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# APPLICATION OF GENERALIZED AUTOREGRESSIVE CONDITIONAL HETEROSCEDASTICITY FOR EXCHANGE RATE VOLATILITY IN NIGERIA

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## ABSTRACT

*In this study, we want to examine impact of exchange rate volatility in Nigeria using an application of Generalized Autoregressive Conditional Heteroscedasticity. The naira exchange rate has exhibited presence of asymmetry in the currency confirmed by the non-zero leverage parameters, naira exchange rate. The results suggest the sum of ARCH and GARCH terms must be nonnegative and less than one. i.e. ARCH+GARCH < 1 existence of volatility clustering in the currency is highly volatile followed by calm period and responds significantly to shock. The Durbin-Watson statistics adjusted the data even better by detecting the presence of autocorrelation in the residual, leading to better estimates for AIC, SIC and HIC.*

**Keywords:** Exchange Rate Volatility, Jaque-Bera, GARCH Model, Volatility Clustering

## INTRODUCTION

Currency volatility problems arising in stock exchange markets, which have become more pronounce in the last twenty years back, are especially visible cases of large exchange rate fluctuations. This has been of major concern to developing nations and emerging market economies. Also, the transition to a market-based system often involves major adjustments in the international value of these economy currencies.

The proliferation of financial hedging instruments over the last 20 years could reduce firm’s vulnerability to the risks arising from volatile currency movements. In addition, for multinational firms, fluctuations in different exchange rates may have offsetting effects on their profitability. As a growing fraction of international transactions is undertaken by these multinational firms, exchange rate volatility may have a declining impact on world trade.

On the balance, it is not clear whether the major changes in the world economy over the past two decades have operated to reduce or increase the extent to which international trade is adversely affected by fluctuations in exchange rates. One area of this issue is the extent to which such volatility itself has changed, and another is the degree to which firms are sensitive to exchange rate risk and can take steps to mitigate it at low cost. It is therefore necessary to examine new empirical evidence at this issue, especially the consistency of exchange rate volatility. Since 1986, the Nigerian naira’s relationship with the US dollar (and other foreign currencies) like Pounds, Euro, Dollar, Yuan, Yen, etc. has been unpredictable, violent and full of heartbreak and tears. The regulations by the government bye laws has also made a lot of people very rich and vice vasa.

Giraitis, *et al.* (2009) examines ARCH(∞) models, their stationarity, long memory properties and the limit behaviour of partial sums of their processes and their modifications like: linear ARCH, and bilinear models. In line with other theoretical studies, Ling and McAleer (2002) derive the necessary and sufficient conditions for the existence of higher order moments for GARCH and asymmetric *power* GARCH models. The standard deviations method and its applied versions do not incorporate the phenomenon of "volatility clustering" that is usually observed in financial time series or elements of heteroskedastic variance. ARCH and GARCH models have been debated extensively in the literature and are considered more effective in generating proxies for volatility variables because of their ability to capture persistence in "shocks" or "news" components, which are observed mainly in financial time series. These models are also more flexible and accurate than others when applied to long time-series data since they allow more precise estimates of the parameters used Matei (2009).

Caporale and Doroodian (2014) apply the GARCH (1,1) specification to generate a proxy for the "volatility" of the real exchange rate. Matei (2009) assesses forecasting techniques and evaluates the superiority of advanced complex models by reviewing the 50 most important studies on this subject. He concludes that, as a forecasting model, GARCH is superior to other models, but is sensitive to the frequency of data and performs better when using high-frequency data.

Greene (2008) observes that uncertainty associated with exchange rates is an unobservable variable of economic importance and since the development of autoregressive conditional heteroscedasticity (ARCH) models in the 1980s; several extensions have been proposed ranging from: GARCH, EGARCH, TARCH, TGARCH, DTARCH, VGARCH, APARCH, STARCH, STAR, STGARCH, to SQGARCH, among others. Several versions of these models have been applied to inflation e.g. Engle (1982), the stock market e.g. Engle, et al., 1987; Hammoudeh and Li (2008) and Zivot (2009), and the exchange rates see Andersen and Bollerslev, 1998a and Kasman et al. (2011). A related but slightly distinct class of volatility models includes: the stochastic volatility (SV) models (e.g. Shephard and Andersen, (2009), autoregressive conditional duration (ACD) models Engle and Russel, (1998) and dynamic conditional correlation (DCC) models see Engle, (2002).

The data used for this paper were retrieved from Central Bank of Nigeria database.

## METHODOLOGY

### The Arch Model

The Autoregressive Conditionally Heteroscedastic process for the series in order to model the volatility clustering in economic variables, an ARCH process of order q can be written as follows:

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$$\varepsilon_t = z_t \sigma_t$$

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

## Testing for Arch Effects in a Time Series

### Engle's lm test:

Assume that if $x_t$ is conditionally heteroskedastic, then it has an ARCH(*m*) form, i.e.,

$X_t = ht\frac{1}{2}vt, V_t \approx$ *independent and identical distribution N(0,1)*

$$h_t = \eta + \delta_1 X_{t-1}^2 + \ldots + \delta_m X_{t-m}^2 \text{ i} \tag{2}$$

$\eta$ and $\delta's$ satisfy stationarity and non-negative constraints.

$H_0 : \delta_1 = 0, \quad i = 1, \ldots, m$

$H_1 : \delta_1 \neq 0, \quad i = 1, \ldots, m$

$LM = TR^2 \to D\chi^2(m)$

where $R^2$ is the *R*-square from the regression of $X_t^2$ on 1, $X_{t-1}^2, \ldots, X_{t-m}^2$ and $T$ is the number of observations used in that regression.

## The Garch Model

Generalized ARCH (GARCH) model, which models current conditional variance with geometrically declining weights on lagged squared residuals. The GARCH (p, q) model can be expressed as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j.}^2 \tag{3}$$

To ensure that $\sigma_t^2$ is strictly positive we have to impose some restrictions with respect to the parameters in the conditional variance equation:

$$\omega \succ 0, \alpha_i \geq 0, \textit{ for } \; i = 1, q, \beta_j \geq 0, \textit{ for } \; j = 1, p \quad \textit{and} \sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j \prec 1$$

Using the lag (or backshift) operator *L*, the GARCH (p, q) model becomes:

$\sigma_t^2 = \omega + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2,$ (i.e. good news and bad news have a declining impact on future volatility).

With $\alpha(L) = \alpha_1 L + \alpha_2 L^2 + \ldots + \alpha_q L^q and \beta(L) = \beta_1 L + \beta_2 L^2 + \ldots + \beta_q L^q.$ As in the ARCH case, some restrictions are needed to ensure $\sigma_t^2$ to be positive for all t.

## The Exponential Generalized Autoregressive Conditionally Heteroscedastic Model (EGARCH)

The Exponential GARCH model (EGARCH) models the logarithm of conditional variance and it captures asymmetric responses of the conditional variance to good and bad news.

The equation of the EGARCH model can be written in the following form:

$$\log(\sigma_t^2) = \omega + \sum_{i=1}^{q} \alpha_i \frac{|\varepsilon_{t-i}|}{\sigma_{t-i}} + \sum_{k-1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} + \sum_{j=1}^{p} \beta_j \log(\sigma_{t-j}^2) \tag{4}$$

Where $\gamma_k$ represents the asymmetry parameter (leverage effect). $\gamma_k \neq 0$ points out the presence of asymmetry, while $\gamma_k < 0$ shows that volatility rises more after bad news ($\varepsilon_{t-i} < 0$) than after good news ($\varepsilon_{t-i} > 0$).

**The Threshold Autoregressive Conditionally Heteroscedastic Model (TARCH)**

The difference between the Threshold ARCH (TARCH) model introduced by Zakoian (1994) is given by using the specification on the conditional standard deviation instead of conditional variance. Hence, the conditional variance for the TARCH model is represented by equation (2)

$$\sigma_t = \omega + \sum_{i=1}^{q} (\alpha_i^+ .\varepsilon_{t-i}^+ + \alpha_i^- .\varepsilon_{t-i}^-) + \sum_{i=1}^{q} \beta_j .\sigma_{t-j} \tag{5}$$

Where

$$\varepsilon^+ = \begin{cases} \varepsilon, & \varepsilon \succ 0 \\ 0, & \varepsilon \prec 0 \end{cases} \quad \text{and} \quad \varepsilon^- = \begin{cases} \varepsilon, & \varepsilon \succ 0 \\ 0, & \varepsilon \prec 0 \end{cases}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} (\alpha_i + \gamma_i .\prod \varepsilon_{t-1}).\varepsilon_{t-i}^2) + \sum_{i=1}^{q} \beta_j .\sigma_{t-j} \tag{6}$$

where $\prod$ - represents the indicator function, $\prod_\varepsilon = \begin{cases} 0, & \varepsilon \geq 0 \\ 1, & \varepsilon \prec 0 \end{cases}$

**Power Arch (PARCH)**

The Power ARCH model (PARCH) introduced by Ding et al. (1993) is an asymmetric model and it has the following representation:

$$\sigma_t^\delta = \omega + \sum_{i=1}^{q} \alpha_i f_i(\varepsilon_{t-1}) + \sum_{i=1}^{q} \beta_j \sigma_{t-j}^\delta \tag{7}$$

Where:

$f_i(\varepsilon_{t-1}) \equiv (|\varepsilon_{t-i}| - \gamma_i .\varepsilon_{t-i})^\delta, i = 1, q.$

$\alpha_i$ = the standard ARCH term;

$\beta_j$ = the standard GARCH term;

$\gamma_i$ = the leverage parameter $(|\gamma_i| \prec 1)$;

$\delta$ = the parameter for the power term $(\delta \succ 0)$.

To ensure that is strictly positive we have to impose some restrictions with respect to the parameters in the conditional variance equation:

$\omega \succ 0, \alpha_i \geq 0,$ with at least one $\alpha_i \succ 0,$ $(i = 1, q)$ and $\beta_j \geq 0$ $(j = 1, p)$.

It is worth mentioning that for $\sigma = 2$, PARCH model becomes a classic GARCH model that allows for asymmetry, while $\sigma = 1$ leads to the estimation of the conditional standard deviation.

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**Leverage Effect**

A leverage effect in which large negative returns are more likely to predict high volatility than large positive returns. which can be expressed as

$$\sigma_t^2 = \omega + \sum_{i=1}^{q}(\alpha_i \varepsilon_{t-1}^2 + \gamma_i S_{t-1}^- \varepsilon_{t-1}^2) + \sum_{j=1}^{p}\beta_j \sigma_{t-1}^2, \tag{8}$$

where $S_{t-1}^-$ = 1 when $\varepsilon_t^2$ < 0 and 0 otherwise.

**Data Analysis and Interpretation**

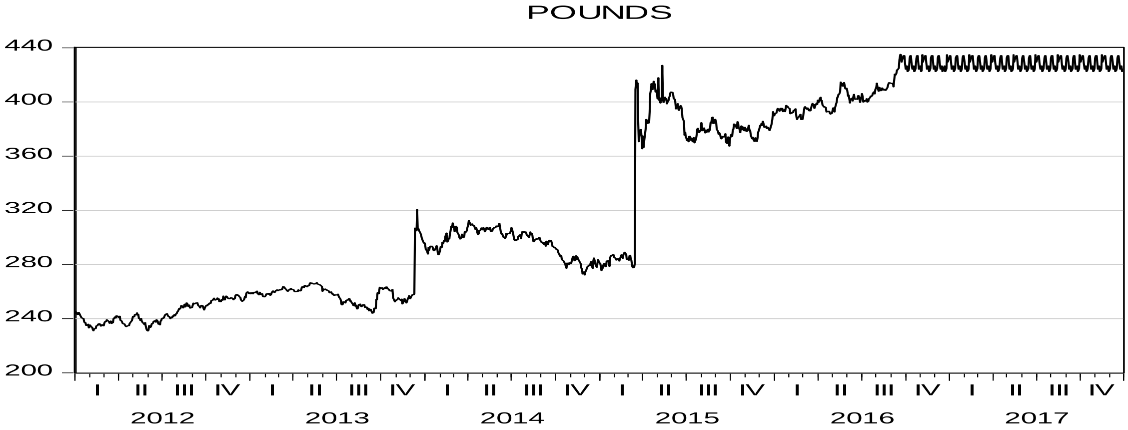


**Fig. 1: Pound Strelling Time Series Plot for Daily Exchange Rates in Nigeria**

From the above plot, it could be seen that there is a gradual increase on the currency which depict the changes in currency over time, it fluctuates up and down movement which shows how pounds strongly perform against the Nigeria naira in the foreign exchange market. British Pounds open with ₦246 in January 2012 and close with ₦429 in December 2017 over the period of 6 years.


**Fig. 2: Euro Time Series Plot for Daily Exchange Rates in Nigeria**

The time series plot for EURO clearly revealed that the volatility clustering in the data, especially in the start and at the end of sample. The Naira exchange rate experienced wild swings (periods of high volatility clustering) where high exchange rate volatility followed one another. The market became highly volatile between 2012 and 2014 and was relatively calm from 2016 to the later part of the study.

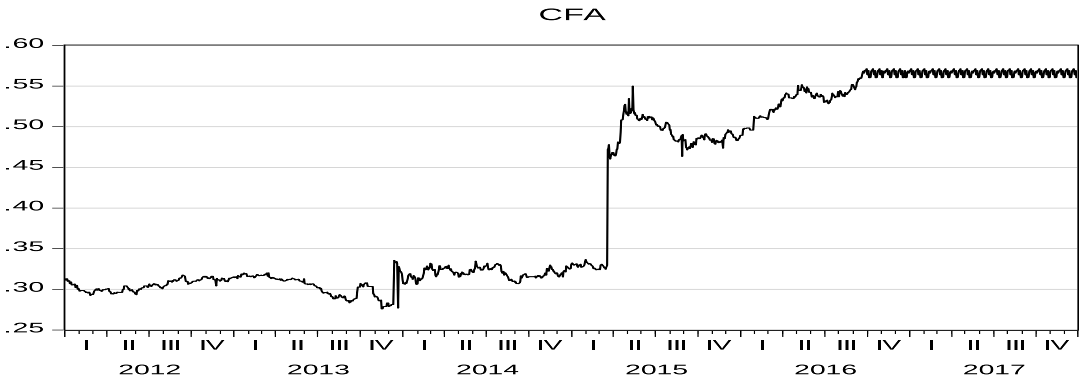


**Fig. 3: Franc CFA Time Series Plot for Daily Exchange Rates in Nigeria**

There is clearly indication in the early CFA periods of the study there are fluctuations that results to more upward trend in the series plot. Although, at the middle periods of the studied years, there was a spike of upward trend in the series more specifically in the later periods and shows how active CFA plays against Naira currency.

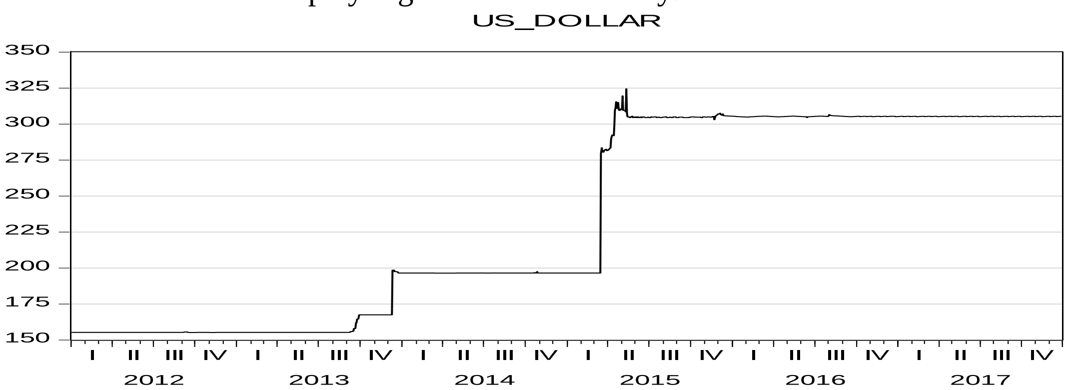


**Fig. 4: United State Dollar Time Series Plot for Daily Exchange Rates in Nigeria**

From the US DOLLAR plot above reveals that some periods are riskier than others. Also, large changes tend to be followed by large changes and small changes tend to be followed by small changes which brings about fluctuations in the series is not constant over time. This is an indication of shock persistence in the Nigeria exchange market.

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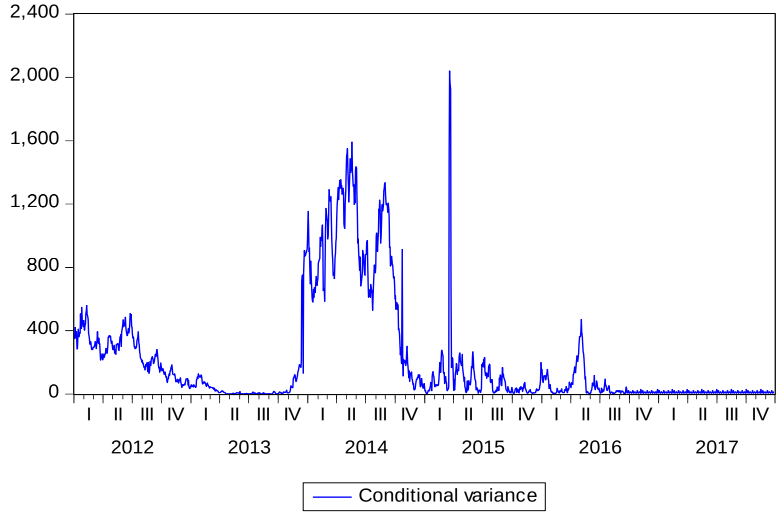
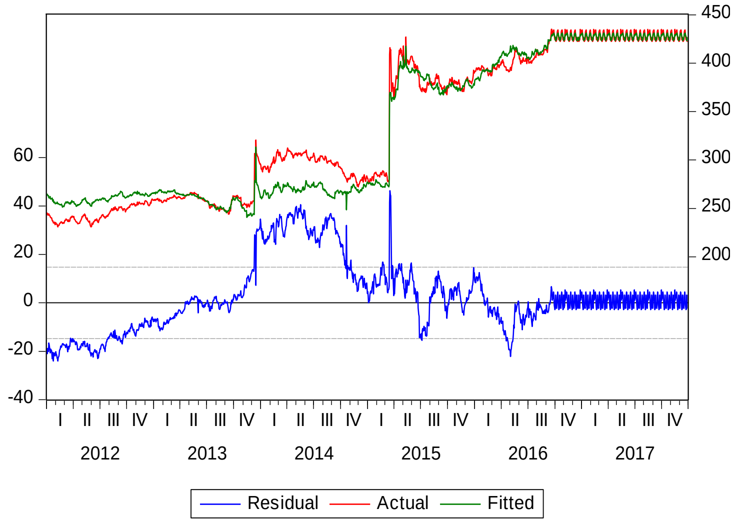



**Fig. 5: Estimated Conditional Volatility of the Exchange Rate Graph for Garch (1, 1)**

The above graph clearly shows that, the estimated volatility function is skewed and thus reveals asymmetry as display a U-shaped structure, .i.e. Both bad (negative information) and good (positive information) news have the same and equal impact on exchanger rate uncertainty.




We can observe that downward movements in the daily exchange rate return are follows by higher volatilities than upward movements of the same size of changes. That is the abnormal return will have more volatility especially for the negative abnormal.

**Table 1: Parameter Estimates of Garch (2, 2) Models Extension**

| PARAMETER | GARCH (2, 2) | TGARCH (2, 2) | EGARCH (2, 2) | PARCH (2, 2) | CGARCH (2, 2) |
|---|---|---|---|---|---|
| C | 64.48033 | 67.21963 | 63.13810 | 64.20776 | 69.36299 |
| ARCH | 0.542978 | 0.402631 | 0.778389 | 0.171207 | 0.522538 |
| GARCH | 0.198247 | 0.126831 | 0.080842 | 0.107498 | 0.285824 |
| ARCH+GARCH | 0.741225 | 0.529462 | 0.859231 | 0.278705 | 0.808362 |
| Log likelihood | -5489.171 | -5525.936 | -5388.972 | -5421.936 | -5338.732 |
| Durbin-Watson stat | 0.040965 | 0.041792 | 0.044004 | 0.040926 | 0.046474 |
| Akaike info criterion | 7.026417 | 7.074678 | 6.899644 | 6.944327 | 6.835440 |
| Schwarz criterion | 7.057216 | 7.108899 | 6.933866 | 6.985393 | 6.869661 |
| Hannan-Quinn criter. | 7.037866 | 7.087400 | 6.912366 | 6.959593 | 6.848162 |

We deduce that CGARCH (2, 2) with Asymmetric order 2 and Normal Gaussian distribution is the most adequate model for estimating the conditional variance having the minimum AIC which is 0.787957, minimum SIC of 6.869661 and minimum HIC of 6.848162 for the parameter estimate. The presence of asymmetry in the currency confirmed by the non-zero leverage parameters. In addition, the sum of ARCH and GARCH terms must be nonnegative and less than one. i.e. (ARCH+GARCH < 1). The Durbin- Watson statistics adjusted the data even better by detecting the presence of autocorrelation in the residual, leading to better values of AIC, SIC and HIC.

## CONCLUSION

From the results of the analysis, inference is made given that the naira exchange rate is highly volatile and responds significantly to information shock, results suggest existence of conditional heteroscedasticity or volatility clustering. The policy implication of these results is the fact that exchange rate forecasting is very important to gauge the benefits and cost of international trade, policy makers should be aware of the possible effect of asymmetry when modelling volatility of an exchange rate. It is recommended that reducing exchange rate volatility in Nigeria, monetary management policies should be put in place for stabilizing the exchange rate of Nigeria currency in order to reduce exchange rate risk/fluctuation.

## REFERENCE

Bollerslev, T. (1990). "Modeling the Coherence in Short- Run Nominal Exchange Rates: A Multivariate Generalized ARCH Model", *The Review of Economics and Statistics*, 498–505.

Giraitis, *et al.* (2009) The effect of real and nominal uncertainty on inflation and output growth: Some GARCH-M evidence. Journal of Applied Econometrics, 15(1), 45–58.

Greene, W. H. (2008). *Econometric Analysis*, Sixth Edition, Pearson Education, Inc.

Hammoudeh, S. and Li, H. (2008). Sudden changes in volatility in emerging markets: The case of Gulf Arab markets, *International Review of Financial Analysis*, 17: 47–63.

Kasman, S., Vardar, G.and Tunc, G. (2011). "The impact of interest rate and exchange rate volatility on banks" stock returns and volatility: Evidence from Turkey", *Economic Modelling*, 28:1328-1334

Ling and McAleer (2002) Modeling and forecasting volatility of returns on the Ghana Stock Exchange using GARCH models (MPRA Paper No. 593). Munich, Germany: University of Munich. Retrieved from http://ssrn.com/abstract=927168

Matei, M. (2009). Assessing volatility forecasting models: Why GARCH models take the lead. Romanian Journal of Economic Forecasting, 12(4), 42–65.

Caporale, T., & Doroodian, K. (2014). Exchange rate variability and the flow of international trade. Economics Letters, 46, 49–54.

Zakoian (1994) Practical issues in the analysis of univariate GARCH models (Working Paper No. UWEC-2008-03-FC). Seattle, WA: University of Washington, Department of Economics