Detecting Financial Crisis in Nigerian Capital Markets Using Markov Switching Generalized Autoregressive Conditional Heteroscedasticity

Omeruruike Gideon Wobo
Captain Elechi Amadi ,Polytechnic ,Rumuola , Port Harcourt

Deebom Zorle Dum
Rivers state Universal Basic Education Board,
PortHarcourt, Rivers state

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Abstract
Financial crisis is often a thing of major concern in many countries. It has led so many experts to be interested in identifying the causes and the general statistical pattern associated with them. Based on the causes, pattern and characteristics exhibited by the financial crisis, it is expected that experts should be able to develop a model to detect the financial crisis. The financial crisis in Nigerian stock markets can be observed as a macro-economic indicator. Therefore, the aim of this study is to develop a model using a macro-economic indicator (All share index) that can explain the combined nature of volatility and switching characteristics associated with Nigerian capital markets. The data used for the study is the All Share Index (ASI) of Nigerian stock markets spanned from the month of January, 1985 – January 2021. The series is fitted to conditionally compound monthly return and the result obtained was used in fitting volatility and Markov switching GARCH models. Based on the AIC and SIC, the EGARCH model was found to be the appropriate model for modeling Nigerian stock markets. However, structural changes in the model were tested using the Chow breakpoint test. The results obtained based on the test of structural changes, found that there was a structural change in the real exchange rate in the period between February 1998 and July 2010. For MSGARCH (3,1.1), the results show that the conditional probability of surviving in the high volatility state in the next period is 0.984. Also, the conditional probability of surviving in a medium volatility state in the next period is 0.617 and the conditional probability of surviving in a low volatility state in the next period is 0.410. The results showed that the MSGARCH (3,1,1) model could explain that the period from February 1997 until July 2020 had probability values of more than 0.6. This reveals high volatility confirming the occurrence of a crisis.

Key Words: *Volatility, Nigeria, capital, Markets, GARCH, TGARCH, EGARCH, MSGARCH*

1.1 Background to the study

Aggregation of volatility is a well-documented feature of the financial rate of return: large price changes in magnitude tend to occur in clusters rather than equal distances. The natural question is how long the financial markets will remain volatile? This is because forecasting of volatility is essential to calculating optimal hedge ratios and option prices.

In fact, we study the behavior of option-embedded market volatility to find out certain stylized facts that parametric volatility models should capture. Two stylized facts that traditional volatility models, in particular generalized autoregressive conditional heterogeneity (GARCH, Bollerslev (1986)), find it difficult to reconcile are that conditional volatility can increase significantly in a short time at the onset of a turbulent period and the mean reverting rate in capital market volatility appears to vary positively and non-linearly with the level of volatility(Adam, 2020).

In other words, capital market volatility is not consistently two or three times higher above its normal level in the same way that it could stay at 30-40% above normal. Therefore, this has attracted the attention of investment analysts, capital market analysts, and risk managers in modeling and forecasting financial markets volatility.

When modeling capital market volatility, most financial analysts are particularly interested in obtaining valuable estimates of conditional variance (the hallmark of volatility) to improve portfolio equity or manage its risk. Over the years, a number of models have been developed to assess the conditional volatility of the capital markets. For example, Engle's (1982) generalized conditional autoregressive (GARCH) models are the models commonly used to predict volatility in capital markets. So , accurate measurement and prediction of volatility were applied to asset pricing models as a simple measure of risk, as well as to derivative pricing and trading theories (Aliyu & Wambai, 2018).

It is noted that before the introduction of conditional volatility models, there were Box-Jenkins (1976) models, specifically automatic moving average regression (ARIMA) models. However, ARIMA models are more of art than science, with no theoretical foundation and also, they are based on assumptions of inaccurate constant variance of the time series of capital market returns. These shortcomings of ARIMA models have given rise to various extensions in the applications of Engle-like models. These new approaches adopted various extensions of the GARCH models such as GARCH-M, IGARCH, EGARCH, TGARCH and PARCH that take into account the potential for variations in the capital markets (Aikaterini, 2016).

However, GARCH-M, IGARCH, EGARCH, TGARCH and PARCH models also have their shortcomings. For example, in volatility modeling, conditional changes that occur in the data are ignored, but in a Markov model change, conditional changes in the data are an unobservable variable called the state. Also, Hamilton and Sussmel (1994) and Lamoreaux and Lystrabs (1993) highlight the prediction difficulties of traditional GARCH models by showing that they can provide worse multi-period results. Volatility predictions from static variance models. In particular, GARCH's multi-period volatility predictions are very high in the above-normal volatility period. Aikaterini(2016). addressed the issue of prediction by not allowing the conditional variance in the GARCH model to respond proportionally to "large" and "small" shocks.

This prevents the conditional variance from increasing to a level where expectations of volatility are undesirably high. The drawback of this approach is that in such a model, conditional volatility may reduce the true variance by not responding adequately to large shocks, and thus never under pressure to show mean reversion.

Thus, these "threshold" models do not necessarily address the above-mentioned typical facts p sharp upward jumps in volatility, followed by a fairly rapid reversal to near-normal levels.

This study is designed to model fluctuations that can handle several stylized realities within the class of GARCH models with Markov switch parameters. In addition, the study will model returns in Nigerian capital markets using MS-GARCH with the intent: to determine whether the Nigeria capital markets can fit into the volatility model, and to test the impact of the current ARCH on the return volatility of Nigeria's capital markets All Share Index, determine the effect of price volatility on the Nigeria capital markets of All Share Index, the impact of news on the capital markets of Nigeria All Share Index, conditional changes in the data and also to detect during the period when a financial crisis may occur in the capital markets of Nigeria . Therefore, this study will be of great interest in contributing to knowledge by defining the pattern of volatility in the Nigerian capital markets and the impact of ARCH's effect on the volatility of its returns, in order to make informed policy decisions and regulate the capital markets of Nigeria.

Methodology

3.1 Sources of Data and the software used in the Data Analysis

The study uses All Share Index (ASI) from Nigerian capital Markets which was extracted from the Central Bank of Nigeria (CBN) statistical database website (www.cbn.goving). The data spanned from the month of January, 1985 – January 2021. The series capital Markets is fitted to conditionally compound monthly return computed as, $r_t = \log\left(\frac{ASIt}{ASI_{t-1}}\right) X \frac{100}{1}$

(3.1)

For t = 1, 2, …….t-j where ASIRt is the return on Nigerian capital Markets at time t, and $ASIR_{t-1}$ is return on All Share Index(ASI) at time "$_{t-1}$".

3.2 Model Specification

3.2.1 Autoregressive Moving Average (ARMA) Model

This is a model that is combined from the AR and MA models. In this model, the impact of previous lags along with the residuals is considered for forecasting the future values of the time series. The autoregressive moving average (ARMA) model with (p, q) order of the log return data r1 can be written as $r_t = \phi_0 + \sum_{i=1}^{p} \phi_i \varepsilon_{t-1} - \sum_{j=1}^{q} \theta_j \sigma_{t-j} + \alpha_t$

3.2

Where ϕ_0 denotes the constant, p denotes the order of autoregression (AR), $\phi_{1,2,\ldots,P}$ denotes the AR parameters, q denotes the order of the moving average (MA), $\phi_{1,2,3,\ldots,q}$ denotes the MA parameter, and α_t denotes the model residual at time t. Tsay(2005) further observed that the highest MA order determined by ACF plot which cut off after the p^{th} lag while AR order determined by PACF plot which cut off after the q^{th} lag. The Heteroskedasticity effect of ARMA model can be tested with Lagrange multiplier (LM) test.

Heteroskedasticity Test

This is done to confirmed whether the residuals ε_t obtained from ARMA process exhibit time-varying heteroscedasticity. This is done using the Lagrange multiplier test as proposed by Engle in 1982. This procedure is as follows:

1. Calculate the best fitting autoregressive model AR(q)

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + \ldots\ldots + \alpha_q r_{t-q} + \varepsilon_t = \alpha_0 + \sum_{t=1}^{q} \alpha_i r_{t-i} + \varepsilon_t$$

2. Obtain the squares of the error $\hat{\varepsilon}^2$ and regress them on a constant and q lagged values:

$$\hat{\varepsilon}_t^2 = \alpha_0 + \sum_{t=1}^{q} \hat{\alpha}_i \hat{\varepsilon}_{t-1}^2$$

where q is the length of ARCH lags. The null hypothesis is that, in the absence of ARCH components, we have $\alpha_i = 0$ for all $i = 1,2.........q$. The alternative hypothesis is that, in the presence of ARCH components, at least one of the estimated α_i coefficients must be significant. In a sample of T residuals under the null hypothesis of no ARCH errors, the test statistic $T'R^2$ follows χ^2 distribution with q degrees of freedom, where T^1 is the number of equations in the model which fits the residuals vs the lags (i.e. $T^1 = T - q$). If $T'R^2$ is greater than the Chi-square table value, we *reject* the null hypothesis and conclude there is an ARCH effect in the ARMA model. If $T'R^2$ is smaller than the Chi-square table value, we do not reject the null hypothesis.

Autoregressive Conditional Heteroscedasticity (ARCH) Model

To model a time series using an ARCH process, let ε_t denote the error terms (return residuals, with respect to a mean process), i.e. the series terms. These ε_t are split into a stochastic piece

r_t and a time-dependent standard deviation σ_t characterizing the typical size of the terms so that $\varepsilon_t = \sigma_t Z_t$

The random variable Z_t is a strong white noise process. The series σ_t^2 is modelled by

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + ... + \alpha_q \varepsilon_{t-q}^2$$

where $\alpha_0 > 0$ and $\alpha_i \geq 0$, $i > 0$. An ARCH(q) model can be estimated using ordinary least squares. An ARCH(q) model can be estimated using ordinary least squares.

3.2.2 Volatility Models in Normal Error Distribution Assumptions

The volatility models in normal error distribution assumptions used in this study include Generalized ARCH (GARCH) Model, Threshold GARCH (TGARCH) Model and Exponential GARCH (EGARCH) Model. However, these models were subject to the normal error distribution assumptions.

3.2.2.1. Generalized ARCH (GARCH) Model

By definition the standard GARCH model used in the estimation of the Nigerian capital market returns is considered using the residual of the ARMA process obtained in equation (3.2) and the residual could be written as shown below:

$$\sigma_t = \sigma_t \varepsilon_t \text{ for } \varepsilon_t \sim N(0,1) \text{ and } \sigma_t / f_{t-1} \sim N(0, \sigma_t^2) \quad (3.3)$$

The standard symmetric GARCH (1,1) model can be written as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (3.4)$$

Where $\alpha_0 \geq 0$, $\alpha_1 \geq 0$ and $\beta \geq 0$, i.e. all these parameters must be positive in order to guarantee a positive conditional variance, and where $\alpha_1 + \beta < 1$ represents the persistence of shocks to volatility (Yue-Jun *et al*, 200)

3.2.2.2 Threshold GARCH (TGARCH) Model

According to Brook (2006), the TGARCH was found by Glisten *et al.*(1993) and it defined as GJR-GARCH model. The variance of the model is defined as TGARCH (1,1) model could be written as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-i}^2 + Y_i \ \varepsilon_{t-1}^2 d_{t-i} + \beta_1 \sigma_{t-1}^2 \quad (3.7)$$

Where $d_{t-i} = 1$ if $\varepsilon_{t-i} < 0$ and 0 if $\varepsilon_{t-i} \geq 0$, and the condition for non-negativity is

$\alpha_0 > 0, \alpha_1 > 0, \beta_1 \geq 0$, and $\beta_1 + Y \geq 0$.

In equation (3.7), when $\varepsilon_{t-1}^2 > 0$ implies good news whereas $\varepsilon_{t-1}^2 < 0$ implies bad news and under these conditions, (shocks) of equal magnitude have differential effects on conditional variances (Deebom & Essi, 2017). Similarly, good news has an impact magnitude of α_1 while bad news has an impact magnitude of α_1+ I which in a way cause increase in volatility. Also, if $Y_1 > 0$, this invariably means that there is the existence of leverage effect of the 1st order. When Y_1=0, then this means that news impact is asymmetric in nature. Although, given the standard GARCH model in equation (3.7) assumes that the effect of positive and negative information is symmetric which may not be completely applicable in a market situation (Yue-June *et al.*, 2008)

3.2.2.3 Exponential GARCH (EGARCH) Model

Nelson (1991) proposes the Exponential GARCH (EGARCH) model to examine the asymmetric features of asset price volatility, and which according to him the logarithm of the conditional variances of Crude Oil price returns can be stated as thus:

$$\log\left(\sigma_t^2\right) = \alpha_0 + \alpha_1 \left|\frac{a_t - 1}{\sigma_{t-1}^2}\right| + \sum^{e} \frac{\sum_{t-1}}{\sigma_{t-1}} + \beta\ log\ \left(\sigma_{t-1}^{2}\right) \quad (3.8)$$

$\alpha_0 \geq 01 \alpha_1 \geq 0$ Σ >0 and $\beta_1 \geq 0$

Similarly, $\varepsilon_{t-1} > 0$ simply depict good news and $\varepsilon_{t-1} < 0$ means bad news respectively whereas the total effects of bad and good news are given as $(1-\xi)[\varepsilon_{t-1}]$ and $(1+\xi)[\varepsilon_{t-1}]$ respectively

In this case, we accept the null hypothesis that ξ = 0 which shows that there is the presence of leverage effect and this simply mean bad news have stronger effect than good news on the volatility of the return series (Deebom & Essi, 2017)

3.2.2.4 Normal Error Distribution Assumptions

In modelling the conditional variance of the Nigerian stock markets , there is need to subjects to conditional distributions for the standardized residuals of the returns modernism and the Gaussian (Normal) was considered appropriate. The Gaussian (Normal) error distribution assumed a log-likelihood contribution is of the form;

$$LogL(\theta_t) = \sum_{t=1}^{T} L(\theta_t) = -\frac{1}{2} Log[2\prod] - \frac{1}{2}\sum_{t=1}^{T}\log(\sigma_t^2) - \frac{1}{2}\sum_{t=1}^{T}\frac{(y_t - \gamma y_t)^2}{\sigma_t^2} \quad (3.24)$$

3.2.5 Markov Switching Generalized Autoregressive Conditional Heteroscedasticity (MSGARCH)Model

According to Hamilton and Susmel (1994), mathematically define the Markov Switching Autoregressive Conditional Heteroscedasticity (MSARCH)Model as

$$r_t = \mu_t + a_t, \quad a_t = \sigma_t \varepsilon_t, \quad \sigma^2_{t,st} = a_{o,st} + \sum_{i=1}^{m} \alpha_{i,st} \sigma^2_{t-i}$$

$\varepsilon_t \sim \mathrm{N}(0,1)$ and $s_t = \{1,2............\mathrm{K}\}$. The equation above is a Markov Switching Autoregressive Conditional Heteroscedasticity (MSWARCH) process with k state and m order and it is represented as $a_{t,st} \sim \mathrm{MSARCH(k, m)}$. The Markov Switching Autoregressive Conditional Heteroscedasticity (MSWARCH) process with k state and m order is further modified into Markov Switching Generalized Autoregressive Conditional Heteroscedasticity (MSWARCH) process with k state , p and q order written as : $\sigma^2_{t,st} = a_{o,st} + \sum_{i=1}^{p} \alpha_{i,st} \varepsilon^2_{t-i} + \sum_{i=1}^{q} \beta_{i,st} \sigma^2_{t-i}$

$\varepsilon_t \sim \mathrm{N}(0,1)$ and $s_t = \{1,2............\mathrm{K}\}$. The equation above is a Markov Switching Generalized Autoregressive Conditional Heteroscedasticity (MSGARCH) process with k state, P and q order of the ARCH and GARCH terms . It is represented as $\sigma^2_{t,st} \sim$MSGARCH (k,p,q)

3.2.5.1 Detecting financial crisis in Nigeria Capital Markets

Ford, Santoso, and Horsewood,(2007) , Hermosillo and Hesse,(2009) and Sugiyanto, Yuliana, & Anis,(2018) revealed that filtered probability and smoothed probability can be used to financial crisis. Sopipan , Sattayatham & Premanode, (2012), further explained that filtered probability is the probability of a state in the t-period based on observational data until it transit to the t-period . Hermosillo and Hesse(2009), further explained that the filtered probability in state 3 can be written as

$$\Pr[S_t = 3/\psi_t] = 1 - \Pr[S_t = 1/\psi_t] - \Pr[S_t = 2/\psi_t]$$

Where ψ_t is an a_t set until time t, $\Pr[S_t = 1/\psi_t]$ is filtered probability at state 1 and $\Pr[S_t = 2/\psi_t]$ is filtered probability at state 2.

In another development, Sopipan , Sattayatham & Premanode, (2012), explained that financial crisis can be detected from the value of filtered probability at state 3 in the period of the data. Furthermore, Sopipan , Sattayatham & Premanode, (2012), said the filtered probability forecasting can be written as : $\Pr[S_t = j/\Psi_t] = \sum_{i=1}^{3} P_{(i,j)} \Pr(S_{t-1} = i/\Psi_{t-1})$

Where $P_{(i,j)}$ is the transition probability from state i to state j and $\Pr(S_{t-1} = i/\Psi_{t-1})$ is filtered probability at state i and time t-1.

According to Hermosillo and Hesse (2009), the value of filtered probability of more than 0.6 is in state 3 with high volatility or can be said to occur the crisis in that data period. The value of filtered probability between 0.4 and 0.6 is in state 2 with medium volatility or can be interpreted as prone to crisis. While the filtered probability value less than 0.4 is in state 1 with low volatility or stable condition. In a two states conditions, Ford, Santoso, and Horsewood, (2007) suggested that the period for a data set have filtered probability value more than 0.5 can be said to be in volatility condition or can indicate the occurrence of a crisis. Similarly, Hermosillo and Hesse,(2009) confirmed that in three states, the period of data to have filtered probability value between 0.4 and 0.6 is assumed to be at moderate volatility condition, and less than 0.4 is assumed to be

at the low volatility condition and more than 0.6 is assumed to be in high volatility condition and may indicate the occurrence of a crisis
0n the hands, smoothed probability was introduced by Kuan (2002) and it is defined as

$$\mathbf{P}(\mathbf{S}_{\mathbf{t}} = \frac{i}{z^T}, ø) = \sum_{\mathbf{S}_{\mathbf{t}}=1}^{3} \mathbf{P}(\mathbf{S}_{\mathbf{t+1}} = \frac{i}{z^T}, ø)\mathbf{P}(\mathbf{S}_{\mathbf{t}} = \frac{i}{\mathbf{S}_{\mathbf{t+1}}} = i, z^T; ø)$$

3.5 Estimation Procedure

The estimation techniques/procedures employed in detecting crises in the Nigerian capital markets can be classified into time series, econometric analysis and forecasting. To stem out the problem of spurious regression, it is important that the priori behavior of the variables must be ascertained using the times series properties of the data. This involves a time series plot of the variables (data set), testing for volatility cluster, creating an Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plot of the log return data to determine the appropriate ARMA model.

Secondly, the econometric criteria will be examined by testing the effect of heteroscedasticity by using the Lagrange multiplier test, establishing an appropriate volatility model and combining the volatility model with Markov Switching assuming three states. Calculating the value of filtered probability at state 3 to detect a crisis.

Thirdly, forecasting, which involved model selection/goodness of fit-tests and forecasting evaluation. Forecasting the crisis conditions for one year ahead and determining the relative conditions of Nigerian capital markets indicator

Results

4.1 Time Plot for the Raw Series

Figure 4.1: Time Plot of the Raw series on Nigerian **capital Markets**

4.2 Descriptive Statistic for the Raw & Returns on Nigerian capital Markets

Table 4.1 Descriptive Statistic for the Raw series from Nigerian capital Markets & its Return Innovation.

Variable	Mean	Media	Max	StD	Skewness	Kurtosis	Jarq. Bera	Prob.
NSM	17035.15	13488.00	65652.38	15361.99	0.601	2.494	30.851	0.000
RNSM	1.350	1.473	32.352	6.240	-0.453	9.024	671.120	0.000

4.3 Time Plot for the Return Series on Nigerian capital Markets (Volatility Clustering)

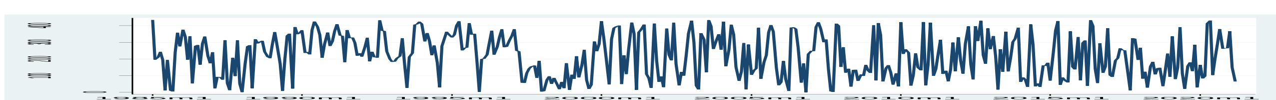

Figure 4.2: Time Plot of the Returns on the Raw series on Nigerian **capital Markets**

Table 4.2 Heteroskedaticity Test Using Lagranger Multiplier

Estimators	Lag (5)		P-value	Lag(10)		P-value	Lag(15)		P-value
F-statistic	11.328	Prob. F(5,422)	0.000	6.262	Prob. F(10,412)	0.0000	4.134	Prob. F(15,402)	0.000
Obs*R-squared	50.647	Prob.Chi-Square(5)	0.000	55.812	Prob. Chi-Square(10)	0.0000	55.865	Prob. Chi-Square(15)	0.000

Results obtained from Volatility Model Estimation in Normal Error Distribution Assumption

ARMA(1,0)

$$\sigma_t^2 = 1.131 + 0.163\varepsilon_{t-1}^2 \qquad (4.1)$$
$$(0.000) \quad (0.001)$$

GARCH(1,1)

$$\sigma_t^2 = 6.343 + 0.192\varepsilon_{t-1}^2 + 0.661\sigma_{t-1}^2$$
$$(0.000) \quad (0.000) \quad (0.000)$$
(4.2)

TGARCH (1,1)

$$\sigma_t^2 = 7.217 + 0.151 * \varepsilon_{t-1}^2 + 0.236 * \varepsilon_{t-1}^2 * (\varepsilon_{t-1}^2 < 0) + 0.611 * \sigma_{t-1}^2 \qquad (4.3)$$
$$(0.000) \quad (0.000) \quad (0.000) \qquad\qquad (0.000)$$

EGARCH (1,1)

$$\mathrm{LOG}(\sigma_t^2) = 0.356 + 0.380 * \left(\left| \left(\frac{\varepsilon_{t-1}^2}{\sqrt{(\sigma_{t-1}^2)}} \right| - 0.134 * \left(\frac{\varepsilon_{t-1}^2}{\sqrt{(\sigma_{t-1}^2)}} \right) \right) + 0.834 * \mathrm{LOG}(\sigma_{t-1}^2)$$
$$(0.000) \quad (0.000) \qquad (0.000) \qquad (0.000)$$
(4.4)

Table 4.3 Diagnostic Tests for the selected Volatility Model Using Q-Statistics, Lagranger Multiplier, Normality test, and chow test

Model	Information criteria (IC)		Q-Statistics test		Lagrange Multiplier		Normality test				Chow
			Q (5)	Q(10)	F (2,427)	F (5,421)	Skewness	Kurtosis	JB	Pvalue	
GARCH (1,1)	AIC	6.415									
	SIC	6.443									
TGARCH	AIC	6.404									
	SIC	6.441									
EGARCH	AIC	6.389	7.902 [0.548]	11.521 [0.174]	0.89383 [0.410]	1.4389 [0.209]	0.2354	2.004	76.60	2.30e-017	95.214 [0.000]
	SIC	6.426									

Combination of Volatility and Markov Switching Model

$$r_t = \begin{cases} 2.553, & for \quad state\,1 \\ 0.854 & for \quad state\,2 \\ 4.394 & for \quad state\,3 \end{cases} \tag{4.5}$$

This value indicates that the average of log returns of Nigerian stock markets data every month in state 1 (stable) is 2.553, state 2 (volatile) is 0.854 and state 3 (volatile) is 4.394. MSGARCH (3,1) model can be written as follows

$$\sigma_t^2 = \begin{cases} 1.730 + 0.539\varepsilon_{t-1}^2 + 0.000\sigma_{t-1}^2, & for \quad state\,1 \\ 2.469 + 0.493\varepsilon_{t-1}^2 + 0.000\sigma_{t-1}^2 & for \quad state\,2 \\ 2.034 + 0.493\varepsilon_{t-1}^2 + 0.669\sigma_{t-1}^2 & for \quad state\,3 \end{cases} \tag{4.6}$$

Transition probability matrix of the Nigerian stock markets data can be written as follows

$$\boldsymbol{p} = \begin{vmatrix} \mathbf{0.984} & \mathbf{0.000} & \mathbf{0.010} \\ \mathbf{0.004} & \mathbf{0.617} & \mathbf{0.579} \\ \mathbf{0.013} & \mathbf{0.383} & \mathbf{0.410} \end{vmatrix} \tag{4.7}$$

Matrix ***P*** explained that the probability to survive in condition of high volatility is 0.984, survive in condition of medium volatility is 0.617 and survive in condition of low volatility is 0.410.

Filtered Probability

The next step is to calculate filtered probability of MSGARCH (3,1,1) model with an average of conditional ARMA (1,0). Scatter plot of filtered probabilities for the three states condition is shown in Figure 4.3

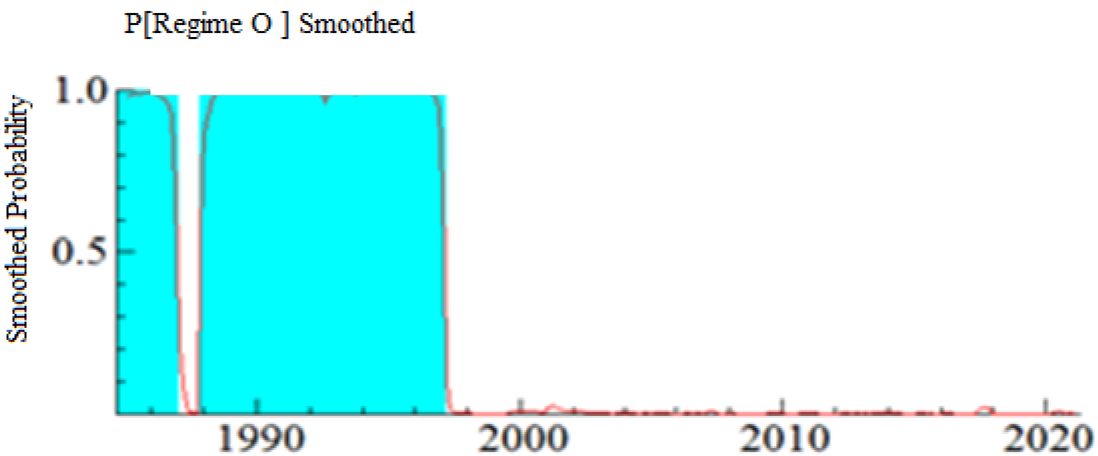

Figure 4.5: Scatter plot of filtered probabilities for one state condition

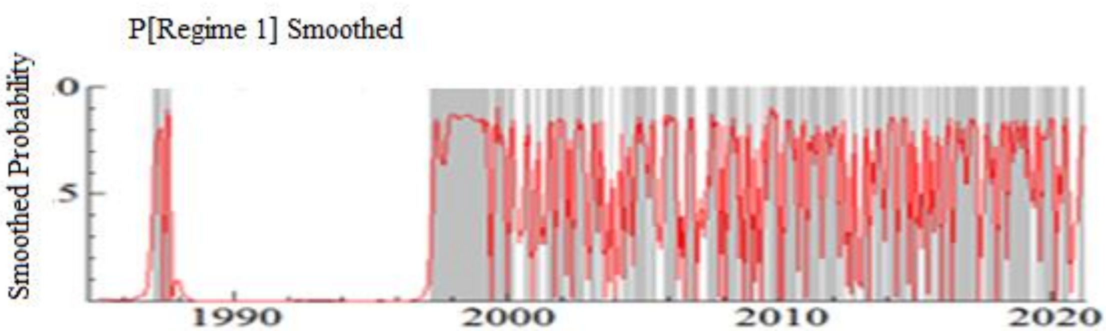

Figure 4.6: Scatter plot of filtered probabilities for two states condition

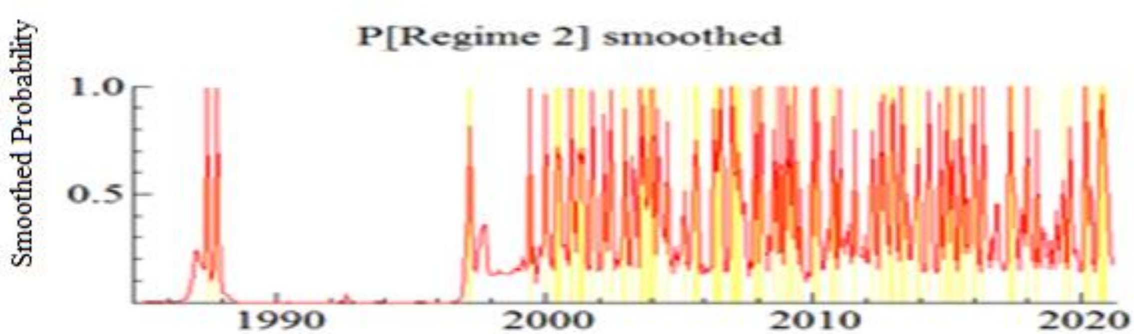

Figure 4.7: Scatter plot of filtered probabilities for three states condition

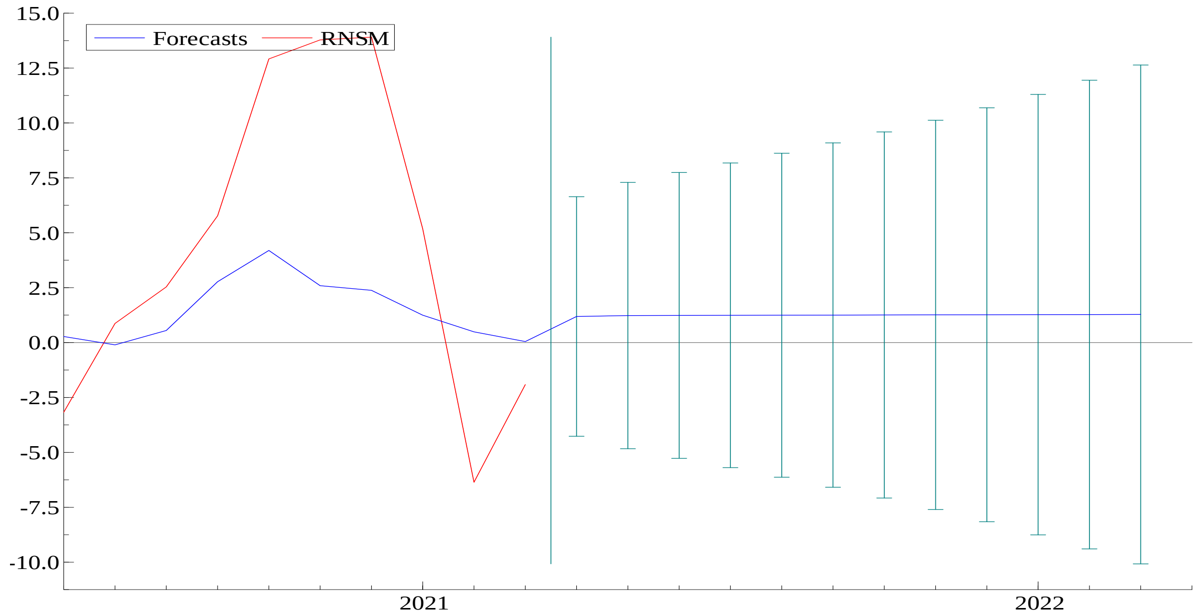

Figure 4.8: One Year Forecast plot for MSGARCH (3,1,1) model used in detecting financial crisis in Nigeria stock markets

5.1 Discussion of Results

Figure 4.1 shows the time plot of the raw series on Nigerian capital markets. From our visual examination, the time plot shows the presence of trends, intercepts but no volatile clustering. From our visual examination, the result revealed an upward trend in the series between 2005 and 2010. This shows an increase in tradable assets that constitute the Nigerian capital markets. According to Lars (2002), fluctuations in traded assets constitute what forms market risk. The fluctuations in prices for tradable assets are what exposes the markets to risk and these adverse market movements are one of the primary concerns in the financial world (Deebom, Essi & Emeka, 2021).

Figure 4.2 contains the time plot for the returns on the raw series from the Nigerian capital market. From our visual examination, the result revealed a clustering volatility. However, this is in line with Lars' (2002) assertion. Lars (2002) asserted that in the theory of financial returns, the basic is that returns follow a stationary time series model having stochastic volatility structure. The presence of stochastic volatility in the returns series implies that returns on prices are not necessarily independent over time. The returns series describes the relative changes over time of the price process.

Table 4.1 shows the descriptive statistics for the raw series from Nigerian capital markets and its returns series. The results show that both raw series from the Nigerian stock markets and its returns have a positive mean value of NSM (17035.15) and RNSM (1.350) respectively. Also, their respective standard deviations are ASI (15361.99) and RNSM (6.240), revealing that the raw series is more volatile than the computed return series. Similarly, skewness revealed that the raw series has a positive skewed value of NSM (0.601), while the return series has a negative skewed value of (-0.453). The negative skewed value shows that the series has a distribution skewed to the left and this simply means that the left tail is heavier than the right tail in the distribution. Also, the positive skewed value shows a right skewed distribution with a right tail heavier than its left tail.

Similarly, Kurtosis for both raw series on the series from the Nigerians capital markets and its returns were estimated. This was necessary because Kurtosis measures the extent to which observed data falls near the centre of a distribution or in the tails and from the results obtained the kurtosis of the raw is ASI (2.494), while its returns show the value (9.024). This simply means that the return series has excess kurtosis displaying a leptokurtic distribution. Having a value greater than that of a standard, normal distribution, which shows that the distribution has a high peak, a thin midrange, and fat (heavy) tails (Lars, 2002). Also, for the raw series to have a kerosa value less than 3, it means that the raw series has a fat midrange on either side of the mean and a low peak.

The Jarq- barra for the raw series is (30.851) and its return is (671.120), indicating that these indicators are not normally distributed. The causes of these series not being normally distributed could be attributed to the presence of extreme observations. Hence, the null hypothesis of normality is rejected while the alternative hypothesis that these indicators are not normally distributed is accepted.

Table 4.2 contains the results for the heteroskedaticity test using lagranger multiplier. the results show that from both the F-statistic and n*R2 test there is the existence of an ARCH effect on an increase in the variable even at a 1% level of significance for the first order autoregressive process. The test for higher order lags is neglected. This is because the test results for Lag 5, 10 and 15 show adequate reasons to confirm that there is the existence of an ARCH effect and the applications of the GARCH model in modeling of volatility of the return series will be appropriate.

Table 4.2 contains the results to test the presence of ARCH effect in the returns series from the emerging Nigerian stock markets. The results of the estimated probability values of the Engle's Lagrange Multiplier ARCH tests are less than 5 percent, a significant level with up to 15 lags corresponding to the one-month trading period reported in the study. This should that the null hypothesis of no ARCH effects(homoskedasticity) in the returns on the series from Nigerian capital markets should be rejected, while the alternative which says that ARCH effects(heteroscedasticity) is presence in the return volatility of the emerging Nigerian capital markets. This means that the variances of log returns are heteroskedastic and suggests the use of the ARCH/GARCH model in capturing the varying volatility in the return series (Deebom& Essi, 2017).

Based on the results obtained for the normality test, residuals from the model are not normally distributed. Therefore, the model was re-estimated using the quasi-maximum likelihood estimate (QMLE) method suggested in Chow (1960). It was found that the best model for modeling volatility in the Nigerian stock markets is the ARCH (1) model with the average conditional ARMA (1, 0) which is shown in equation (4.1).

The result in equation (4.2) is the conditional variance equation otherwise referred to as the GARCH(1,1) model, which three parts; the first the intercept, the lag of the squared residual from the conditional variance equation is the ARCH term , while the other part is the GARCH term. The intercept, ARCH (α1) and GARCH (β1) coefficients are positive and fulfil the condition of the model. Also, the coefficient of the lagged conditional variance ARCH term () with the value of 0.192 is positive and greater than zero, signifying the impact of historical news on the volatility of the Nigerian capital. All these values indicate that there is volatility clustering in the Nigerian capital markets. The value of the ARCH coefficient implies that the square lagged error terms has a positive and significant impact on the current period volatility of Nigerian capital markets returns. The ARCH coefficient also revealed that the previous error term has a positive and significant effect on current period volatility and the degree to which volatility reacts to market events is high. Also, the speed of reaction of stock volatility to market events is high. Similarly, the co-efficient of GARCH is (β) 0.661. GARCH is a positive value and is greater than zero. This indicates a long time in the current variance. The estimated GARCH (1,1) model shows that all the parameter estimates of the variance equation are positively significant at 5%, implying that previous period volatility has a significant effect on the conditional volatility in the current period. This also confirmed that there is a strong GARCH effect on the returns on Nigerian capital markets. For both indicators, the addition of ARCH and GARCH (β) coefficients is 0.853, indicating a strong persistent volatility clustering.

The result in equation (4.3) is the conditional variance equation otherwise referred to as the GARCH(1,1) model, which three parts; the first the intercept, the lag of the squared residual from the conditional variance equation is the ARCH term (), followed by the co-efficient for determining leverage effect and GARCH() term. The ARCH (α1), the co-efficient for determining the leverage effect, and GARCH (β1) coefficients are positive and fulfill the condition for non-negativity of the model. Also, the coefficient of the lagged conditional variance ARCH term with the value of 0.151 is positive and greater than zero, signifying the impact of historical news on the volatility of the Nigerian capital markets. The ARCH term suggests that the tendency of volatility of Nigerian capital markets to react to market shocks is significant, and the extent to which it reacts to this shock is high. Also, previous period volatility does not have an effect on current period volatility and is covariance stationarity since $\alpha 1$ is less than. Similarly, the asymmetric coefficient "d" is . This value is positive (d>0) and statistically significant. This implies that downward movement of the stock returns is followed by higher volatility than upward movement of the same magnitude. The underlying concept behind the asymmetric or leverage effect is that volatility in Nigerian capital markets rises more following price declines (bad news) than it does with prices in Nigerian capital markets increases (good news) of the same size. The positive values of ARCH and GARCH terms imply that both historical (past) and current news respond asymmetrically to the stock returns volatility on Nigerian capital markets even at 1% level, but the response is more pronounced in current news than historical news. For both indicators, the addition of ARCH and GARCH coefficient is 0.762, indicating a strong persistent volatility clustering.

The result in equation (4.4) is the conditional variance equation otherwise referred to as the EGARCH(1,1) model, which three parts; the first the intercept, the lag of the squared residual from the conditional variance equation is the ARCH term, followed by the co-efficient for determining leverage effect and GARCH()) term. In the EGARCH model, the intercept and the ARCH term are positive and highly significant, but the GARCH parameter is not significant. The ARCH term suggests that the tendency of volatility to react to the Nigerian capital markets shock is high.

Also, previous period volatility does not have an effect on current period volatility and is covariance stationarity since $\alpha 1$ is less than 1. The leverage effect term, γ is not significant at 5% level, suggesting the absence of leverage effect.

Table 4.3 contains the results of the diagnostic tests for the selected volatility model using Q-statistics, Lagrange multiplier, normality test, and chow test. From the results of the volatility models it was found that the model with the least Akaike information criteria (AIC) is the EGARCH model. Therefore, diagnostic checks were carried out on the model to determine their adequacy using Q-Statistics, Lagrange multiplier normality test, and chow test. The Q-Statistics on squared standardized residuals for correlation was done and the results give the probability of 0.548, and 0.174 respectively. These values are more than 0.05, which means that the residue of ARCH models does not contain autocorrelation. Also, to test for ARCH, the Lagrange multiplier test probability values for the residue of each model were found to be 0.410, and 0.209 respectively. These values are more than 0.05. It means that there is no effect of heteroscedasticity on the residue of ARCH models. Also, the normality test for residue using the joint statistics of skewness, kurtosis and jarque bera. The results are 0.2354, 2.004 and 76.600 respectively. Their probability value is less than 0.05, it means that the residue of ARCH models is not normally distributed. Based on these tests, the appropriate model for the data is the EGARCH model. However, there is a need to determine the structural changes in the model and this was done using the Chow breakpoint test (Chow, 1960). From the results obtained based on the test for structural changes, it was found that there is a structural change in the capital markets in the period between February 1998 and July 2010.

However, the Markov switching model is used to model the changes by condition as recommended by Ford, et al (2007), Hermosillo & Hesse, (2009) and Sugiyanto,et al (2018).

Equation 4.5 indicates that the average log returns of Nigerian capital markets data and the results show that every month in state 1 (stable) is 2.553, state 2 (volatile) is 0.854 and state 3 (volatile) is 4.394. Equation 4.6 contains the MSGARCH (3,1) model and Equation 4.7 shows the transition probability matrix of the Nigerian capital markets data. The results show that the conditional probability of surviving in the high volatility state in the next period is 0.984. Also, the conditional probability of surviving in a medium volatility state in the next period is 0.617 and the conditional probability of surviving in a low volatility state in the next period is 0.410.

Figures 4.5, 4.6 and 4.7 show that the period of February 1997 and July 2020 had filtered probabilities values more than 0.6. It was indicated in a state of high volatility and may indicate the occurrence of a crisis.

5.1 Conclusion

Based on the EGARCH model as the selected appropriate model for the data following the basic information criteria and MSGARCH for detecting the period when a financial crisis may occur in the capital markets of Nigeria, we can conclude that the tendency of the Nigerian capital markets volatility to react to shock is high. All shares of the Nigerian capital markets can be fitted to volatility models. Also, previous period volatility does not have an effect on current period volatility; the covariance term stationarity is less than 1 and also, the leverage effect term is not significant at 5% level, suggesting the absence of leverage effect. To confirm conditional changes in the data structure, the chow test was conducted as part of the routine diagnostic check. From the results obtained based on the test for structural changes, it was found that there was a structural change in the capital markets in the period between February 1998 and July 2010. Also, to detect the period during which a financial crisis may occur in the capital markets of Nigeria, Figures 4.5, 4.6 and 4.7 show that the period between the period of February 1997 and July 2020 had probability values of more than 0.6. This indicates a high volatility state and this maybe a sign of financial crisis.

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