Modelling Nigeria Inflation rate Volatility with Autoregressive Conditional Heteroscedasticity (ARCH) Models

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Abstracts: **This study applied Autoregressive conditional heteroscedasticity (ARCH) models in modelling Nigeria inflation rate. The time plot of the original series showed the present of seasonality and logarithm transformation of return series make it stationary. The return was estimated using both the conditional mean and conditional variance. The study applied both symmetric and asymmetric (GARCH) model that capture the feature of a financial series, such as volatility clustering and leverage effect in modelling the return series of inflation. However, four models were estimated for the conditional mean and seven models were estimated for the conditional variance and asymmetric power autoregressive conditional heteroscedasticity (APARCH (1,1)) was adopted as the best model for the return series and for the conditional mean follow an ARMA (1,1). Finally, the most adequate model for estimating volatility of the inflation rates is the asymmetric APARCH (1.1) model.**

Keywords: **Inflation rate, conditional means, conditional variance, GARCH, Volatility clustering.**

I. INTRODUCTION

The inflationary period is a time of increase in price of goods and services. This period, the quantity and type of products (good and services) purchase by individuals and corporate body at any point in time is low. The problems cause individuals and corporate bodies in the societies to purchase below the deserved quantity of products. During inflation, income earners especially those with poor income and fixed income in the society find it difficult to match with the increasing prices of goods and services. This continues as long as there is increase in price and there is fall in the purchasing power. More values of money is being required by individuals for the purpose of purchasing desired products during the period of inflation as opposed to normal economic situations. [18].

Inflation series are usually very volatile in nature and this pattern can better be model using a stochastics non-linear modelling method that characterisethebehave of the series. Volatility is one of the most important concepts in finance; its measured variances of variable asset return [14]. Volatility is often used as a basic measure of the total risk of financial assets. Policy maker are interested in measuring volatility process to learn about financial market expectation and uncertainty. [8]. A number of models have been developed to investigate volatility across different countries. The most common model to estimate volatility is the GARCH model developed independently by [16]. GARCH model, this modelislinear in mean, but non-linear in variance. The GARCH model is used to estimate the conditional mean and conditional variance. Engle described the conditional variance by a simple quadratic function of its past lagged terms. [4] Extended the basic ARCH mode and describes the conditional variances by its own lagged value and the square of the lagged terms of the shock. The GARCH model provides a good technique for analysing financial time series and estimating conditional variance. [6].

In financial markets, it is a conventional fact that a downward movement is always followed by greater volatility, which can cause a negative shock. In GARCH model, bad shocks increase volatility in financial markets why positive shocks reducing volatility. The process of higher volatility after a negative shocks than after positive shocks of the same size, is call leverage effect. This process was first suggested by [3] for stock returns. He attributed asymmetry feature to leverage effects. In this context, negative shocks increase volatility in asset markets more than positive shocks. In foreign market, any shock which increases the volatility of any seriesin the market, increases the risk of holding the currency. The student is going examined the monthly data of inflation rate using generalized autoregressive conditional heteroscedasticity (GARCH) models and autoregressive integrated moving average. The step involving in this process including modelling the condition means and variance.

II. REVIEW OF RELATED LITERATURE

The ARCH model has dominated the literature on volatility for many years. The ARCH model was developed independently by [4] wish is known as generalise autoregressive conditional heteroscedasticity (GARCH) model. The GARCH model allows the conditional variance to be dependent upon its past lags of the series. [8] The model allows persistence in conditional variance by imposing an autoregressive structure on squared errors of the process. [5]noted that although OLS maintains its optimality properties, the maximum likelihood is more efficient in estimating the parameters of GARCH models. Similarly, examine exchange rate volatility of three currencies to Nigeria

Naira using GARCH model with exogenous break. They fund that volatility is presence in the three currencies and the asymmetric model reject the existence of leverage effect and only model with volatility break that accept leverage effect. [13] Investigate exchange rate volatility between Naira and US dollar using GARCH. In the result, the asymmetric GARCH model showed the existence of asymmetric effect and the model that captured all the common feature of asymmetric properties was selected as the best model.[14], analyse inflation rate volatility using GARCH model. They fund that inflation in Nigeria follow an asymmetric GARCH model (GARCG(1,0) +ARMA (1,0)). This model was recommended for modelling inflation rate in Nigeria.

However, [15], investigate exchange rate volatility using GARCH, Evidence from Arab countries. The result indicates that ten out of the nineteen currencies, the sum of their persistent coefficient exceed unity, imply that volatility is an explosive process. The asymmetric GARCH showed the present of leverage effect for majority of the currencies. [6], examine GARCH model of USD/KES exchange rate return and fund that the asymmetric power autoregressive conditional variance heteroscedasticity (APARCH)model is adequatefor exchange rate series.

III. METHODOLOGY

Inflation series are usually very volatile in nature and this pattern can better be model using GARCH modelling. The GARCH model comprises linear mean and non-linear variance. These involve two type of models, first conditional mean and conditional variance. [8]

3.1 Conditional Mean Model

The conditional mean of a series model using autoregressive moving average modelled. The movement of inflation rate has the component of an AR process and MA process.

3.2 AutoregressiveAR(p)

An autoregressive model is a time series model in which one uses the statistical properties of the past values of the series to predict the future values. The general illustration of an autoregressive model of order p, AR(p) is

$$Y_t=\beta_0 + \beta_1\beta_1 + \beta_2 Y_{t-2} + \beta_3 Y_{t-3} \quad \ldots\beta_p Y_p + \boldsymbol{\varepsilon_t}= \sum_{i=0}^{p} \boldsymbol{\beta_i}\, \boldsymbol{y_{t-p}} + + \boldsymbol{\varepsilon_t} \quad (1)$$

Where the term $\boldsymbol{\varepsilon_t}$ is the error term and is called white noise. $\beta_1,\beta_2$and $\beta_p$are unknown parameters relating Y_t, $Y_{t-1}$and $Y_{t-p}$are estimated from sample.[11]

3.3 Moving Average Models MAq).

A moving average term in a time series is past error multiplied by the co-efficient. The notation MA(q) also refers to the moving average term of order q. Generally represented by

$$Y_t= \boldsymbol{\varepsilon_t} \quad +\boldsymbol{\alpha_1 \varepsilon_{t-1}}+\boldsymbol{\alpha_2 \varepsilon_{t-2}} + \boldsymbol{\varepsilon_{t-q}}=\sum_{j-1}^{q} \boldsymbol{\alpha_j}\, \boldsymbol{\varepsilon_{t-q}} \quad (2)$$

Where the $\boldsymbol{\alpha_1}$, ...,$\boldsymbol{\alpha_q}$are the constraints of the model, $\boldsymbol{\varepsilon_t}$ is the expectation of Y_t (often assumed to equal to 0), and the $\boldsymbol{\varepsilon_t}$, $\boldsymbol{\varepsilon_{t-1}}$,... $\boldsymbol{\varepsilon_{t-q}}$are white noise error terms.

3.4 Autoregressive-Moving-Average Models:ARMA(p,q)

The AR model includes lagged terms of the past values of series and that the MA model includes lagged terms of error term. By including both lagged terms, we arrive at ARMA model. [2] Therefore ARMA (p,q), where p is the order of autoregressive term and q the order of the moving-average term, these can generally be represented as [17]

$$\boldsymbol{y_t}= \sum_{i=1}^{p} \boldsymbol{\alpha_i}\, \boldsymbol{y_{t-1}} + \boldsymbol{\varepsilon_t}+ \sum_{j-1}^{q} \boldsymbol{\beta_j}\, \boldsymbol{\varepsilon_{t-q}} \quad (3)$$

A series $\{y_t\}$ is said to follow an autoregressive moving average model *of orders p and q,* designated ARMA (p, q), where β_j and α_i are constants such that the model is stationary as well as invertible and $\{\varepsilon_t\}$ is a white noise process. [1]

3.5 Conditional variance

The methods to model volatilities is divide in to two main category, symmetric and asymmetric models. In symmetric model the conditional variance only depend on the greatness and not the sign of the underlying asset, while in asymmetric model the negative and positive shock of the size have different effect of the future volatility. [7].

3.6 Symmetric Model

In symmetric model the conditional variance only depends on the magnitude and not the sign of asset, example of symmetric model is ARCH, GARCH and GARCH in Mean.

3.6 .1 ARCH (1)

The autoregressive conditionalheteroscedastic (ARCH) model is used to model conditional variance of a series. This model is often used to describe the increase and descries in variation. Suppose we are modelling the variance of a series y_t, the ARCH (1) model for the variance for y_t is condition on Y_{t-1} at time t is given as follow

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 \quad (4)$$

Such that $\alpha_0 \geq 0$ and $\alpha_1 \geq 0$ to avoid negative variance

3.7 GARCH (1, 1) Model

The generalized autoregressive conditional heteroscedastic model used value of the past squared observation and past variance to model the variance at time t. the model allows the conditional variance to dependent upon previous lags itself. The models Measures the extent to which a volatility shock today feed through into the next period's volatility. An example of GARCH (1, 1) model is below

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (5)$$

This is a GARCH (1, 1) model.σ_t^2Is known as the conditional variancesince it is a one-period ahead estimate for the variance.

3.8 GARCH specification of conditional and unconditional variance

The conditional variance of μ_t changes from time to time, but the unconditional variance ofμ_t, is constant at time t and its given by

$$\boldsymbol{Var\ (\alpha_t)} = \frac{\alpha_0}{1-(\alpha_1+\beta)} \quad (6)$$

If $\alpha_1+\beta < 1$, then the variance changes from time to another, if $\alpha_1+\beta \geq 1$, the unconditional variance of μ_t is undefined and lead to non-stationarity in variance. If $\alpha_1+\beta = 1$, the process is called the unit root variance or the integrated GARCH (IGARCH). Unconditional variance does not have a solid theoretical enthusiasm for its survival, as would be the case for non-stationarity in the mean. However, a GARCH model whose $\alpha_1+\beta \geq 1$ would have some highly undesirable properties.[7].

3.9 GARCH- M (1,1)

In financial market, high risk is expected to produce high return. In this type of condition, one may consider the GARCH IN MEAN model. The model allows the condition mean of a sequence to depend on its conditional variance.

The model is as follow

$$\gamma_t = \mu + \lambda\sigma_t^2 + y_t \quad (7)$$

$$y_t = \sigma_t \varepsilon_t$$

$$\varepsilon_t \sim (0, \sigma_t^2)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 y_{t-1}^2 + \beta_t \sigma_{t-1}^2 \quad (8)$$

Where $\lambda\ and\ \mu$ are constant, if λ is positive the return is also positive related to volatility

3.10 Asymmetric Models

Since bad news (negative shocks) tends to have a large impact on volatility than good news (positive shocks), hence there is need to talk about the Asymmetric GARCH modeland

We restricted our analysis to the more popular models of asymmetric GARCH, such asEGARCH, TS-GARCH, APARCH.

3.11 EGARCH Model:

The exponential GARCH (EGARCH) model has several advantages over the general GARCH process. First, since the log (σ_i^2) is modelled, then even if the parameters are negative, (σ_i^2), will be positive. There is thus no need to artificially impose non-negativity constraints on the model parameters. Second, asymmetries are allowed for the EGARCH formulation, since the relationship between volatility and returns is negative.γ, will be negative the model.the can be represented as follow.

$$Logh_t = \alpha_0 + \sum_{i=1}^{p} \alpha_1 \frac{|\varepsilon_{t-1}| + \gamma_i\, \varepsilon_{i-1}}{h_{t-1}^{\frac{1}{2}}} + \sum_{j=1}^{q} \beta_j \ \log h_{t-j} \quad (9)$$

Where, γ is leverage effect co-efficient.(If $\gamma > 0$ it indicates the presence of leverage effect).

Note that when ε is positive there is good news, when ε is negative there is bad news

3.12 TS- GARCH Model:

Another GARCH method that is capable of modelling leverage effects is the Threshold GARCH. The threshold GARCH (TGARCH) is similar to the GJR model, the only different is the specification of the standard deviation, instead of the variance.

TS-GARCH model, which has the following form:

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_1\ \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \gamma_1\, \varepsilon_{t-1}^2 s_{t-1} + \sum_{j=i}^{q} \beta_j\, h_{t-1}$$

$$Where\ s_{t-1} = \begin{cases} 1\ if\ \varepsilon_{i-1} < 0 \\ 0\ if\ \varepsilon_{t-1} \geq 0 \end{cases}$$

$\gamma$is leverage effects coefficient. (if$\gamma > 0$ it indicates the present of leverage effect). That is depending on whether ε is above or below the threshold value of zero,

ε_t^2has different effects on conditional variance h_t when ε_{t-i} is positive.

3.13 APARCH (1,1)

Asymmetric power ARCH (APARCH) model, this is able to accommodate asymmetric effect and power transformation of the variance. Its specification for the conditional variance is as follow

$$\sigma_t^2 = \alpha_0 z_t + \sum_{i=1}^{q} \alpha_i (|u_t| - \gamma_t u_t) + \sum_{j=1}^{p} \beta_j\, \sigma_{t-1}^2 \quad (11)$$

Where $\sigma_t = \sqrt{h_t}$, the parameter γ (assumed positive and ranging between 1 and 2)

IV. METHODS OF ESTIMATION OF GARCH MODELS

The method used for estimating GARCH model is the maximum likelihood estimator. The method is used to find the most likely value of the parameters given the actual series. The following step are involved in estimating GARCH model

(i) Specify the mean and variance equation, example (AR (1) and GARCH (1,1) models)

$$y_t = \mu + \theta y_{t-1} + \mu_t \mu \sim (0, \sigma_t^2) \quad (12)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (13)$$

(ii) Estimate the likelihood function to maximise the normality assumption of disturbance terms.

$$log\ L = -\frac{T}{2} log(2\pi) \quad -\frac{1}{2}\sum_{t=1}^{T} log(\sigma_t^2) - \frac{1}{2}\sum_{t=1}^{T} \frac{\mu_t^2}{\sigma_t^2}. \tag{14}$$

4.1 Unit Root Test

In order to determine the integration of the variance we apply the augmented Dickey Fuller test wish base on the equation below

$$\Delta y_t = \varphi + \beta_t + \alpha_1 y_{t-1} + \sum_{i=1}^{k} d_i\, \Delta y_{t-1} + \mu_t \tag{15}$$

Where μ_t is a white noise process, the equation is use to test null hypothesis of unit root against the alternative hypothesis.

4.2 Data Transformation

The monthly inflation rate series from January2003 to December 2016 are used. This make a total of 156 observation and are transformed for the needs of fitting the model to a logarithm returns. Let the series (e_t) denoted inflation rate in Nigeria. The logarithm returns series γ_t is

$$\gamma_t = log^{(\frac{e_t}{e_{t-1}})} = log^{(\frac{inflation\ return_t}{inflation\ return_{t-1}})} \tag{16}$$

Where e_t is the inflation rate at time t and e_{t-1} represent the inflation return series at time?

t-1.

V. EMPIRICAL RESULT

5.1 Data Properties

The time plot of original series of inflation rate without transformation is showed in figure (1).To remove the seasonal pattern, we take the first difference (d) of the logarithms (I) transformation of the data and the series are transformed in to financial time series showed in figure (2). Figure 3 & 4 is the square and absolute return of inflation rate series.

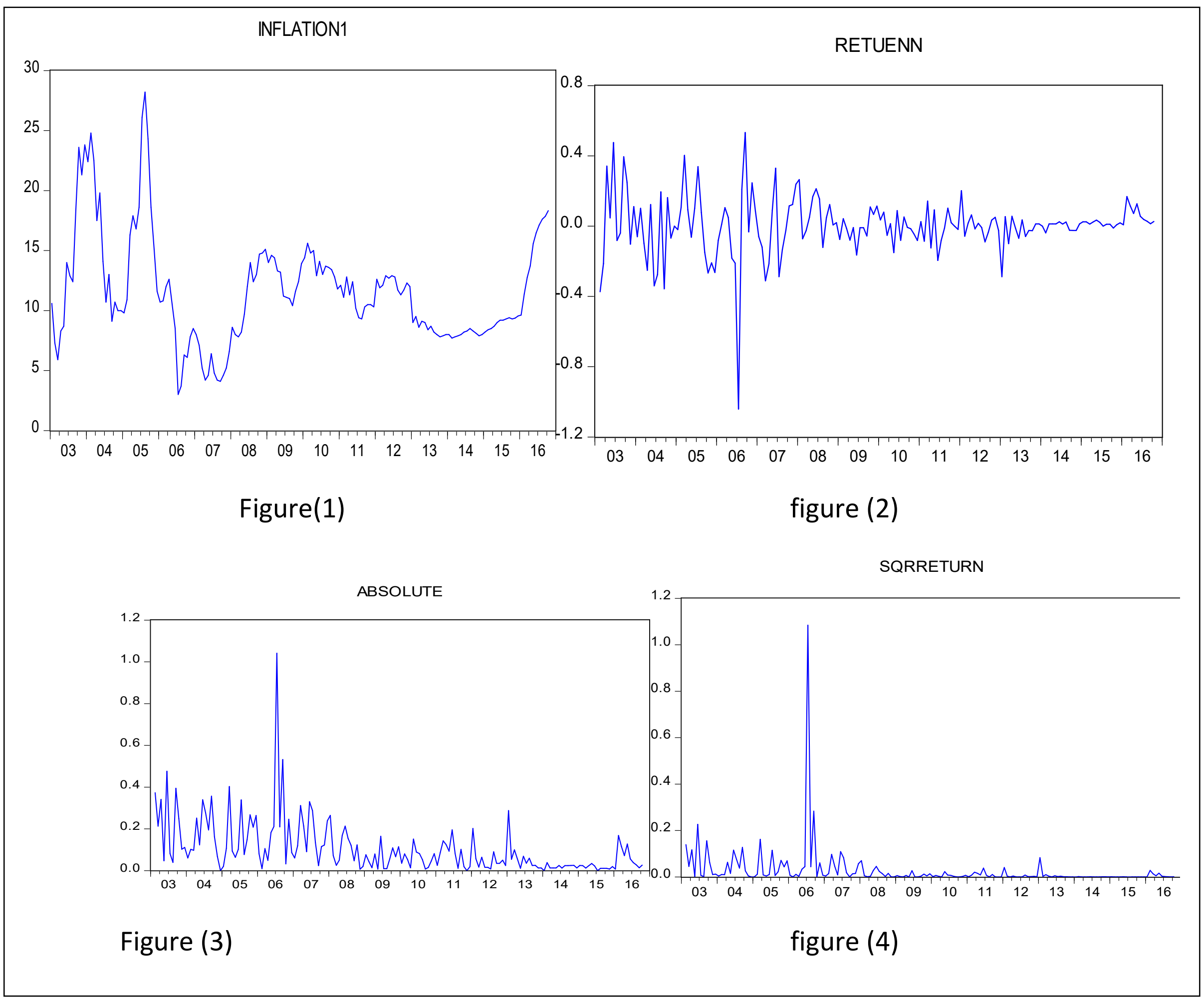


Figure 1.0 .Time plot Original Series and Differences data

Table (1.0)Value of Unit Root Test of inflation rate return

Critical value	ADF test statistics (-11.62868)
1%	-3.470427
5%	-2.879047
10%	-2.576182

The value of inflation rate return after logarithm transformation and first differences is stationary, since the value of ADF test statistics is less than the critical at (1%, 5% and 10%) as showed in table (1).

Table (1.1)Summary Statistics for the returns of inflation rates (return, square and absolute values)

data	Sample size	Mean	median	max	min	Stddev	skewness	kurtosis	Jarque Bera	probability
R	165	0.00332	0.011	0.532	-1.04	0.166	-1.197	12.39	645.273	0.000
ASB R	165	0.0275	0.004	1.085	0.00	0.093	9.351	104.68	73485.4	0.000
SQ R	165	0.1057	0.064	1.042	0.00	0.128	3.183	19.732	2203.26	0.000

Table 1.1.Gives the summary statistics of R, absolute values of R and R square. The kurtosis for monthly inflation rate return is 12.39 which is greater than the value of the normal distribution (kurtosis=3). The kurtosis for inflation rate square return is 19.732 and the kurtosis of inflation rate absolute return is 104.68. The value shows the financial time series have the fat-tail behaviours. The JarqueBera for inflation rate absolute return is 73485.48. The high Jarque-Bera statistics indicates the non-normality of the return series.[12]

Table (1.2) Autocorrelation Analysis of return absolute and square return series of inflation rate

	Return				Absolute				square			
Lag	Acf	Pacf	Q-S	Pro	Ac	Pa	Q-S	pro	Acf	Pac	Q-s	Pro
1	0.106	0.106	1.8873	0.170	0.295	0.295	14.591	0.000	0.106	0.106	1.8873	0.170
2	-0.046	-0.058	2.2409	0.326	0.374	0.315	38.252	0.000	-0.046	-0.058	2.2409	0.326
3	-0.017	-0.006	2.2928	0.514	0.156	-0.015	42.403	0.000	-0.017	-0.006	2.2928	0.514
4	-0.130	-0.132	5.1859	0.269	0.221	0.091	50.778	0.000	-0.130	-0.132	5.1859	0.269
5	0.053	0.083	5.6674	0.340	0.100	-0.007	52.497	0.000	0.053	0.083	5.6674	0.340
6	-0.016	-0.048	5.7130	0.456	0.161	0.060	56.985	0.000	-0.016	-0.048	5.7130	0.456
7	-0.010	0.005	5.7291	0.572	0.243	0.203	67.269	0.000	-0.010	0.005	5.7291	0.572
8	0.069	0.050	6.5662	0.584	0.258	0.124	78.996	0.000	0.069	0.050	6.5662	0.584
9	-0.033	-0.031	6.7582	0.662	0.324	0.162	97.542	0.000	-0.033	-0.031	6.7582	0.662
10	-0.130	-0.133	9.7402	0.464	0.228	0.018	106.76	0.000	-0.130	-0.133	9.7402	0.464
11	-0.202	-0.183	17.070	0.106	0.236	0.020	116.75	0.000	-0.202	-0.183	17.070	0.106
12	-0.185	-0.156	23.255	0.026	0.332	0.246	136.61	0.000	-0.185	-0.156	23.255	0.026
13	0.086	0.086	24.604	0.026	0.175	-0.039	142.18	0.000	0.086	0.086	24.604	0.026
14	0.066	0.006	25.395	0.031	0.151	-0.075	146.33	0.000	0.066	0.006	25.395	0.031
15	-0.054	-0.091	25.927	0.039	0.193	0.101	153.16	0.000	-0.054	-0.091	25.927	0.039

We examine the autocorrelation of return, absolute return and square return from lag 1 to 15 of inflation rate. The first lag autocorrelationof return, absolute return and square return are as follow 0.106, 0.295 and 0.106 which are highly positive. This means that inflation rate return is highly volatile, this one of the characteristics of financial time series.

5.2 Estimating the Conditional Mean

The ARMA (p,q) is used to model the conditional mean and dynamic error in the series. The autoregressive function and moving average function are used to determine the order of ARMA (p,q) models. To get the parameters p and q of AMRA model to fit in the series, we use Akaike Information Criterion and Schwarz criterion

Table 1.3 Selection of ARMA(p.q) model with AIC and SC

models	AIC	SC
ARMA(1,1)	-0.68455	-0.60894
ARMA(2,1)	-0.673193	-0.597587
ARMA(1,2)	-0.674205	-0.598599
ARMA(2,2)	-0.164296	-0.088690

Four models were estimated with Akaike information criterion (AIC) and schwarz criterion are shown in table 1.3.

The best model is models that minimise information criterion and schwarz criterion (ARMA (1,1) with AIC *(-0.68455) SC (-0.60894)*. The return mean equation follow ARMA(1,1) process.[2]

Table 1.4 Testsfor ARCH Effect

Heteroskedasticity Test: ARCH

F-statistic	0.238604	Prob. F(5,154)	0.9449
Obs*R-squared	1.229975	Prob. Chi-Square(5)	0.9420

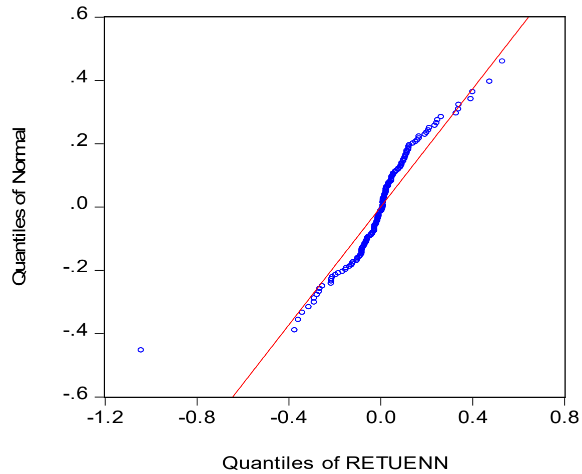
Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 08/15/18 Time: 13:36
Sample (adjusted): 2003M07 2016M10
Included observations: 160 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.084819	0.270292	4.013508	0.0001
WGT_RESID^2(-1)	0.011956	0.080346	0.148805	0.8819
WGT_RESID^2(-2)	0.025388	0.080228	0.316447	0.7521
WGT_RESID^2(-3)	-0.008095	0.080264	-0.100857	0.9198
WGT_RESID^2(-4)	-0.055943	0.080258	-0.697034	0.4868
WGT_RESID^2(-5)	-0.059298	0.080338	-0.738103	0.4616

R-squared	0.007687	Mean dependent var	0.996784
Adjusted R-squared	-0.024531	S.D. dependent var	2.510803
S.E. of regression	2.541412	Akaike info criterion	4.740095
Sum squared resid	994.6512	Schwarz criterion	4.855414
Log likelihood	-373.2076	Hannan-Quinn criter.	4.786922
F-statistic	0.238604	Durbin-Watson stat	2.004860
Prob(F-statistic)	0.944882		

The table above showed the present ARCH since both the *F*-version and the *LM*-statistic are statistically significant, suggesting the presence of ARCH in inflation rate return series in Nigeria.[9]

Figure 1.1 Quantile –Qauntile test for normality of inflation rate return series



The plot of normal quantile–quantile of inflation rate return series plots shows strong departures from normality.

Table 1.5 Parameter Estimation for ARCH Model of inflation rate Return series

Models/ Parameter.	ARCH (1,1)	GARCH (1,1)	GARCH-M (1,1)	APARCH (1,1)	TS-GARCH (1,1)	EGARCH (1,1)	GJR-GARCH (1,1)
C	0.00428 (0.000)	0.709922 (0.1606)	0.123576 (0.1527)	0.514253 (0.3197)	0.086039 (00.3425)	0.410524 (0.4515)	0.37133 (0.4387)
α_0	0.00846 (0.000)	0.000334 (0.011)	0.000336 (0.000)	0.008620 (0.3630)	0.000527 (0.0019)	-0.406083 (0.0065)	0.000544 (0.003)
α_1	1.33359 (0.000)	0.178694 (0.00034)	0.183655 (0.00033)	0.172235 (0.0004)	0.008633 (0.2834)	0.234161 (0.0017)	0.086295 (0.2871)
β		0.817274 (0.000)	0.813682 (0.000)	0.565763 (0.0068)	0.296403 (0.007)	-0.106797 (0.0150)	0.286895 (0.0008)
γ				0.806920 (0.000)	0.755350 (0.000)	0.94658 (0.000)	0.760207 (0.000)
λ				0.935366 (0.006)			
$\alpha + \beta$		0.995497	0.997337	0.737998	-0.38236	0.12736	0.37379
$\log L$	84.7093	106.9236	4106.7049	111.7676	109.2969	107.8529	109.1167
AIC	-1.0025	-1.24756	-1.244908	-1.28203	-1.264204	-1.2467	-1.26202
SC	-0.9649	-1.17226	-1.1696	-1.169087	-1.170085	-1.15258	-1.67907
Obs	165	165	165	165	165	165	165

From the table, The GARCH models for the return series of inflation rate all satisfy the covariance stationary condition,$\alpha + \beta < 1$. The symmetric effect $\alpha > 0$in all the ARCH models, means the volatility is very high in bad news than in good news. The result showed thepresence of leverage effect γ , they arestatistically significant at 5% level which means that bad news generates high volatility than good news. Comparing the Log Likelihood and information criterion Schwarz criterion within the conditional distribution, the model with conditional distribution of maximum Log-Likelihood and minimum information criterion, statistically estimate the better fitted model.

The APARCH model is found to be the best model, because it has the higher log-likelihood estimate and minimum AIC and SC information criterion (LogL=111.76776, AIC=-1.28203, SC= -1.169087). the coefficient on both the lagged squared residual and lagged conditional variance term in the conditional variance equation are highly statistically significant and the sum of the coefficient on the lagged squared error and lagged conditional variance is close to unity *(0.737998), which*example of GARCH models for financial asset return series. This implies that shocks to the condition variance will be highly persistent, that is ($\beta > 1$)

However, Good news and Bad news have difference effect on the conditional variance: Good news has an impact on α while Bad news has an impact on $(\alpha + \gamma)$. In APARCH model, the Good news has an impact on 0.172235 while Bad news has an impact on 0.978955. The value of λ is positive and statistically significant. This implies that, increased risk, given by an increase in the conditional variance which lead to a rise in the mean return of inflation rate.

The coefficient of the mean equation has a positive sign and statistically significant. This indicate that in inflation rate return series, there is feedback from the conditional variance to the conditional mean.

VI. CONCLUSION

This paper examined the monthly inflation rate return series January 1981 to December 2015. The study applied generalized autoregressive conditional heteroscedasticity (GARCH) models, including both symmetric and asymmetric model that capture the feature of a financial series, such as Fat tails, Excess kurtosis, Volatility Clustering, Long Memory and Leverage Effects. However, four models were estimated for conditional mean and ARMA (1,1) was selected and seven models were estimated from the GARCH family and the asymmetric power autoregressive conditional heteroscedasticity (APARCH (1,1)) was adopted as the best model for inflation rate series in Nigeria.

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