -0.073473 | | 0.522728 | | | -0.003965 |
| | GARCH(2, 2) | 0.004142 | 0.196576** | -0.093979 | | 0.477563 | -0.004714 | | -0.004077 |
| | E-GARCH(1, 1) | -5.549953** | 1.365304** | | | 0.594444** | | 0.343897** | -0.030317* |
| | E-GARCH(1, 2) | -4.110825** | 0.159584** | | | -0.052359** | 1.387252** | -0.981015** | -0.267766** |
| | E-GARCH(2, 1) | -6.947548** | 1.311339** | 0.294884** | | 0.523658** | | 0.172873** | -0.098547** |
| | E-GARCH(2, 2) | -6.927521** | 1.302047** | 0.303727** | | 0.520277** | 0.167164** | 0.008454 | -0.100983** |
| | TARCH(1, 1) | 0.000363** | 5.684310** | | | 0.005136 | | -5.116270** | -0.000112** |
| LAWUNION | ARCH(1) | 0.000453** | 0.532188** | | | | | | -0.000209** |
| | ARCH(2) | 0.000372** | 0.455261** | 0.255742** | | | | | -0.000211** |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | ARCH(3) | 0.000302** | 0.407693** | 0.190474** | 0.258386** | | | | -0.000194** |
| | GARCH(1, 1) | 1.13 x $10^{-5}$** | 0.168003** | | | 0.051593** | | | -9.87 x $10^{-6}$** |
| | GARCH(1, 2) | 1.49 x $10^{-5}$** | 0.276092** | | | 0.267966** | 0.493133** | | -1.29 x $10^{-5}$** |
| | GARCH(2, 1) | 8.98 x $10^{-6}$** | 0.285134** | -0.118785** | | 0.855631** | | | -7.78 x $10^{-6}$** |
| | GARCH(2, 2) | 1.70 x $10^{-5}$** | 0.228645** | 0.098761** | | -0.017382 | 0.734773** | | -1.48 x $10^{-5}$** |
| | E-GARCH(1, 1) | -0.451078** | 0.268525** | | | -0.018169** | | 0.956946** | -0.047876** |
| | E-GARCH(1, 2) | -0.980625** | 0.121379** | | | 0.022217** | 0.451623** | 0.427186** | -0.067313** |
| | E-GARCH(2, 1) | 0.339725** | 0.440794** | -0.23657** | | -0.021795** | | 0.967728** | -0.035861** |
| | E-GARCH(2, 2) | -0.466532** | 0.420677** | -0.147345** | | -0.024897** | 0.738705** | 0.216679** | -0.047921** |
| | TARCH(1, 1) | 1.2 x $10^{-5}$** | 0.166717** | | | 0.831598** | | 0.055682** | -9.83 x $10^{-6}$** |
| NEM | ARCH(1) | 0.001190** | 0.349210** | | | | | | -0.000680** |
| | ARCH(2) | 0.001211** | 0.281492** | 0.221150** | | | | | -0.000847** |
| | ARCH(3) | 0.001190** | 0.265545** | 0.182405** | 0.181524** | | | | -0.000945** |
| | GARCH(1, 1) | 0.000412** | 0.292840** | | | 0.653475** | | | -0.000381** |
| | GARCH(1, 2) | 0.000490** | 0.297220** | | | 0.897124** | -0.232626** | | -0.000458** |
| | GARCH(2, 1) | 0.000455** | 0.261149** | 0.049446 | | 0.630360** | | | -0.000421** |
| | GARCH(2, 2) | 0.002033** | 0.218706** | 0.079893 | | 0.418112** | -0.085309** | | -0.001772** |
| | E-GARCH(1, 1) | -2.761874** | 0.348923** | | | 0.594471** | | 0.035363 | -0.474964** |
| | E-GARCH(1, 2) | -2.636114** | 0.338985** | | | 0.035320 | 0.719009** | -0.103746 | -0.441557** |
| | E-GARCH(2, 1) | -2.850477** | 0.346879** | 0.012137 | | 0.035046 | | 0.580553** | -0.495016** |
| | E-GARCH(2, 2) | -0.317840** | 0.526263** | -0.493989** | | 0.028090** | 1.985812** | -1.027633** | 0.001204 |
| | TARCH(1, 1) | 0.000437** | 0.254763** | | | 0.661106** | | 0.059178 | -0.000407** |

****significance at 1%, * significance at 5%**

Table 4.7: Parameter Estimates of the heteroscedastic models of NIGERINS, PRESTIGE, UNIC and WAPIC

| | | Parameters Estimates | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Insurances | Model | $\alpha_0$ | $\alpha_1$ | $\alpha_2$ | $\alpha_3$ | $\beta_1$ | $\beta_2$ | $\gamma$ | $\delta_1 D_{Shift}$ |
| NIGERINS | ARCH(1) | 0.000569** | 2.411643** | | | | | | 0-000197** |
| | ARCH(2) | 0.000396** | 0.457784** | 1.797308** | | | | | -0.000122** |
| | ARCH(3) | 0.000281** | 0.400595** | 1.913240** | 0.170278** | | | | -4.03 x $10^{-5}$** |
| | GARCH(1, 1) | 2.55 x $10^{-5}$** | 1.107434** | | | -0.713453** | | | -2.18 x $10^{-5}$** |
| | GARCH(1, 2) | 0.000774** | 0.911256** | | | 0.395912** | 0.192960** | | -0.000766** |
| | GARCH(2, 1) | 3.07 x $10^{-5}$** | 0.369194** | 0.480764** | | 0.691948** | | | -2.59 x $10^{-5}$** |
| | GARCH(2, 2) | 6.07 x $10^{-5}$** | 0.246357** | 1.216567** | | 0.021147** | 0.429776** | | -5.13 x $10^{-5}$** |
| | E-GARCH(1, 1) | -1.201204** | 1.091828** | | | 0.555485** | | 0.863769** | -0.269194** |
| | E-GARCH(1, 2) | -0.299011** | 0.137050** | | | 0.103992** | 0.044508** | 0.921806** | -0.007308** |
| | E-GARCH(2, 1) | -1.695976** | 0.132956** | 0.617107** | | 0.099629** | | 0.736092** | -0.162614** |
| | E-GARCH(2, 2) | -6.22795** | 0.485505** | 0.564740** | | 0.409586** | 0.072541** | 0.147713** | -0.352482** |
| | TARCH(1, 1) | 2.5 x $10^{-5}$** | 1.106952** | | | 0.740445** | | -0.713044** | -2.16 x $10^{-5}$** |
| PRESTIGE | ARCH(1) | 0.001622** | 0.381281** | | | | | | 0.002212** |
| | ARCH(2) | 0.000399** | 0.300501** | 0.444226** | | | | | 0.002536** |
| | ARCH(3) | 0.000776* | 0.255295** | 0.244930** | -0.001434** | | | | 0.001895** |
| | GARCH(1, 1) | 0.000124** | 0.343015** | | | 0.584547** | | | 0.001086** |
| | GARCH(1, 2) | 0.000189** | 0.306789** | | | 0.700160** | - | | 0.002139** |
| | GARCH(2, 1) | 0.002403** | 0.080574** | -0.042101** | | 0.502210** | 0.165881** | | 0.000257** |
| | GARCH(2, 2) | 0.002469 | 0.077297** | -0.037866 | | 0.456860 | | | 0.000273 |
| | E-GARCH(1, 1) | -0.284985** | 0.042581** | | | -0.017395** | 0.017086 | 0.961111** | 0.053088** |
| | E-GARCH(1, 2) | -0.680407** | 0.183025** | | | -0.012592** | | 0.444352** | 0.168226** |
| | E-GARCH(2, 1) | -1.481429** | 0.225856** | 0.010699 | | 0.003500 | 0.472859** | 0.807790** | 0.386868** |
| | E-GARCH(2, 2) | -1.043110** | 0.257289** | -0.040400 | | -0.006191 | | 0.188253 | 0.260315** |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | TARCH(1, 1) | 0.000127** | 0.377383** | | | 0.586002** | 0.681939 | -0.082956 | 0.001158** |
| UNIC | ARCH(1) | 0.000892** | 0.922466** | | | | | | -0.000792** |
| | ARCH(2) | 0.000737** | 0.674998** | 0.409029** | | | | | -0.000702** |
| | ARCH(3) | 0.000659** | 0.585304** | 0.240969** | 0.285278** | | | | -0.000650** |
| | GARCH(1, 1) | 0.001268** | 0.333989** | | | 0.525055** | | | -0.001266** |
| | GARCH(1, 2) | 0.001275** | 0.219732** | | | 0.512936** | 0.026444 | | -0.001274** |
| | GARCH(2, 1) | 0.001277** | 0.165640** | 0.078663** | | 0.514105** | | | -0.001276** |
| | GARCH(2, 2) | 0.001286** | 0.160815** | 0.083924* | | 0.462501** | 0.024886 | | -0.001284** |
| | E-GARCH(1, 1) | -0.389482** | 0.192889** | | | -0.052131** | | | -0.038210** |
| | E-GARCH(1, 2) | -0.240392** | 0.128505** | | | -0.028767** | 0.532535* | 0.965301** | 0.007753** |
| | E-GARCH(2, 1) | -0.176364** | 0.269192** | -0.158864* | | -0.024051** | | 0.450057** | 0.011481** |
| | E-GARCH(2, 2) | -0.376363** | 0.171840** | 0.028003** | | -0.077531** | 0.438586** | 0.986282** | -0.055469** |
| | TARCH(1, 1) | 0.001287** | 0.262833** | | | 0.545749** | | 0.0003555 | -0.001286** |
| WAPIC | ARCH(1) | 0.000725** | 1.788643** | | | | | | -0.000155** |
| | ARCH(2) | 0.000662** | 1.790699** | 0.156249** | | | | | -0.000292** |
| | ARCH(3) | 0.003750** | 0.334744** | 0.161726** | -0.000872** | | | | -0.000325** |
| | GARCH(1, 1) | 0.001792** | 0.474146** | | | 0.050508** | | | -0.001618** |
| | GARCH(1, 2) | 0.000595** | 1.925519** | | | 0.081577** | -0.002749 | | -0.000272** |
| | GARCH(2, 1) | 0.000799** | 2.828744** | 0.141375** | | -0.001782** | | | -0.000488** |
| | GARCH(2, 2) | $2.70 \times 10^{-5}$** | 1.168353** | -0.943461** | | 0.858555** | - | | $-2.41 \times 10^{-5}$** |
| | E-GARCH(1, 1) | -5.040781** | 1.255809** | | | 0.596857** | 0.027777** | 0.361576** | -0.046490 |
| | E-GARCH(1, 2) | -5.273761** | 1.266183** | | | 0.595229* | | -0.061643* | -0.041490 |
| | E-GARCH(2, 1) | -7.857651** | 1.116577** | 0.625484** | | 0.613013** | 0.388317** | -0.030337 | -0.153876** |
| | E-GARCH(2, 2) | -7.430896** | 1.103515** | 0.705319** | | 0.597730** | | 0.113779** | -0.201297** |
| | TARCH(1, 1) | 0.000651** | 3.228761** | | | 0.051865** | -0.073731 | - 2.801941** | -0.000141** |

****significance at 1%, * significance at 5%**

## 4.7 Model Selection Criteria and Goodness of fit

Out of the twelve competing models, the selection of the model that could give best prediction was carried out using Akaike Info Criteria (AIC, 1973) and Schwarz Information Criterion (SIC, 1978) and the log-likelihood for the goodness of fit . Schwarz Information has been considered to be the best of these criteria to as SIC give the heaviest penalties for loss of degrees of freedom (Afees and Ismail,2012) and values with a bold SIC are considered for selection of best models and the corresponding Log likelihood with the SIC to be the best goodness of fit. Hence, it was EGARCH (2, 2) for AIICO, NEM, WAPIC and EGARCH (2, 1) for GUINNESS, LAWUNION, UNIC and TARCH (1, 1) for NIGERINS and PRESTIGE. Results are presented in Table 4.8 and Table 4.9.

Table 4.8: Model Selection and Goodness of fit criteria and diagnostic checking of AIICO GUINNESS, LAWUNION and NEM

| | | Model selection Criteria | | | Diagnostic check for ARCH Effect | |
|---|---|---|---|---|---|---|
| Insurances | Model | Log-Likelihood | AIC | SIC | F statistic | P value |
| AIICO | ARCH(1) | 6045.050 | -3.660133 | -3.662739 | 0.023563 | 0.8658 |
| | ARCH(2) | 6101.796 | -3.693903 | -3.684666 | 0.007724 | 0.9300 |
| | ARCH(3) | 6101.875 | -3.693350 | -3.682259 | 0.007712 | 0.9300 |
| | GARCH(1, 1) | 6219.597 | -3.765281 | -3.756039 | 0.002649 | 0.9590 |
| | GARCH(1, 2) | 5591.796 | -3.384305 | -3.373214 | 0.731843 | 0.3923 |
| | GARCH(2, 1) | 6101.874 | -3.693350 | -3.682259 | 0.007732 | 0.9299 |
| | GARCH(2, 2) | 6101.874 | -3.692744 | -3.679805 | 0.007865 | 0.9293 |
| | E-GARCH(1, 1) | 6091.083 | -3.686812 | -3.675721 | 94.92425 | 0.0000 |
| | E-GARCH(1, 2) | 6128.344 | -3.708782 | -3.695842 | 57.23603 | 0.0000 |
| | E-GARCH(2, 1) | 6258.722 | -3.787755 | -3.774832 | 0.017820 | 0.8938 |
| | **E-GARCH(2, 2)** | **6319.827** | **-3.824191** | **-3.809403** | 0.326808 | 0.5676 |
| | TARCH(1, 1) | 6246.355 | -3.780888 | -3.769797 | $1.03 \times 10^{-8}$ | 0.9992 |
| GUINNESS | ARCH(1) | 5982.689 | -3.622350 | -3.614950 | 0.047890 | 0.8268 |
| | ARCH(2) | 7112.285 | -4.306140 | -4.296898 | 0.004435 | 0.9469 |
| | ARCH(3) | 6051.456 | -3.662803 | -3.651712 | 0.076088 | 0.7827 |
| | GARCH(1, 1) | 5881.237 | -3.560277 | -3.551034 | 0.001440 | 0.9697 |
| | GARCH(1, 2) | 6318.345 | -3.824505 | -3.813414 | 0.006886 | 0.9339 |
| | GARCH(2, 1) | 5826.806 | -3.526692 | -3.515601 | 0.443412 | 0.5055 |
| | GARCH(2, 2) | 5886.497 | -3.563464 | -3.550524 | 0.173199 | 0.6773 |
| | E-GARCH(1, 1) | 7424.154 | -4.494489 | -4.483398 | 0.031588 | 0.8589 |
| | E-GARCH(1, 2) | 6637.697 | -4.017387 | -4.004447 | 75.19469 | 0.0000 |
| | **E-GARCH(2, 1)** | **7427.089** | **-4.495661** | **-4.482721** | 0.023469 | 0.8783 |
| | E-GARCH(2, 2) | 7427.085 | -4.495053 | -4.80265 | 0.018841 | 0.8908 |
| | TARCH(1, 1) | 7300.223 | -4.419402 | -4.408311 | 0.008973 | 0.9245 |
| LAWUNION | ARCH(1) | 7766.867 | -4.703343 | -4.695949 | 0.057020 | 0.8113 |
| | ARCH(2) | 7875.705 | -4.768679 | -4.759436 | 0.016039 | 0.8993 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | ARCH(3) | 7991.378 | -4.838157 | -4.827066 | 0.092906 | 0.7605 |
| | GARCH(1, 1) | 8731.146 | -5.286971 | -5.277729 | 3.313763 | 0.0688 |
| | GARCH(1, 2) | 8742.428 | -5.293201 | -5.282110 | 1.095194 | 0.2954 |
| | GARCH(2, 1) | 8741.210 | -5.292463 | -5.281370 | 0.953929 | 0.3288 |
| | GARCH(2, 2) | 8743.204 | -5.293065 | -5.280125 | 2.252450 | 0.1335 |
| | E-GARCH(1, 1) | 8962.703 | -5.426660 | -5.415569 | 12.21933 | 0.0000 |
| | E-GARCH(1, 2) | 8080.650 | -4.891689 | -4.878699 | 46.53113 | 0.0000 |
| | **E-GARCH(2, 1)** | **9043.422** | **-5.474960** | **-5.462021** | 0.367288 | 0.5445 |
| | E-GARCH(2, 2) | 8997.851 | -5.446744 | -5.431956 | 0.735968 | 0.3910 |
| | TARCH(1, 1) | 8735.242 | -5.28847 | -5.277756 | 2.797523 | 0.0945 |
| NEM | ARCH(1) | 6654.086 | -4.029134 | -4.021740 | 0.015385 | 0.9013 |
| | ARCH(2) | 6675.085 | -4.041251 | -4.032008 | 0.033424 | 0.8549 |
| | ARCH(3) | 6699.606 | -4.055502 | -4.044411 | 0.039862 | 0.8418 |
| | GARCH(1, 1) | 6713.959 | -4.064804 | -4.055562 | 0.032062 | 0.8579 |
| | GARCH(1, 2) | 6697.307 | -4.054109 | -4.043018 | 0.059223 | 0.8077 |
| | GARCH(2, 1) | 6713.118 | -4.063688 | -4.052597 | 0.050222 | 0.8227 |
| | GARCH(2, 2) | 6378.151 | -3.860134 | -3.847194 | 0.812828 | 0.3674 |
| | E-GARCH(1, 1) | 6671.191 | -4.038286 | -4.027195 | 0.000815 | 0.9772 |
| | E-GARCH(1, 2) | 6671.451 | -4.037837 | -4.024898 | 0.000732 | 0.9784 |
| | E-GARCH(2, 1) | 6670.871 | -4.037486 | -4.024547 | 0.000680 | 0.9792 |
| | **E-GARCH(2, 2)** | **7022.910** | **-4.250173** | **-4.235385** | 0.120800 | 0.7282 |
| | TARCH(1, 1) | 6710.006 | -4.061803 | -4.050712 | 0.034329 | 0.8530 |

**AIC is the Info Criteria, SIC is the Schwarz info criterion, Log is the log likelihood**

**Bolded SIC and Log Likelihood are the best model and goodness of fit criteria.**

Table 4.9: Model Selection and Goodness of fit criteria and diagnostic checking of NIGERINS, PRESTIGE, UNIC and WAPIC.

| | | Model selection Criteria | | | | |
|---|---|---|---|---|---|---|
| Insurances | Model | Log-Likelihood | AIC | SIC | F statistic | P value |
| NIGERINS | ARCH(1) | 6041.817 | -3.658174 | -3.650780 | 0.013995 | 0.9058 |
| | ARCH(2) | 6338.803 | -3.837505 | -3.828263 | 0.011229 | 0.9156 |
| | ARCH(3) | 6378.672 | -3.861055 | -3.849964 | 0.023157 | 0.8791 |
| | GARCH(1, 1) | 6865.353 | -4.156530 | -4.147287 | $7.66 \times 10^{-6}$ | 0.9978 |
| | GARCH(1, 2) | 6443.547 | -3.900362 | -3.889271 | $1.89 \times 10^{-11}$ | 1.0000 |
| | GARCH(2, 1) | 6874.028 | -4.161180 | -4.150089 | 0.018535 | 0.8917 |
| | **GARCH(2, 2)** | **6964.494** | **-4.215386** | **-4.202446** | 0.092115 | 0.7615 |
| | E-GARCH(1, 1) | 6918.048 | -4.187351 | -4.176760 | 0.012121 | 0.9123 |
| | E-GARCH(1, 2) | 6128.450 | -3.708846 | -3.695906 | 851.8590 | 0.0000 |
| | E-GARCH(2, 1) | 6230.074 | -3.770418 | -3.757478 | 177.7913 | 0.0000 |
| | E-GARCH(2, 2) | 6347.140 | -3.840739 | -3.825951 | 659.1661 | 0.0000 |
| | TARCH(1, 1) | 6880.248 | -4.164949 | -4.153858 | 0.011420 | 0.9149 |
| PRESTIGE | ARCH(1) | 6071.889 | -3.696394 | -3.669000 | 0.006891 | 0.9338 |
| | ARCH(2) | 6163.899 | -3.731535 | -3.722293 | 0.017037 | 0.8962 |
| | ARCH(3) | 6085.502 | -3.683430 | -3.672339 | 0.042095 | 0.8375 |
| | **GARCH(1, 1)** | **6176.482** | **-3.739159** | **-3.729916** | 0.005523 | 0.9408 |
| | GARCH(1, 2) | 6104.832 | -3.695142 | -3.684051 | 0.052522 | 0.8187 |
| | GARCH(2, 1) | 5102.288 | -3.087724 | -3.076632 | 3.079360 | 0.0794 |
| | GARCH(2, 2) | 5128.262 | -3.102855 | -3.089915 | 3.188343 | 0.0743 |
| | E-GARCH(1, 1) | 5887.479 | -3.563453 | -3.552362 | 560.7922 | 0.0000 |
| | E-GARCH(1, 2) | 6161.531 | -3.728889 | -3.715949 | 0.411519 | 0.5212 |
| | E-GARCH(2, 1) | 6128.065 | -3.708612 | -3.695673 | 0.106498 | 0.7442 |
| | E-GARCH(2, 2) | 6166,719 | -3.731426 | -3.716638 | 0.003799 | 0.9509 |
| | TARCH(1, 1) | 6177.254 | -3.727930 | -3.727930 | 0.005359 | 0.9414 |

| | | | | | | |
|---|---|---|---|---|---|---|
| UNIC | ARCH(1) | 7286.944 | -4.412568 | -4.405174 | 0.095173 | 0.7577 |
| | ARCH(2) | 7688.622 | -4.655330 | -4.646087 | 0.021590 | 0.8832 |
| | ARCH(3) | 8252.387 | -4.996297 | -4.985205 | 0.002862 | 0.9573 |
| | GARCH(1, 1) | 8697.586 | -5.266638 | -5.257395 | 0.000376 | 0.9845 |
| | GARCH(1, 2) | 8649.952 | -5.237172 | -5.226080 | 0.006041 | 0.9380 |
| | GARCH(2, 1) | 8616.648 | -5.216994 | -5.205902 | 0.048111 | 0.8264 |
| | GARCH(2, 2) | 8641.043 | -5.231168 | -5.218228 | 0.053066 | 0.8178 |
| | E-GARCH(1, 1) | 8988.611 | -5.442358 | -5.431266 | 0.102757 | 0.7486 |
| | E-GARCH(1, 2) | 9187.473 | -5.562237 | -5.549298 | 0.046806 | 0.8287 |
| | **E-GARCH(2, 1)** | **9258.969** | **-5.605556** | **-5.592616** | 0.033931 | 0.8539 |
| | E-GARCH(2, 2) | 9137.266 | -5.531212 | -5.516424 | 0.004915 | 0.9441 |
| | TARCH(1, 1) | 8669.908 | -5.249263 | -5.238171 | 0.002572 | 0.9596 |
| WAPIC | ARCH(1) | 5848.465 | -3.541027 | -3.533633 | 0.000183 | 0.9892 |
| | ARCH(2) | 5876.886 | -3.557641 | -3.548398 | 0.000333 | 0.9854 |
| | ARCH(3) | 5442.712 | -3.293979 | -3.282887 | 0.021170 | 0.8843 |
| | GARCH(1, 1) | 5875.411 | -3.556747 | -3.547505 | 0.000194 | 0.9889 |
| | GARCH(1, 2) | 5874.766 | -3.555751 | -3.544659 | 0.000194 | 0.9896 |
| | GARCH(2, 1) | 5789.903 | -3.504334 | -3.493243 | 0.000169 | 0.9964 |
| | GARCH(2, 2) | 5982.443 | -3.620383 | -3.607444 | $2.07 \times 10^{-5}$ | 0.9829 |
| | E-GARCH(1, 1) | 6197.620 | -3.751360 | -3.740269 | 0.000462 | 0.8961 |
| | E-GARCH(1, 2) | 6200.209 | -3.752323 | -3.739383 | 0.017069 | 0.8892 |
| | E-GARCH(2, 1) | 6246.834 | -3.780572 | -3.767632 | 0.019415 | 0.9531 |
| | **E-GARCH(2, 2)** | **6253.674** | **-3.784111** | **-3.769322** | 0.003459 | 0.9582 |
| | TARCH(1, 1) | 6029.095 | -3.649255 | -3.638163 | 0.014998 | 0.9025 |

**AIC is the Info Criteria, SIC is the Schwarz info criterion, Log is the log likelihood**

**Bolded SIC and Log Likelihood are the best model and goodness of fit criteria.**

## 4.8 Model Diagnostic Checking

After fitting different heteroscedastic model, effort was also made to check if the ARCH effect was still present. This diagnosis was performed using the Lagrange Multiplier test (ARCH- LM test). The results obtained revealed that the ARCH effects initially present were totally removed by each of the heteroscedastic model considered up to lag 10. The F Statistic was very low for most of the models and the probability values were also greater than 0.05 for all models fitted. Therefore, heteroscedasticity which was initially present has been completely removed by each of the heteroscedastic models considered. Results obtained were presented in Table 4.8 and Table 4.9.

## 4.9 Forecasting the performance of Estimated Models

Forecasting performance of these estimated models were investigated using our sample data and statistics like Root Mean Square Error, Mean Absolute Error as well as the Mean Absolute Percentage error were computed. Model with the smallest Mean Square Error was considered to the most suitable for forecasting. Hence, from the results obtained showed that some Insurance stocks are having model than one model suitable. Therefore we are going to adopt the Principle of Parsimony – "that the best model is the simplest model that can captures the important features of the data". Hence EGARCH (1, 1) proved to most suitable for AIICO and NEM, LAWUNION is EGARCH (2, 1), GUINNESS is GARCH (1, 2) while ARCH (1) for NIGERINS, UNIC and WAPIC while ARCH (2) suitable for PRESTIGE. The results are shown in Table 4.10 and 4.11.

Table 4.10: Forecast Performance of estimated model of AIICO, GUINNESS, LAWUNION and NEM.

| Insurance | Heteroscedastic models | Statistic | | |
|---|---|---|---|---|
| | | RMSE | MAE | MAPE |
| AIICO | ARCH(1) | 0.043916 | 0.026295 | 66.24321 |
| | ARCH(2) | 0.043969 | 0.026578 | 66.32234 |
| | ARCH(3) | 0.043969 | 0.026576 | 66.32053 |
| | GARCH(1, 1) | 0.043856 | 0.025684 | 66.49007 |
| | GARCH(1, 2) | 0.044286 | 0.027610 | 67.56222 |
| | GARCH(2, 1) | 0.043969 | 0.026576 | 66.32090 |
| | GARCH(2, 2) | 0.043969 | 0.026576 | 66.32070 |
| | E-GARCH(1, 1) | **0.043855** | 0.025399 | 66.67920 |
| | E-GARCH(1, 2) | **0.043855** | 0.025401 | 66.68043 |
| | E-GARCH(2, 1) | **0.043855** | 0.025395 | 66.67687 |
| | E-GARCH(2, 2) | **0.043855** | 0.025396 | 66.67734 |
| | TARCH(1, 1) | **0.043855** | 0.025684 | 66.49007 |
| GUINNESS | ARCH(1) | 0.039412 | 0.016955 | 43.56628 |
| | ARCH(2) | 0.039411 | 0.016939 | 43.57113 |
| | ARCH(3) | 0.039410 | 0.016921 | 43.57648 |
| | GARCH(1, 1) | 0.039406 | 0.016807 | 43.61010 |
| | GARCH(1, 2) | **0.039403** | 0.016715 | 43.63736 |
| | GARCH(2, 1) | 0.039406 | 0.016802 | 43.61165 |
| | GARCH(2, 2) | 0.039414 | 0.016996 | 43.55442 |
| | E-GARCH(1, 1) | 0.039405 | 0.016779 | 43.61840 |
| | E-GARCH(1, 2) | **0.039403** | 0.016715 | 43.63736 |

| | | | | |
|---|---|---|---|---|
| | E-GARCH(2, 1) | 0.039405 | 0.016758 | 43.62453 |
| | E-GARCH(2, 2) | 0.039406 | 0.016725 | 43.61436 |
| | TARCH(1, 1) | 0.039411 | 0.016949 | 43.56814 |
| LAWUNION | ARCH(1) | 0.026086 | 0.014222 | 35.00189 |
| | ARCH(2) | 0.026085 | 0.014204 | 35.00426 |
| | ARCH(3) | 0.026079 | 0.013969 | 35.03598 |
| | GARCH(1, 1) | 0.026078 | 0.013797 | 35.05909 |
| | GARCH(1, 2) | 0.026078 | 0.013786 | 35.06050 |
| | GARCH(2, 1) | 0.026078 | 0.013787 | 35.06034 |
| | GARCH(2, 2) | 0.026078 | 0.013787 | 35.06043 |
| | E-GARCH(1, 1) | 0.026079 | 0.013639 | 35.08029 |
| | E-GARCH(1, 2) | 0.026079 | 0.013639 | 35.08028 |
| | E-GARCH(2, 1) | **0.026076** | 0.013521 | 35.06023 |
| | E-GARCH(2, 2) | 0.026079 | 0.013639 | 35.08025 |
| | TARCH(1, 1) | 0.026078 | 0.013812 | 35.05708 |
| NEM | ARCH(1) | 0.039412 | 0.016954 | 43.56684 |
| | ARCH(2) | 0.039411 | 0.016938 | 43.57145 |
| | ARCH(3) | 0.039411 | 0.016930 | 43.57370 |
| | GARCH(1, 1) | 0.039406 | 0.016800 | 43.61229 |
| | GARCH(1, 2) | 0.039406 | 0.016800 | 43.61233 |
| | GARCH(2, 1) | 0.039406 | 0.016802 | 43.61157 |
| | GARCH(2, 2) | 0.039414 | 0.016996 | 43.55443 |
| | E-GARCH(1, 1) | **0.039405** | 0.016776 | 43.61930 |
| | E-GARCH(1, 2) | **0.039405** | 0.016766 | 43.62253 |
| | E-GARCH(2, 1) | 0.039414 | 0.017002 | 43.55257 |
| | E-GARCH(2, 2) | 0.039416 | 0.017042 | 43.54060 |
| | TARCH(1, 1) | 0.039426 | 0.017209 | 43.49129 |

**Bolded values are the least values of RMSE. RMSE is the Root Mean Square Error.**

Table 4.11: Forecast Performance of estimated model of NIGERINS, PRESTIGE, UNIC and WAPIC.

| Insurance | Heteroscedastic models | Statistic | | |
|---|---|---|---|---|
| | | RMSE | MAE | MAPE |
| NIGERINS | ARCH(1) | **0.060377** | 0.020892 | 57.20856 |
| | ARCH(2) | 0.060378 | 0.020952 | 58.07010 |
| | ARCH(3) | 0.061892 | 0.023027 | 51.17111 |
| | GARCH(1, 1) | 0.060416 | 0.023198 | 51.60603 |
| | GARCH(1, 2) | 0.060442 | 0.023157 | 52.91916 |
| | GARCH(2, 1) | 0.061552 | 0.023471 | 52.02622 |
| | GARCH(2, 2) | 0.061406 | 0.023289 | 51.89754 |
| | E-GARCH(1, 1) | 0.061864 | 0.021661 | 50.92395 |
| | E-GARCH(1, 2) | 0.061864 | 0.021662 | 50.92393 |
| | E-GARCH(2, 1) | 0.061864 | 0.021661 | 50.92396 |
| | E-GARCH(2, 2) | 0.061864 | 0.021661 | 50.92396 |
| | TARCH(1, 1) | 0.061587 | 0.023605 | 51.43241 |

| | | | | |
|---|---|---|---|---|
| PRESTIGE | ARCH(1) | 0.050967 | 0.018683 | 39.31535 |
| | ARCH(2) | **0.050963** | 0.018352 | 39.21700 |
| | ARCH(3) | **0.050963** | 0.018234 | 39.19354 |
| | GARCH(1, 1) | **0.050963** | 0.018387 | 39.22383 |
| | GARCH(1, 2) | 0.050966 | 0.018256 | 39.19802 |
| | GARCH(2, 1) | 0.050972 | 0.017997 | 39.13251 |
| | GARCH(2, 2) | 0.050965 | 0.018231 | 39.08664 |
| | E-GARCH(1, 1) | 0.050965 | 0.017978 | 39.14307 |
| | E-GARCH(1, 2) | 0.050974 | 0.017965 | 39.14045 |
| | E-GARCH(2, 1) | 0.050974 | 0.018935 | 39.45446 |
| | E-GARCH(2, 2) | 0.050965 | 0.017974 | 39.14225 |
| | TARCH(1, 1) | 0.050964 | 0.018387 | 39.22383 |
| UNIC | ARCH(1) | **0.037339** | 0.021143 | 52.39968 |
| | ARCH(2) | **0.037339** | 0.020926 | 52.45966 |
| | ARCH(3) | 0.037340 | 0.020841 | 52.48334 |
| | GARCH(1, 1) | 0.037340 | 0.020856 | 52.47930 |
| | GARCH(1, 2) | **0.037339** | 0.020896 | 52.46822 |
| | GARCH(2, 1) | 0.037346 | 0.020909 | 52.53300 |
| | GARCH(2, 2) | 0.037340 | 0.020828 | 52.48704 |
| | E-GARCH(1, 1) | 0.037342 | 0.020784 | 52.49921 |
| | E-GARCH(1, 2) | 0.037342 | 0.020784 | 52.49928 |
| | E-GARCH(2, 1) | 0.037342 | 0.020784 | 52.49921 |
| | E-GARCH(2, 2) | 0.037342 | 0.020784 | 52.49920 |
| | TARCH(1, 1) | **0.037339** | 0.020788 | 52.47030 |
| WAPIC | ARCH(1) | **0.017852** | 0.012190 | 30.46455 |
| | ARCH(2) | 0.017853 | 0.012136 | 30.53715 |
| | ARCH(3) | 0.017400 | 0.015122 | 39.42793 |
| | GARCH(1, 1) | 0.018179 | 0.010530 | 32.69196 |
| | GARCH(1, 2) | 0.018098 | 0.010750 | 34.38379 |
| | GARCH(2, 1) | 0.018568 | 0.016399 | 33.65042 |
| | GARCH(2, 2) | 0.018148 | 0.018665 | 37.38135 |
| | E-GARCH(1, 1) | 0.018507 | 0.016031 | 38.92679 |
| | E-GARCH(1, 2) | 0.018498 | 0.015976 | 38.82007 |
| | E-GARCH(2, 1) | 0.018410 | 0.015242 | 39.59612 |
| | E-GARCH(2, 2) | 0.018427 | 0.015414 | 39.84669 |
| | TARCH(1, 1) | 0.018095 | 0.015074 | 38.56607 |

**Bolded values are the least values of RMSE. RMSE is the Root Mean Square Error.**

## 4.10 Recommended Models for Volatility Forecast

The recommendation of the best model to be used among the twelve competing models in forecasting was based on the Root Mean Square statistics and not AIC or SIC. This is because scholars like (Lopez 2001) suggested that the good performance in parameters estimates models and model selection of fitted statistics like Aikaike Information criteria (AIC), Schwarz Criterion (SC) and other criteria do not guarantee accurate of forecast of any volatility models. He added that the forecast evaluation statistics like Root Mean Square Error (RMSE), Mean Absolute Error

should be used instead of model selection of fitted statistics. Hence, based on the Root Mean Square Error, the EGARCH (1, 1) was suitable for AIICO and NEM, LAWUNION EGARCH (2, 1), GUINNESS GARCH (1, 2), ARCH (1) for NIGERINS, UNIC and WAPIC while ARCH (2) suitable for PRESTIGE. But looking at the Insurance and by evaluation one can say ARCH (1) was most suitable followed by EARCH (1, 1).

Below are the most suitable models for each of the Insurance stock

**[1]. AIICO**

$$\ln\left(\delta_t^2\right) = -0.214902 + 0.016909 \ln \delta_{t-1}^2 + \left[\frac{0.065416\,\varepsilon_{t-1}}{\sqrt{\delta_{t-1}^2}} + 0.972833\left(\frac{|\varepsilon_{t-1}|}{\sqrt{\delta_{t-1}^2}} - \sqrt{\frac{2}{\pi}}\right)\right] - 0.007654\,\Delta$$

If $\Delta = 0$ or 1 then,

$$\ln\left(\delta_t^2\right) = -0.214902 + 0.016909 \ln \delta_{t-1}^2 + \left[\frac{0.065416\,\varepsilon_{t-1}}{\sqrt{\delta_{t-1}^2}} + 0.972833\left(\frac{|\varepsilon_{t-1}|}{\sqrt{\delta_{t-1}^2}} - \sqrt{\frac{2}{\pi}}\right)\right]$$

$$\ln\left(\delta_t^2\right) = -0.22256 + 0.016909 \ln \delta_{t-1}^2 + \left[\frac{0.065416\,\varepsilon_{t-1}}{\sqrt{\delta_{t-1}^2}} + 0.972833\left(\frac{|\varepsilon_{t-1}|}{\sqrt{\delta_{t-1}^2}} - \sqrt{\frac{2}{\pi}}\right)\right]$$

**[2]. NEM**

$$\ln\left(\delta_t^2\right) = -0.2761874 + 0.594471 \ln \delta_{t-1}^2 + \left[\frac{0.348923\,\varepsilon_{t-1}}{\sqrt{\delta_{t-1}^2}} + 0.035363\left(\frac{|\varepsilon_{t-1}|}{\sqrt{\delta_{t-1}^2}} - \sqrt{\frac{2}{\pi}}\right)\right] - 0.474964\,\Delta$$

If $\Delta = 0$ or 1 then,

$$\ln\left(\delta_t^2\right) = -2.761874 + 0.594471 \ln \delta_{t-1}^2 + \left[\frac{0.348923\,\varepsilon_{t-1}}{\sqrt{\delta_{t-1}^2}} + 0.035363\left(\frac{|\varepsilon_{t-1}|}{\sqrt{\delta_{t-1}^2}} - \sqrt{\frac{2}{\pi}}\right)\right]$$

$$\ln\left(\delta_t^2\right) = -3.23684 + 0.594471 \ln \delta_{t-1}^2 + \left[ \frac{0.348923\,\varepsilon_{t-1}}{\sqrt{\delta_{t-1}^2}} + 0.035363\left( \frac{|\varepsilon_{t-1}|}{\sqrt{\delta_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right) \right]$$

**[3]. LAWUNION**

$$\ln\left(\delta_t^2\right) = 0.339725 - 0.021795 \ln \delta_{t-1}^2 + \left[ \frac{0.440794\,\varepsilon_{t-1}}{\sqrt{\delta_{t-1}^2}} - \frac{0.23657\,\varepsilon_{t-2}}{\sqrt{\delta_{t-2}^2}} + 0.967728\left( \frac{|\varepsilon_{t-1}|}{\sqrt{\delta_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right) \right] - 0.035861\,\Delta$$

If $\Delta = 0$ or 1 then,

$$\ln\left(\delta_t^2\right) = 0.339725 - 0.021795 \ln \delta_{t-1}^2 + \left[ \frac{0.440794\,\varepsilon_{t-1}}{\sqrt{\delta_{t-1}^2}} - \frac{0.23657\,\varepsilon_{t-2}}{\sqrt{\delta_{t-2}^2}} + 0.967728\left( \frac{|\varepsilon_{t-1}|}{\sqrt{\delta_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right) \right]$$

$$\ln\left(\delta_t^2\right) = 0.303864 - 0.021795 \ln \delta_{t-1}^2 + \left[ \frac{0.440794\,\varepsilon_{t-1}}{\sqrt{\delta_{t-1}^2}} - \frac{0.23657\,\varepsilon_{t-2}}{\sqrt{\delta_{t-2}^2}} + 0.967728\left( \frac{|\varepsilon_{t-1}|}{\sqrt{\delta_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right) \right]$$

**[4]. GUINNESS**

$$\delta_t^2 = 0.003409 + 2.854225\,\varepsilon_{t-1}^2 - 0.0023765\,\delta_{t-1}^2 + 0.001797\,\delta_{t-2}^2 - 0.003215\,\Delta$$

If $\Delta = 0$ or 1 then,

$$\delta_t^2 = 0.003409 + 2.854225\,\varepsilon_{t-1}^2 - 0.0023765\,\delta_{t-1}^2 + 0.001797\,\delta_{t-2}^2$$

$$\delta_t^2 = 0.000194 + 2.854225\,\varepsilon_{t-1}^2 - 0.0023765\,\delta_{t-1}^2 + 0.001797\,\delta_{t-2}^2$$

**[5]. NIGERINS**

$$\delta_t^2 = 0.000569 + 2.411643\,\varepsilon_{t-1}^2 + 0.000197\,\Delta$$

If $\Delta = 0$ or 1 then,

$$\delta_t^2 = 0.000569 + 2.411643\,\varepsilon_{t-1}^2$$

$$\delta_t^2 = 0.000766 + 2.411643\,\varepsilon_{t-1}^2$$

**[6]. UNIC**

$$\delta_t^2 = 0.000892 + 0.922466\,\varepsilon_{t-1}^2 - 0.000792\,\Delta$$

If $\Delta = 0$ or 1 then,

$$\delta_t^2 = 0.000892 + 0.922466\,\varepsilon_{t-1}^2$$

$$\delta_t^2 = 0.0001 + 0.922466\,\varepsilon_{t-1}^2$$

**[7]. WAPIC**

$$\delta_t^2 = 0.000725 + 1.788643\,\varepsilon_{t-1}^2 - 0.000155\,\Delta$$

If $\Delta = 0$ or 1 then,

$$\delta_t^2 = 0.000725 + 1.788643\,\varepsilon_{t-1}^2$$

$$\delta_t^2 = 0.00057 + 1.788643\,\varepsilon_{t-1}^2$$

**[8]. PRESTIGE**

$$\delta_t^2 = 0.000399 + 0.3000501\,\varepsilon_{t-1}^2 + 0.444226\,\varepsilon_{t-2}^2 + 0.002536\,\Delta$$

If $\Delta = 0$ or 1 then,

$$\delta_t^2 = 0.000399 + 0.3000501\,\varepsilon_{t-1}^2 + 0.444226\,\varepsilon_{t-2}^2$$

$$\delta_t^2 = 0.002935 + 0.3000501\,\varepsilon_{t-1}^2 + 0.444226\,\varepsilon_{t-2}^2$$

### 4.11 Analysis of Nigeria Insurance stock recovering

As a result of the global economic meltdown of 2008, Nigerian Insurance stocks have recorded unprecedented losses. Stocks from developed countries have started recovering from this global recession. Effort was made to study the recovering pattern of Nigerian Insurance stocks using time plot of the closing price of these stocks within the period under study. The figures obtained are shown in AppendixB.

## CHAPTER 5

# SUMMARY, CONCLUSION AND RECOMMENDATION

This study examined the volatility pattern of some of the Nigerian Insurance stocks. Twelve different heteroscedastic models were considered by also incorporating an indicator variable

using data set gathered which is the daily closing price between 2nd January, 2000 to 26th May, 2014.

## 5.1 Summary

### 5.1.1 Symmetric and Asymmetric distribution of the return in Nigerian Insurance stock

The symmetric nature of the return as observed in this study for majority Insurance stocks, is an indication that government regime shift has a significant impact on the return pattern of some of the Nigerian Insurance stock while the asymmetric nature of the return as observedin this study for majority Insurance stocks, is an indication that government regimeshift has a significant impact on the return pattern of Nigerian Insurance stocks. This phenomenon is referred as the leverage effect. This finding supported some of their studies in Nigeria (Dellah& Ade 2010). This result is not consistent with other studies conducted in other emerging capital market in other countries of the world (Sulimon, 2012; Moustafa, 2011; Hein, 2008) based on the symmetric nature of the return on some of the stocks.

### 5.1.2 Model used for forecasting

The result of study showes that symmetric volatility models are more superior to asymmetric models in dealing with regime switching. The Autoregressive Conditional Heteroscedasticity model (ARCH) proves to be the most suitable among the twelve competing volatility models considered. The result is considered to be in agreement with some of Dallah and Ade (2010) and Moustafa (2011) whose study observed that EGARCH (1, 1) model performed more than other volatility models, because in this study ARCH model is competing with EGARCH models. But in this study we find out that some of the stock actually exhibit asymmetric models, that is, EGARCH (1, 1) for AIICO and NEM, LAWUNION is EGARCH (2,

1), GUINNESS is GARCH (1, 2) while ARCH (1) for NIGERINS, UNIC and WAPIC while ARCH (2) for PRESTIGE. To make a clear classification one can say that symmetric models are most suitable but one cannot ignore the changes in the trend of the series than to work with the appropriate suitable models for each of the stocks.

### 5.1.3 Summary of the Indicator variable on the volatility model

When the regime changes are incorporated into the model, it is found that the highly persistent volatility of the Insurance stock return rate is reduced for most of the stock, from the results presented in Table 4.6 and Table 4.7 in chapter four (4) above it gives a clear view in the parameter coefficient of the abrupt shift or pattern of the Insurance stocks on each of the volatility models using the indicator variable. It was observed that some of the stock did not actually exhibit downward shift in each of the volatility model carried out in this study while some exhibit a downward shift which indicate that their trend tend to drop from the series.

For AIICO Insurance, all heteroscedastic model fitted had all their parameter significant ($p< 0.05$) except that some of the model in the abrupt shift showed a positive values with significant level of 0.01.

The abrupt shift in modelling the time series using time plot of the closing price of some of the Insurance stocks is showed in appendix B.

Moreover, NEM, PRESTIGE and UNIC all the parameter estimated were significant except the leverage effect of the TARCH (1, 1) model ($p>0.05$). For PRESTIGE Insurance, the indicator variable is positive throughout the models indicating that the shift was positive. Results are presented in Table 4.6 and Table 4.7 with others Insurance stocks

### 5.1.4 Summary of finding

The preliminary analysis of the data obtained showes that the distribution of the returns in some of the Nigerian Insurance stocks were all stationary and that there was presence of ARCH effect (Heteroscedasticity) on eight of the Insurance. The results of the finding also revealed that the Nigerian Insurance stocks exhibit level of leverage which means that positive (good news) and negative (bad news) have a significant effect on the daily return pattern of the Nigerian Insurance stocks. Volatility persistence and clustering was also observed in the eight Insurance stocks. Finally, the results of the finding also revealed that the symmetric models outperformed their asymmetric counterpart in terms of forecasting ability.

## 5.2 Conclusion

This study had examined the daily return volatility of Nigerian Insurance sector stocks. The best model was computed using the AIC and SIC, the bolded models are considered the best fits model to be used in each of the stocks. The forecasting performance of several variants of conditional heteroscedasticity volatility models were evaluated using model evaluation performance measures like the Root Mean Square Error. The post estimation evaluation carried out revealed various conditional heteroscedasticity models to be most suitable for modelling the return pattern of the each Insurance. The EGARCH (1, 1) was suitable for AIICO and NEM, LAWUNION is EGARCH (2, 1), GUINNESS is GARCH (1, 2) while ARCH (1) for NIGERINS, UNIC and WAPIC while ARCH (2) suitable for PRESTIGE. But looking at the Insurance and by evaluation one can say ARCH (1) was most suitable followed by EGARCH (1, 1). This finding is very crucial and informative to investors and intending investors who might want to invest in Insurance stocks.

## 5.3 Recommendation

Although the results of this study has proven to be consistent with some similar studies conducted in other emerging capital markets like Nigerian, the result should be treated with caution as this study covers some volatility models. We therefore recommend that appropriate models should be used in each of the Insurancestocks considered for this study in term of model selection, goodness of fit and forecasting.

## 5.4 Suggestion for further study

This study suggest further work on other useful volatility models like Multivariate GARCH models, stochastic volatility model, comparison of this research with dynamic conditional correlation models and hypotheses distribution with a more updated data even as the Nigerian Insurance stocks is developing. This will better inform investors, intending investors and investment analyst as volatility is the major index used to evaluate stock performance instead of price.

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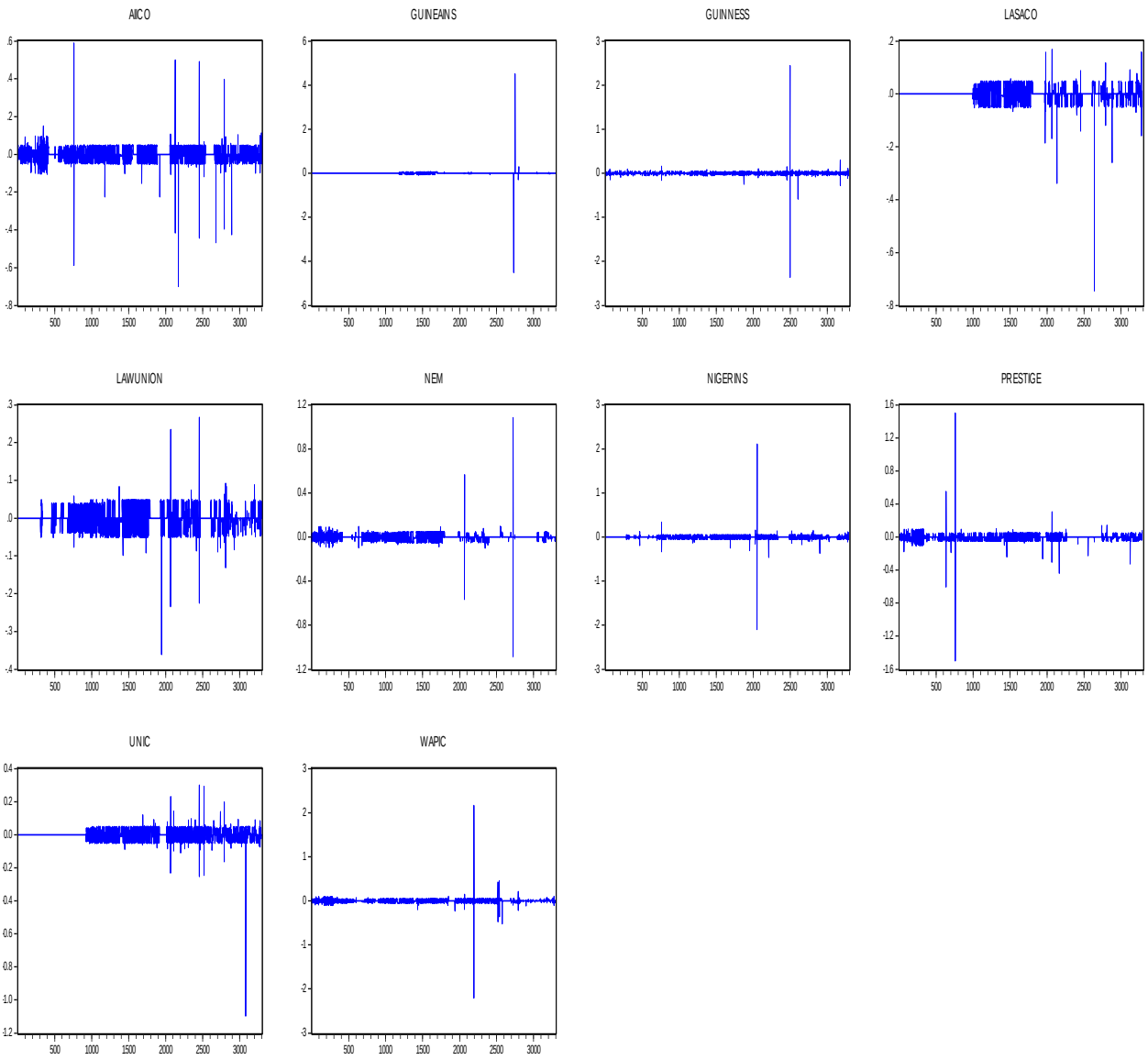
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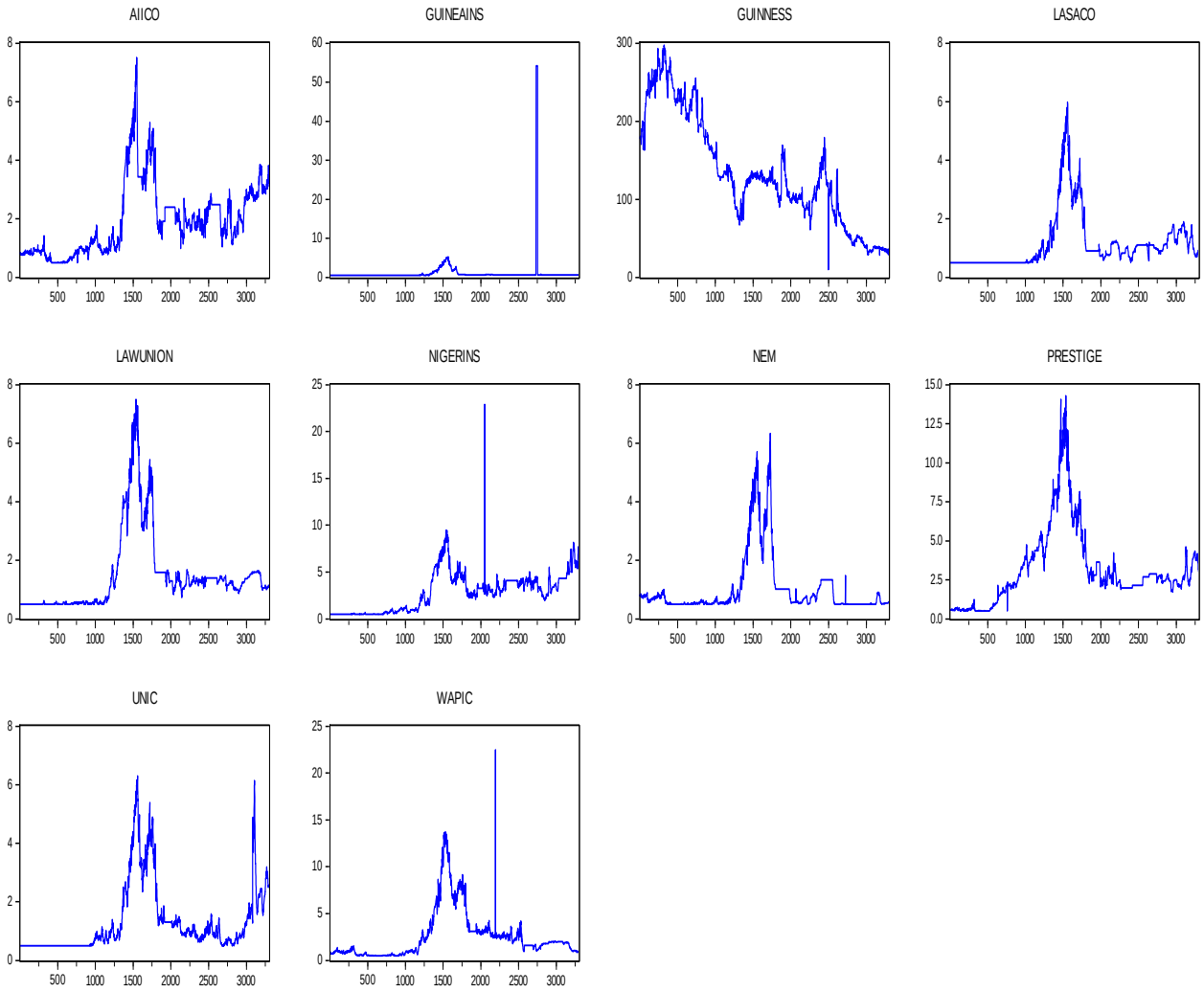
# Appendix A

### Stationarity plot of the series




# Appendix B

## Time plot for closing price of each Insurancestock


AIICO
GUINEAINS
GUINNESS
LASACO
LAWUNION
NIGERINS
NEM
PRESTIGE
UNIC
WAPIC