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ESTIMATION OF GARCH MODEL USING ERROR DISTRIBUTIONS FOR ACCURACY MEASURE OF THE NIGERIAN ECONOMY

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Abstract
The study examined the performance of some symmetric and asymmetric GARCHmodels onNigeria's economy using the real gross domestic product cost at a constant factor (RGDPCF).The series comprises all the monthly values of the data covering the period from January 2000 to December 2019. It filled the lacuna by explicitly modeling and comparing four different GARCH models for the variable mentioned above. The order of the GARCH models was specifiedand the comparison among all the models was done on the bases of the error distribution and model selection criteria. The result of the symmetric model GARCH in normal error distribution assumption was found to have the highest volatility of 150.1 percent persistence impact, however, GARCH in generalized error distribution assumption with the Akaike model Information Criterion(AIC=4.289) is considered the most appropriate symmetric model. Similarly, the TGARCH in Generalized error distribution assumption has the highest impact volatility persistence of 217.6 percent. The leverage effect of the TGARCH-Normal is -0.114 (p-value=0.000), andthat of TGARCH-GED is -1.247 (p-value=0.000,). Hence, the overall best fit model for the Real Gross Domestic Product at Constant Factor Cost (RGDPCF) based on the Akaike information model selection criterion (AIC = 4.065) is the TGARCH model in Generalized Error Distribution Assumption.

Keywords: Error distribution, GARCH model, Real gross domestic product, Variance model, Volatility.

Introduction

Financial time series data such as stock prices, exchange rates, inflation rates, crude oil prices, gross domestic product, savings accumulation, etc. are some of the variables that often exhibit the characteristics of clustering., a period otherwise referred to as volatility clustering. This is explained as a period whereby prices show wide swings within an extended time and it will later show relative calmness. This applies to almost all micro-economic variables.For instance, all the indicators and determinants of employment and production, consumption, investment in raising productive capacity, and how much a country imports and exports (John, 2003) also suffer the same fate. They suffer sudden fluctuations and these continual fluctuations affect so many things thereby contributing to the increase in price volatility and revenue profile of these products. And these are some of the causes of economic shocks widely experienced in the world. According to Agenor et al. (2000), the macroeconomic effects of macro-econometric variables and trade shocks arising from price volatility have a great and very significant effect on developing countries. Again, studying the performance of macroeconomics is variable because it helps in exposing the financial and economic health of a nation, thereby prescribing how trade and other financial activities influence the country in general (Victor-Edema&Essi, 2020).

These shocks are major sources of aggregate economic volatility and they have a large impact on private and public savings because of their economic effects (Agenor et al., 2000). They are also associated with global business cycles which manifest in the form of sharp volatility in foreign exchange earnings of primary producing economies as in the case of Nigeria. Such development usually results in macroeconomic instability, insufficient allocation of resources, recessions, and low output growth. According to Gujarati (2009), the awareness of volatility is of crucial importance in many areas. For example, considering it sudden sharp changes in prices investors and traders alike cannot know the appropriate time to invest and when not to as a result of instability in the world's prices. This does not guarantee safer investment especially now that the crude oil market and other financial markets like stock and foreign exchange markets are more dependent on each other than ever before. For traders in these markets or decision markers, volatility in its entirety may not be bad, but its variability may not be good enough because this makes financial planning cumbersome. This is also applicable to importers, exporters, and traders in foreign exchange markets. This variability in the exchange rates may account for excessive losses or profits. According to Gujarati (2009) investors in the stock market are interested in the volatility of stock price, for high volatility could mean huge losses or gains and hence greater uncertainty.

The usual traditional regression tools have proved their limitation in the modeling of high-frequency (weekly, daily, or intra-daily) data (Shamiri et al., 2009). The Autoregressive conditional heteroskedasticityARCH has variance extensions such as Generalized ARCH, GJR-GARCH (TGARCH), Exponential GARCH, component – GARCH, and GARCH-M. In some cases, the first-order GARCH family models have been extensively proven to be appropriate for modeling and forecasting financial time series. (Hsieh, 1991; Bera&Hagging, 1993; Eric, 2008; Olowe, 2011;Hojatallah et al., 2011). But in these studies little or no attention was given to their suitable error distribution assumptions for modelling, especially the normality and generalized error distribution assumption. This is considered because a review of relevant literature shows that several researchers have neglected the contribution of the error distribution assumptions while modelling market price volatility. The wrong use of appropriate error distribution in the volatility model for financial time series may cause misspecification in the volatility model, leptokurtic, and autocorrelation behaviour of such series. Whereas Klar et al. (2012) posited that the appropriate specification of the concept distribution may lead to a sizeable loss of correctness of the corresponding estimators, wrong risk determination, inaccurately priced options, and inadequate assessment of value-at-risk (VAR). In modelling volatility, there is a need to specify the form of the error distribution to be used in the estimation. Hence, this study seeks to investigate and as well as close-gap the vacuum in several works of literature by estimatingSymmetric, and Asymmetric GARCH family models in their various error distribution forms; normal, student t, and generalized error distribution (GED) to compare them while considering the best-fitted model (with the best error distribution) for measures and forecasting volatilityof the RGDPCF and by implication the Nigeria economy within the years under consideration.

Materials and Methods

The study employed Generalised Autoregressive Conditional Heteroscedasticity (GARCH) Models developed by Bollerslev (1986), in determining the volatility of the naira exchange rate for the period under study. The choice of the model is based on the fact that the GARCH model is very robust in modelling the volatility in financial data characterized by volatility clustering and heteroscedasticity. Musyokiet al.(2012) noted that GARCH *(1, 1)* is the most widely used specification in the Autoregressive Conditional Heteroscedasticity (ARCH) family. The classic ARCH model and the extension GARCH model, are introduced. Also, the five different GARCH models were stated. The study seeks to compare the five GARCH models: The Generalized ARCH (GARCH) Model, the Threshold GARCH (TGARCH) Model, the Exponential GARCH (EGARCH) Model, Asymmetric Power ARCH (APARCH) Model, and the Power GARCH (PGARCH) Model to determine which one will best predict the Nigerian Economy using Accuracy measures. Data used for this study was sourced from the Central Bank of Nigeria (CBN) statistical database website (www.cbn.gov. ng). The variables comprised monthly Capital formation, Gross Domestic Product, Labour force, Savings accumulation, and Capital market for the period of January 2000 - December 2021.

Investigating the residuals for the confirmation of heteroscedasticity is imperative in this study. The presence of conditional heteroskedasticity if not accounted for leads to misleading results. To test the incidence of heteroscedasticity in the residual of the return series, The Lagrange Multiplier (LM) test for Autoregressive conditional heteroscedasticity (ARCH) is used.

Autoregressive Conditional Heteroskedasticity (ARCH) Models

Engle (1982) proposed the ARCH model (Auto-regressive Conditional Heteroskedastic Model). conditionalheteroskedasticity in a return seriesy_t can be modeled using the ARCH model expressing the mean equation in the form:

$$y_t = E_{t-1}(y_t) + \varepsilon_t \tag{1}$$

where

$\varepsilon_t = \varphi_t \sigma_t$

$\varepsilon_t$is the error gotten from the mean equation at time t

$E_{t-1}$is the expectation conditioned on the information available at time t-1

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$\varphi_t$is a sequence of independent, identically distributed random variables whose mean is zero with unit variance.

Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Models

The GARCH model is an extension of the ARCH model developed by Engle (1982) which considers the variance of the current error term to be a function of the variances of the previous timeperiod's error terms. The GARCH (1,1) model is estimated by maximum likelihood estimation (MLE) specifying the density of the error term as a generalized error distribution (GED), Nelson (1990). The GARCH effects in the models are examined using correlograms of the squares of the exchange rate returns. Autocorrelations larger than the critical values give evidence of the presence of GARCH effects.

The conditional variance for the GARCH (p, q) model is expressed generally as:

$$\sigma_t{}^2 = \beta_0 + \sum_{i=1}^{q} \alpha_i\, \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_j\, \varepsilon_{t-1}^2 \tag{2}$$

where p is the order of the GARCH terms, $\sigma^2$and q, the order of the ARCH terms, ε^2, the disturbance where

$$\beta_0 > 0, \alpha_i > 0, i = 1,2,3 \ldots q-1,\ \ j = 1,2,3, \ldots, p-1$$

is the conditional variance and

$\varepsilon^2{}_t$, disturbance term.

Threshold GARCH (TGARCH) Model

The generalized specification for the conditional variance using TGARCH (p, q) is given as:

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{q} \alpha_i\, \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \tau_j\, I_{t-1}\varepsilon_{t-j}^2 + \sum_{i=1}^{p} \beta_j \sigma_{t-j}^2 \tag{3}$$

where

$I_{t-1} = 1$if$\varepsilon\ {}^2_t < 0$and 0 otherwise.

The Exponential GARCH (EGARCH) Model

The conditional variance of EGARCH (p, q) model is specified generally as

$$\log(\sigma_t^2) = \beta_0 + \sum_{i=1}^{q} \left\{\alpha_1 \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \gamma\left(\frac{\varepsilon_{t-i}}{\sigma_{t-1}}\right)\right\} + \sum_{j=1}^{p} \beta_j\, log\left(\sigma_{t-j}^2\right) \tag{4}$$

$\varepsilon_{t-I}^2 > 0$implies good news while $\varepsilon_{t-i}^2 < 0$ implies bad news. Their total effects are $1-\gamma_i$and $(1-\gamma_i)|\varepsilon_{t-1}|$ respectively. When$\gamma_i < 0$, the expectation is that bad news would have a higher impact on volatility. The EGARCH model achieves covariance stationarity when $\sum_{j=1}^{p} \beta_j < 1$.

Power GARCH (PGARCH) Model

The PGARCH model is an asymmetric model that takes the leverage effect into account. The condition for the non-negativity parameter is the same as that of the GARCH model and also has some other GARCH model nested within it.Ding et al. (1993) expressed conditional variance using PGARCH (p, d, q) as

$$\sigma_i^\delta = \alpha_0 + \sum_{i=1}^{p} \alpha_i(|e_{t-1}| + \gamma_i\, e_{t-1})^\delta + \sum_{i=1}^{q} \beta_j \sigma_{t-j}^\delta \tag{5}$$

where

$\delta \geq 0,\ \alpha_0 > 0,\ \alpha_i > 0\ ,\ \beta_j > 0and|\gamma_i| < 1$ for $(i = 1,2,3, \ldots, p),\ j = 1,2,3, \ldots, q)$. γ is the coefficient of leverage effects. Depending on the value of $\gamma$and δ, the APARCH reduces to the following GARCH-type models when $\delta = 2, \gamma = 0$ and$\beta_j = 0$, it reduces to the ARCH model.

Test for Heteroskedasticity

Testing for heteroskedasticity simply means testing for the ARCH –effect consequently. To test for heteroskedasticity, the Lagrange Multiplier (LM) test was adopted. A null hypothesis of no ARCHeffect was stated. If the test is significant, then the GARCH models are used for the model estimation. The Lagrange Multiplier test involves the use of OLS to estimate the most appropriate regression equation. The essence of using the linear regression model is to obtain the residual.

Error Distributions in Estimation

To further prove that modelling of the return series is inefficient with a Gaussian process for high-frequency financial time series, they are estimated with a normal distribution by maximizing the likelihood function

$$L(\theta_t) = -1/2\sum_{t-1}^{T}(ln2\pi + ln\sigma_t^2 + \frac{\varepsilon_t^2}{\sigma_t^2}) \qquad (6)$$

$\sigma_t^2$is specified in each of the GARCH models.
The assumption that GARCH models follow generalized error distribution GED tends to account for the kurtosis in returns, which are not adequately captured with the normality assumption. The volatility models are estimated with GED by maximizing the likelihood function below:

$$L(\theta_t) = -\frac{1}{2}\log\left(\frac{\Gamma(\frac{1}{v^3})}{\Gamma(\frac{3}{v})(\frac{v}{2})^2}\right) - \frac{1}{2}log\sigma_t^2 - \left(\frac{\Gamma(\frac{3}{v})(y_t - x_t'\theta)^2}{\sigma_t^2\Gamma(\frac{1}{v})}\right)^{\frac{v}{2}} \qquad (7)$$

is the shape parameter that accounts for the skewness of the returns and The higher the value $v$the greater the weight of the tail. GED reverts to normal distribution if$v = 0$.
In the case of t distribution, the volatility models considered are estimated to maximize the likelihood function of a Student's t distribution:

$$L(\theta_t) = -\frac{1}{2}\log\left(\frac{\pi(r)\Gamma r/2^2}{\Gamma((r+1)/2)^2}\right) - \frac{1}{2}log\sigma_t^2 - \frac{(r+1)}{2}log\left(1 + \frac{(y_t - x_t'\theta)^2}{\sigma_t^2(r-2)}\right) \qquad (8)$$

Here, r is the degree of freedom and controls the tail behaviour $r>2$.

Stationarity a Time Series
A time series is said to be stationary if the statistical property e.g. the mean and variance are constant through time. If there are$n$ values of observations $x_1, x_2, x_3, \ldots x_n$ of a time series, a plot of these values against time helps in determining if the time series is stationary. If the n-values fluctuate with constant variation around a constant mean μ, then the time series is stationary and all processes which do not possess this property are called "non-stationary". The stationarity test was using the Augmented Dickey-Fuller test and the return series was stationary.

Results and Discussions
The time Plots for the time series and its return series are given the figures below.

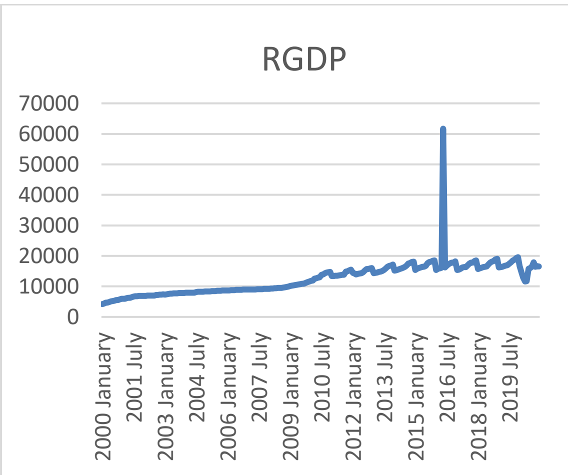

Fig.1: Time plot of the raw series on Real Gross Domestic Product at Constant Factor Cost (RGDPCF).

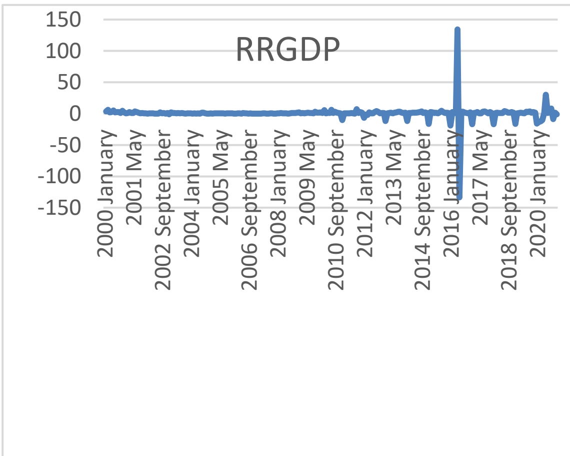

Fig. 2: Time plot of the returns on Real Gross Domestic Product at Constant Factor Cost (RGDPCF)

Figure1 shows the plot of the raw series on Real Gross Domestic Product at Constant Factor Cost (RGDPCF). This is done to determine the trend, intercept, and volatility clustering. Figure 2 is the time plot of the returns on the raw series on Real Gross Domestic Product at Constant Factor Cost (RGDP). The visual examination revealed some sort of clustering volatility.

Table 1: Descriptive Statistics of Real Gross Domestic Product at Constant Factor Cost (RGDPCF) and its Return.

Variable	Mean	Median	Max	StD	Skewness	Kurtosis	Jarq. Bera	Prob.
RGDPCF	12379.77	12733.11	61688.22	4204.34	5253.319	3.204337	31.70638	0.000
RRGDPCF	0.545	0.84	134.338	-133.594	12.673	-0.0699	100.526	0.000

The descriptive statistics of the variable RGDP at constant factor and its return are given in Table 1. The table showed that both series have positive means and medians.

Table 2: ARCH Effect Test Using Lagrange Multiplier

Variables		Lag (5)	Lag(10)	Lag(15)	Remark
	F-stat	8.179	3.921	2.501	
	P-value	0.000	0.000	0.000	Heteroskesdastic
RRGDPCF	$n*R^{-2}$	35.815	35.103	34.380	
	Prob. F(5,10,15,422)	0.000	0.000	0.000	

Footnote:^^ significant at 5%, prob.F(1,236)

Table 2 contains the Lagrange multiplier's Heteroscedasticity test result showing the presence of the ARCH effect (at a probability of 0.0000<0.05) in the Return RGDP at constant factor cost.

Parameter Estimation Table

The estimation of the parameters of the modelis done and the results are shown in Table 3.

Table 3:Parameter Estimation of the Symmetric and Asymmetry GARCH Modelswith Three Error Distribution Assumptions for RGDPCF

Model	Model Parameter	NORMAL	STUDENTS-T (DF=10)	GED.	Highest Impact	Model with the least AIC
	α(Intercept)	1.187 (0.000)	0.298 (0.000)	0.838 (0.000)		
	β(ARCH)	0.501 (.000)	0.175 (0.002)	0.012 (0.001)		
GARCH	α(Intercept)	-0.011 (0.000)	0.006 (.000)	1.347 (.000)		
	β(ARCH)	0.696 (0.000)	0.151 (.000)	0.095 (.000)		
	σ^2(GARCH)	0.805 (.000)	0.824 (0.000)	0.786 (0.000)		
	$(\sigma^2 + \beta)$	**1.501**	0.975	0.886	**1.501**	
	AIC	5.383	4.640	4.289		GARCH(1,1)-GED
	α(Intercept)	0.280 (0.000)	0.303 (0.001)	0.473 (0.000)		
	β(ARCH)	0.122 (0.000)	0.172 (0.000)	0.001 (0.000)		
TGARCH	*α(Intercept)*	-0.011 (0.000)	0.006 (0.000)	0.135 (0.001)		
	β(ARCH)	0.355 (0.000)	0.212 (0.000)	1.487 (0.001)		
	γ (Leverage)	0.898	-0.114	-1.247		

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		(0.000)	(0.000)	(0.001)		
	σ^2(GARCH)	0.898	0.815	0.689		
		(0.000)	(0.000)	(0.000)		
	($\sigma+\beta$)(Volatility)	1.253	1.027	**2.176**	**2.176**	
	AIC	5.316	4.633	4.065		TGARCH(1,1)-GED
	α(Intercept)	-0.592	1.060	0.264		
		(0.000)	(0.000)	(0.005)		
	β(ARCH)	-0.0424	-0.016	0.415		
		(0.000)	(0.003)	(0.030)		
E-GARCH	*α(Intercept)*	6.223	1.858	2.829		
		(0.000)	(0.000)	(0.005)		
	β(ARCH)	0.200	0.182	0.772		
		(0.000)	(0.003)	(0.030)		
	γ (Leverage)	0.758	-0.066	-0.616		
		(0.004)	(0.137)	(0.000)		
	σ^2(GARCH)	-0.796	-0.411	-0.003		
		(0.000)	(0.025)	(0.000)		
	($\sigma+\beta$) (Volatility)	-0.596	-0.229	**0.769**	**0.769**	
	AIC	6.475	5.222	4.054		EGARCH-GED
	α(Intercept)	0.348	0.374	0.860		
		(0.000)	(0.0000)	(0.000)		
P-GARCH	*β(ARCH)*	0.033	-0.022	0.012		
		(0.000)	(0.000)	(0.000)		
	α(Intercept)	2.30E-0.5	-0.015	0.154		
		(0.000)	(0.000)	(0.000)		
	β(ARCH)	0.587	0.188	0.169		
		(0.000)	(0.0000)	(0.000)		
	γ (Leverage)	0.189	-0.468	-0.665		
		(0.000)	(0.000)	(0.000)		
	Z_t	0.541	0.841	0.853		
	σ	6.916	0.342	0.615		
	$\sigma+\beta$ (Volatility)	**7.503**	0.530	0.784	**7.503**	
	AIC	5.266	4.521	4.192	4.192	PGARCH-GED

Table 3 shows the estimate of standard symmetric and Asymmetric GARCH models with varying error distribution assumptions.

Table 7. Model Selection Criteria

		MODEL	NORMAL	ST-T(DF=10)	GED	MIN.	LEASTAIC
		GARCH	5.383	4.640	4.205	4.205	
	AIC	T-GARCH	5.316	4.633	4.065	4.065	4.065T-GARCH(GED)
RRGDP		E-GARCH	6.475	5.222	4.054	4.054	
		P-GARCH	5.266	4.521	4.191	4.191	
		MODEL	NORMAL	ST-T(DF=10)	GED	MIN.	

Discussion of findings

The time plot of the raw series of Real Gross Domestic Product at Constant Factor Cost (RGDPCF) is displayed in Figure 1. From the visual examination, there is the presence of a trend,and intercept but no volatility clustering was spotted. The time plot revealed an upward trend in the series between May 2016 and December 2016. This shows that RGDPCF experiencedan increase. This is been interpreted as an increase in Nigeria's economy. The large increase in the number of traded assets constitutes what forms market risk, i.e., the risk due to adverse market movements,and becomes a primary concern in the financial world (Deebom&Essi 2021). Figure 2 contains the time plot for the returns on the Real Gross Domestic Product at Constant Factor Cost (RRGDPCF). The visual examination revealed clustering volatility. This is in line with Cont's (2007) assertion that time series of financial asset returns often exhibit the volatility clustering property, where large changes in prices tend to cluster together. This results in the persistence of the difference between values at the peak and trough of price changes. The returns series describe the relative changes over time in the price process.

Table 1 shows the descriptive statistic of RGDPCF along with its return series RRGDPCF. Both series, RGDPCF and RRGDP, have a positive mean, 12379.77 and 0.545 respectively withcorresponding standard deviations of RGDP (4204.34) and RRGDP (-133.594),. They are positively skewed, (RGDP = 5253,RRGDP = 12.673) which is an indicationof a right-skewed distribution with the right tail heavier than its left tail.Similarly, Kurtosiswhich measures the extent to which observed data fall near the centre of distribution or in the tails was also calculated. RGDPCF is 3.204337, while RRGDPCFis -0.0699. Also, for the series to have a kurtosis value less than 3, it means that the series has a fat midrange on either side of the mean and a low peak. The results of the LaGrange multiplier heteroscedasticity test in Table 2,evidencedby both the F-statistic and n^*R^2 test, showed the existence of ARCH effect on an increase in the variable even at 1% level of significance for the first order autoregressive process. The test for higher-order lags was neglected since simplified models are parsimonious (Victor-Edema, 2021). This is because Lags 5,10 and 15 tests have shown adequate reasons that there is the existence of the ARCH effect and modelling of volatility models is appropriate using the series under investigation.

Model Estimation

Table 4 contains the estimates of the standard symmetric and asymmetric GARCH models with their various error distribution assumptions. The optimal symmetric and asymmetric GARCH models that best fit the returns on Real Gross Domestic Product at Constant Factor Cost (RGDPCF) were selected. In the estimations ofthe symmetric model, the persistent impact of volatility was consideredin conjunction with the selected information criterion for the symmetric model. In Table 3, the symmetric GARCH model in normal error distribution assumption was found to have the highest volatility of 150.1% persistence impact factor, followed by GARCH in the student–t with degree freedom(df=10), and finally, GARCH in generalized error distribution assumption, However, GARCH in generalized error distribution assumption with the Akaike information criterion = 4.289 is considered the most appropriate symmetric in modelling the returns on Real Gross Domestic Product at Constant Factor Cost (RRGDP).Similarly, for asymmetric models, the persistent impact of volatility and leverage effect in conjunction with the selected information criterion for the symmetric models were considered as basis for the selection of the best model. Again, the best fit model is one with the highest persistence impact of volatility and lowest information criterion (AIC). TGARCH in Generalized error distribution assumption has the highest impact volatility persistence of 217.6 percent, the next is PGARCH in normal error distribution assumption with volatility persistence of 75.03 percent in ascending order of specific model estimations, followed by EGARCH- Generalized error distribution assumption with volatility persistence impact value of 76.9 percent. On the issue of leverage effect, the order is the TGARCH-Normal (-0.114,p=0.000), TGARCH-GED(-1.247,p=0.000,). Similarly, EGARCH_GED (-0.616, p=0.000), EGARCH-Normal (0.066 p=0.137), and PGARCH-student's-t (-0.468, p=0.000) and PGARCH-GED(-0.665, p=0.000) are all revealed to be negative and statistically significant from zero except EGARCH-Normal (0.066, p=0.137). This shows that the leverage effect exists in the series within years under investigation.

Similarly, TGARCH-normal (0.898, p=0.000), EGARCH-normal(0.758, p=0.000), and PGARCH-Normal (0.189, p=0.000) all have positive signs and statistically significant from zero. There is no leverage effect in the series within years under investigation. The ARCH terms in the models are all statistically significant from zero. This simply means the previous month's return information can influence the present month's returns on Real Gross Domestic Product at Constant Factor Cost(RGDPCF).Also, the co-efficient of all ARCH terms in the models is mostly greater than one. This is an indication that the asymmetric model captures the impact of good news more than bad news.The coefficients of all ARCH terms in the models are less than one, which means that the asymmetric models capture the impact of bad news more than good news. Finally, theTGARCH in generalized error distribution assumption (TGARCH-GED) was found to have the least information criterion AIC (4.065) making it the best fit model amongall the competing models suitablefor modelling the returns on Real Gross Domestic Product at Constant Factor Cost (RGDPCF).

Conclusion

In conclusion, there is the presence of heteroscedasticity and persistent volatility impact in the returns on Real Gross Domestic Product at Constant Factor Cost (RRGDPCF) and so, the GARCH modelsare appropriate in modelling its seriesand to determine its impact in Nigeria's economy. The most parsimonious among the competing symmetric and asymmetric GARCH models is the GARCH in generalized error distributionassumption (GARCH-GED) and the TGARCH in generalized error distribution assumption (TGARCH-GED). The Gretl 18 and excel software programmes were used for the statistical analysis and model estimation.

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