Global Scientific JOURNALS

GSJ: Volume 11, Issue 6, June 2023, Online: ISSN 2320-9186
www.globalscientificjournal.com

Modelling And Forecasting Exchange Rate Volatility of Some Major Currencies Relative to the Nigerian Naira Using Some Hetereoscedastic Models

[1]Yahaya, A., [2]Bakari, H.R and [3]Nicholas, P.D
[1,2,3]Department of Mathematical Sciences University of Maiduguri, Nigeria
Email of Corresponding Author: aliyuyahaya.jnr@gmail.com

Abstract

The modelling and forecasting of exchange rate variability has become extremely important in making financial decisions both to governments and traders as its guides on the risk of holding an asset. A problem of forecasting lies in the use of appropriate methods to fit the time series depending on the nature of the data. Whereas one of the major assumptions of the traditional statistical method such as methods of Box-Jenkins ARIMA models is a constant error variance over time which is known as homoscedasticity. But however this assumption does not usually hold when dealing with financial series as they do exhibit heteroscedasticity. The result of the prediction using the traditional methods may be in-accurate and may not give the appropriate picture of what could be the future events. Therefore, it becomes essential to look for other methods which are more appropriate for forecasts when such data is hetereoscedastic. In this study, we compared the performances of the method of generalized Auto-regressive Conditional heteroscedasticity(GARCH) as modern method of forecasting technique with the traditional Box-Jenkins ARIMA methods and Exponential Generalized Autoregressive Conditional Heteroscedastic (EGARCH) Models in modelling and forecasting exchange rate volatility of some major currencies relative to the Nigerian Naira. The best fitting Heteroscedastic model is determined based on the AIC, BIC and HQIC criteria and then evaluate its out-of sample volatility forecasting performance against one another. The GARCH models above in terms of the AIC, BIC and HQIC, GARCH(1,1), is the best for all since their estimated AIC, BIC and HQIC are smaller as compared to other models. Indeed, based on the parameter estimates and the criteria, GARCH(1,1) is chosen as the best model to capture the exchange data

Key words: GARCH, EGARCH, Volatility, Hetereoscedacity, Forecasting, Major Currencies

1. Introduction

Exchange rate policy in Nigeria has gone through many changes spanning between two major regimes. These are fixed and flexible exchange rate systems adopted between 1960 and 1986; while the flexible exchange rate system remains in use from 1986 till date having undergone series of modification. A number of factors have contributed to the dwindling fortunes of the naira in all the foreign exchange markets. Some of them are fundamental while others are secondary (Obadan 2006). Exchange rate movements and fluctuations hold a numerous converse of interest from academics, financial economists and decision makers, especially since the fall of the Breton Woods consensus of pegged exchange rates among major business nations (Suliman, 2012).

Financial time series exhibit certain characteristics such as heavy tails, persistence, long memory, volatility and serial correlation, macroeconomic variables and volatility, non-trading periods etc (Mandelbro, 1963); Fama, 1965; Black, 1976; LeBaron, 1992; and Glosten et al., 1993). To capture these characteristics, Engle (1982) proposed the ARCH model in which variance is assumed to be a function of previous squared shocks. This model captures some of the aforementioned characteristics as well as accommodate empirical observations that variance is varying with time and it seems to depend on past values.

Despite the success of Engle's model, it has been criticized because of the difficulty involved in estimating its coefficients in empirical applications (Rydberg, 2000). This challenge was subsequently addressed in the model by Bollerslev et al., (1992). The Bollerslev's GARCH model though found to be more efficient when compared to the ARIMA still fail to capture a major characteristic of financial time series (Leverage effects). Since then, different specifications of the time varying conditional variance have been conversed in the literature. For instance Nelson (1991), proposed the EGARCH which is suited to capture the leverage effect in which the conditional variance is specified as a function of both the size and sign of the lagged innovations. Other asymmetric models that have been proposed to capture other stylized facts of financial time series data not captured by the ARCH and GARCH models include PARCH, STARCH, TARCH, etc. According to Ashley (2012), these literatures are also frequently motivated by an intrinsic interest in modeling the volatility of returns for asset pricing purposes.

Although modeling of financial time series with ARCH and GARCH models have received much attention in developed markets, they are few or non-existent in emerging markets like the Foreign and Stock Exchange Market in Nigeria. Most of the studies on exchange rate volatility in Nigeria measure the impacts of exchange rate volatility on trade with little attention to the empirical measurement of the shocks (see Yinusa and Akinlo 2008; Ogunleye 2009; Aliyu 2009a; Aliyu 2009b; Olowe 2009; Adeoye and Atanda 2011; Bala and Asemota 2013; and Ayodele, 2014). Of all these studies, only Olowe (2009) and, Bala and Asemota (2013) were found to investigate the volatility of the Nigerian Naira against currencies of some major industrial nation.

Therefore, the aim of this study is to compare the performances GARCH and EGARCH Models to ARIMA model in modelling and forecasting exchange rate volatility of some major currencies relative to the Nigerian Naira.

2. Materials and Methods

The data were obtained from Central Bank of Nigeria statistical bulletin and cover a period of nineteen years (January 2003 to December 2022). The official exchange rate of Naira was considered. Most of the computational works are carried out by using R statistical software. GARCH (p,q) and EARCH (p,q) models were selected to capture the data over time and their performances were compared with ARIMA (p,d,q). In each case, the best fitting of Heteroscedastic model is determined based on the AIC, BIC and HQIC criteria and then evaluate its out-of sample volatility forecasting performance against one another. The data obtained were first analyzed to check if the data is stationary or has a unit root using Augmented Dickey Fuller test (ADF).The heteroscedaticity phenomenon were also tested in various data collected over time using Breusch-Pagan test before the models of different orders were used to fit the data with aim of selecting the best model for the data. Thereafter, the adequacies of the models selected were determined for future forecasting.

2.1 Generalized ARCH (GARCH) Model

The ARCH model though simple, often require many parameters to adequately describe the volatility process of an asset return. Bollerslev (1986) and Taylor (1986) focus on extending the ARCH models to allow for a more flexible lag structure. They introduced a conditional heteroscedasticity model that includes lags of the conditional variance as regressors in the model for the conditional variance (in addition to lags of the squared error terms ($\varepsilon_{t-1}^2, \varepsilon_{t-2}^2, \varepsilon_{t-3}^2, \ldots, \varepsilon_{t-q}^2$).

The GARCH model allows the conditional variance to be explained by past information (past shocks and past variances). The general model GARCH (q,p) is of the form;

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \alpha_j \varepsilon_{1-j}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-1}^2 \qquad (1)$$

Where p is the number of lagged σ^2 terms and q is the number of lagged ε^2 terms. The parameters ω, α_j and β_i are non negative and usually estimated by method of Maximum Likelihood Estimation (MLE). It is required that $\sum_{j=1}^{q} \alpha_j + \sum_{i=1}^{p} \beta_j < 1$ to ensure stationarity. The most popular GARCH model in applications is the GARCH (1,1) model given in (3.6). Hansen and Lunde (2004) provided evidence of its suitability over other volatility models and weakly stationary of the model requires $\alpha + \beta < 1$.

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \varepsilon_{t-1}^2 \qquad (2)$$

2.2 Exponential GARCH (EGARCH) Model

This model was formulated to overcome some weakness of the GARCH model in handling financial time series. This model proposed by Nelson (1991), allows for asymmetric effects between negative and positive returns to be measured. The general form of the model is;

$$ln(\sigma_t^2) = \omega + \sum_{i=1}^{p} \alpha_i \left\{ \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{2}{\pi}} \right\} + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} + \sum_{j=1}^{q} \beta_j ln\left(\sigma_{i-j}^2\right) \qquad (3)$$

Where α, β and γ are constants parameters, it is expected that $\gamma < 0$. 'Good news' generates less volatility than 'bad news', where γ reflects the leverage effect. When ε_{t-1} is positive, the total contribution to the volatility of innovation is $(\alpha + \gamma)$. In opposite case, when ε_{i-1} is negative, the total contribution to the volatility of innovation is (α - γ). The model is different from the symmetric GARCH in that it uses logged conditional variance to relax the positive constraint of model coefficients and the model respond asymmetrically to positive lagged values of $\varepsilon_{i.}$

2.3 Model Adequacy Checking

The adequacy of any model fitted to a data was evaluated using Ljung-Box Statistic. This is used in assessing whether a group of autocorrelation are statistically significant than those expected from white noise. The Q-Statistic

$$Q = \mathrm{N}(N + 2) \sum_{i=1}^{k} \frac{ACF(i)^2}{(N-i)} \qquad (4)$$

Is distributed as a chi-square distribution with k – c degree of freedom, where c is equal to the number of coefficients in the model. If $Q \leq \chi^2_{0.05,k-c}$, then infer ACF patterns are not statistically significantly different than those of white noise otherwise they are statistically significantly different than those of white noise.

3. Analysis and Results

The data obtained were analyzed to examine whether stationary or not using Augmented Dickey Fuller (ADF) statistic. Also, heteroscedasticity phenomenon were tested for various data collected across currencies using Breusch-Pagan (BP) test before the models of different orders were used to fit the data with the aim of selecting the best model. Thereafter, the adequacies of the models selected were determined for future forecasting. Thus, the GARCH (p,q) and EGARCH (p,q) models that best fit and forecast the exchange rate is determined using AIC, BIC and HQIC criteria. The time series plots which display the observations on y axis against equally spaced time intervals on the x axis used to evaluates patterns and behaviour in data over time as displayed in the figure 1.

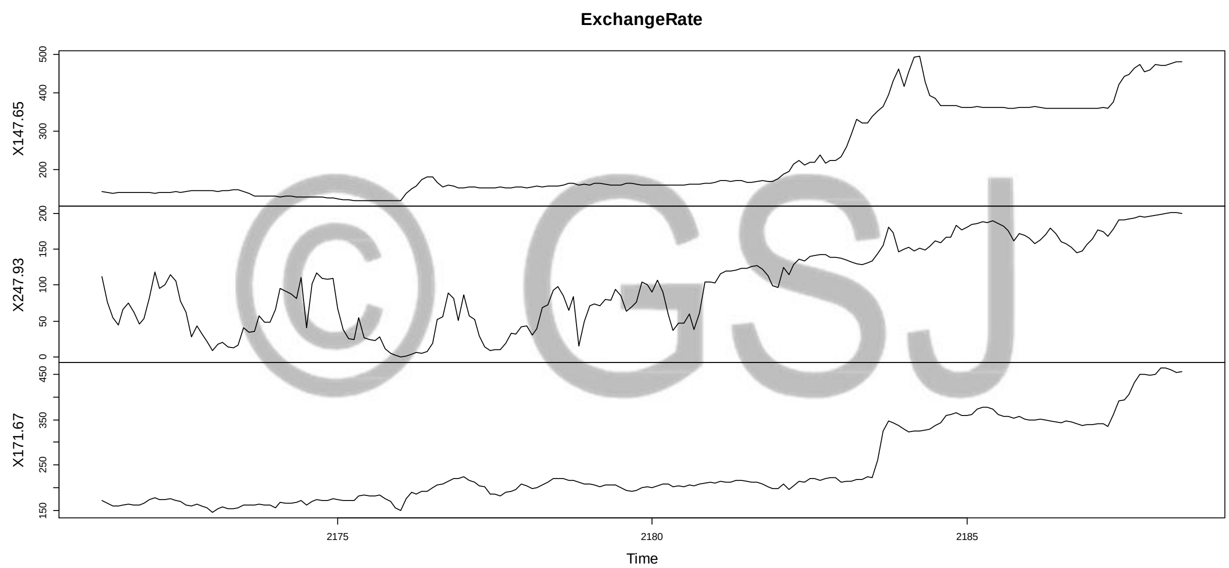

Figure 1 Official Exchange Rate of Dollars, Pounds and Euro

The Figure 1 above indicates clearly that the three exchange rates with respect to Naira, were not constant but rather varied from one year to the other as well as from one month to the other with no systematically visible pattern, structural breaks, outliers, and no identifiable trend components in the time series data or no consistently increasing or decreasing

Table 1 Test for unit Root (Stationarity) of the Exchange Rates

	Dollars			Pounds			Euro		
Test statistic	Value	P-value	Decision	Value	P-value	Decision	Value	P-value	Decision
ADF	-1.95	0.597	The series has Unit root	-3.43	0.051	The series has Unit root	-1.52	0.776	The series has Unit root
PP	-5.91	0.777	The series	-25.27	0.067	The series	-5.81	0.782	The series

			has Unit root			has Unit root			has Unit root
KPSS	3.387	0.01	The series has Unit root	3.274	0.01	The series has Unit root	3.39	0.01	The series has Unit root

Table 1 above shows ADF, PP and KPSS test statistic with their p-values respectively, where ADF and PP have the p-values which are greater than the level of significance $\alpha = 0.05$ while KPSS has a value less than the significant value. We accept null hypothesis of having unit root series for ADF and PP and reject a null hypothesis of being a stationary series for KPSS. Indeed, the three tests confirm that the data series is not stationary. It is clear for the time series plot of the exchange rate data series and stationarity tests suggests that the data need to be transformed or differenced since it is confirm to have a unit root.

Table 2 Test for unit Root (Stationarity) of the Differenced Exchange Rates

	Dollars			Pounds			Euro		
Test statistic	Value	P-value	Decision	Value	P-value	Decision	Value	P-value	Decision
ADF	-5.562	<0.01	The series is stationary	-6.360	<0.01	The series is stationary	-5.71	<0.01	The series is stationary
PP	-142.4	<0.01	The series is stationary	-228.8	<0.01	The series is stationary	-119.3	<0.01	The series is stationary
KPSS	0.0709	0.10	The series is stationary	3.274	0.10	The series is stationary	0.2914	0.10	The series is stationary

Table 2 presents the stationarity tests for the differenced exchange rate over the period of investigation with a null hypothesis of a unit root against alternative hypothesis of a level of stationarity for ADF and PP and vice versa for KPSS. The p-values of 0.01 both for ADF and PP are less than the 5% level of significance while p-value 0.1 for KPSS is greater than the 5% level of significance, which indicate that, the null hypothesis of having a unit root series should be rejected in favour of alternative of being stationary and vice versa for KPSS. Indeed, the data is stationary after the first difference hence we can proceed for fitting and forecasting of the series.

Table 3. Testing for Hetroscedaticity in the Data.

Exchange Rate Type	Test Values	DF	P-value	Hypothesis (H_o)	Decision	Remark
Dollar	1.7031	4	0.9997	No Heteroscedacity	Reject H_o	Data is hetroscedastic
Pound	15.72	4	0.0034	No Heteroscedacity	Reject H_o	Data is hetroscedastic
Euro	10.831 ,	4	0.0285	No Heteroscedacity	Reject H_o	Data is hetroscedastic

It was observed that the p-values of the statistic from the four form of the data are less than the critical value of 0.05 and we therefore reject the null hypothesis of data being homoscedastic in favour of alternative of being heteroscedastic. Indeed, the test confirms that the data series of the three foreign exchange in its original and differenced form.

Table 4: Fitting the GARCH(p. q)

Exchange Rate	Model	μ	ω	α_1	α_2	β_1	β_2	AIC	BIC	HQIC
Dollars VS Naira	(1,1)	0.3941	4.219	0.8962	-	0.2936	-	**6.028**	**6.093**	**6.027**
	(1,2)	0.4054	4.2392	0.8981	-	0.2920	1.00e-08	6.046	6.127	6.079
	(2,1)	0.3875	4.5980	0.8575	0.1178	0.2334	-	6.044	6.125	6.077
	(2,2)	0.3875	4.5980	0.8574	0.1178	0.2333	1.00e-08	6.054	6.151	6.093
Pounds VS Naira	(1,1)	0.3940	4.2192	0.8962	-	0.2935	-	**6.028**	**6.093**	**6.054**
	(1,2)	0.7122	6.7326	0.8881	-	0.4189	0.0099	8.051	8.132	8.084
	(2,1)	0.3875	4.5980	0.8574	0.1177	0.2333	-	6.044	6.125	6.077
	(2,2)	0.7212	9.5367	0.8728	0.3857	0.0001	0.1903	8.060	8.157	8.099
Euros VS Naira	(1,1)	0.3940	4.2192	0.8962	-	0.2935	-	**6.028**	**6.093**	**6.054**
	(1,2)	0.7122	6.7326	0.8881	-	0.4189	0.0099	8.051	8.132	8.084
	(2,1)	9.0568 e-01	3.0265 e+01	4.4765e -01	4.0241e-02	1.0000e-08	-	6.695	6.775	6.727
	(2,2)	9.0568 e-01	3.0265 e+01	4.4765e -01	4.0241e-02	1.0000e-08	1.0000e-08	6.705	6.801	6.744

With regard to the parameters reported in table 4.6 above, The estimated coefficient values of all GARCH (p,q) strictly conforms to the bounds of parameter, between -1 and 1 except GARCH (1,1) which is out of the bound. This has made the models to be stationary. Additionally, comparing the GARCH models above in terms of the AIC, BIC and HQIC, GARCH(1,1), is the best for all since their estimated AIC, BIC and HQIC are smaller as compared to other models. Indeed, based on the parameter estimates and the criteria, GARCH(1,1) is chosen as the best model to capture the exchange data

3.1 Model Adequacy (Diagnostic) checking of estimated models (Standardized Residuals Tests)

Having carried out the fitting comparison analysis, and the GARCH (1,1) is chosen as the best or tentative models as opposed to others, based on the conclusion in Table 4.6 above, the adequacy of the chosen model is further tested to draw empirical conclusions regarding the model as good fit. These tests carried out are Ljung-Box, normality test of the residuals using Shapiro-Wilk normality test statistic and LM Arch Test. The results are reported in Table 4.

Table 5: GARCH Model Diagnostic with Respect to the Exchange Rate

Model		GARCH(1,1)		GARCH(1,2)		GARCH(1,2)		GARCH(1,2)	
Exchange Rate Type	Test statistic	Values	P-value	Values	P-value	Values	P-value	Values	P-value
Dollar VS Naira	Jarque-Bera Test	2558.3	0.000	2525.1	0.000	2578.6	0.000	2578.6	0.000
	Shapiro-Wilk Test	0.7864	4.26e-16	0.7868	4.410e-16	0.7843	3.532e-16	0.7843	3.532e-16
	Ljung-Box Test (R^2)	1.6351	0.9984	1.6674	0.9983	1.6649	0.9983	1.6649	0.9983

	LM Arch Test	1.7031	0.9997	1.7338	0.9997	1.7045	0.9997	1.7045	0.9997
Pounds VS Naira	Jarque-Bera Test	2558.3	0.0000	22.5353	1.277968e-05	2578.6630	0.0000	23.2327	9.017209e-06
	Shapiro-Wilk Test	0.7864	4.250e-16	0.9689752	0.0001	0.7843	3.532115e-16	0.9686	0.0001
	Ljung-Box Test (R^2)	1.6351	0.9984	5.2092	0.8767	1.6649	0.9983	5.2871	0.8711
	LM Arch Test	1.7031	0.9997	8.9781	0.7047	1.7045	0.9997	9.0944	0.6948
Euros VS Naira	Jarque-Bera Test	2558.398	0.000	22.5353	1.277968e-05	709.7498	0.0000	709.7501	0.0000
	Shapiro-Wilk Test	0.7864	4.250967e-16	0.9689752	0.0001	0.8958	8.237819e-11	0.8958	8.237814e-11
	Ljung-Box Test (R^2)	1.6351	0.9984	5.2092	0.8767	3.2790	0.9740	3.2790	0.9740
	LM Arch Test	1.7031	0.9997	8.9781	0.7047	3.1271	0.9945	3.1271	0.9945

The Table 5 shows the Ljung-Box and Jarque-Bera tests for the two exchange rate type with chi-square statistics that give corresponding p- values.

3.2 Forecasting with the GARCH Model

A 10-step ahead sample forecast was conducted on the data of the generating plant noise and the forecast is visually displayed in Figure 2, 3 and 4. The 10 horizons were forecasted based on data from the preceding time intervals. The forecast was obtained by using data from the previous periods to estimate the future occurrence period using the GARCH (1,1) and GARCH (1,2), GARCH (2,1) and GARCH (2,2)models.

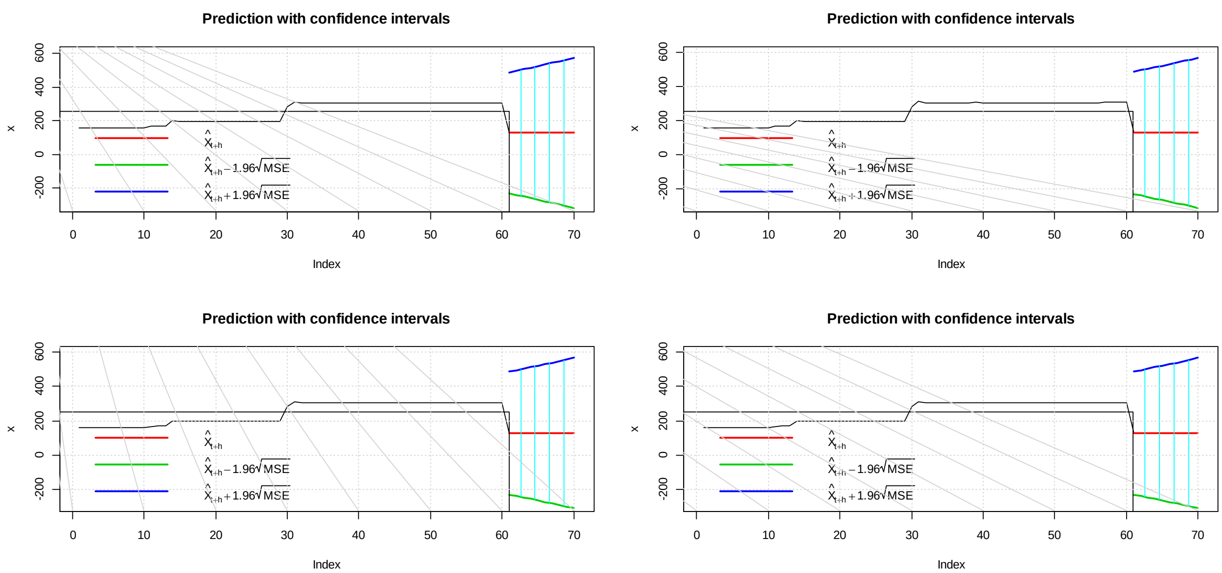

Figure 2: Forecast for Future Occurrence of US Dollars exchange rate using the four models

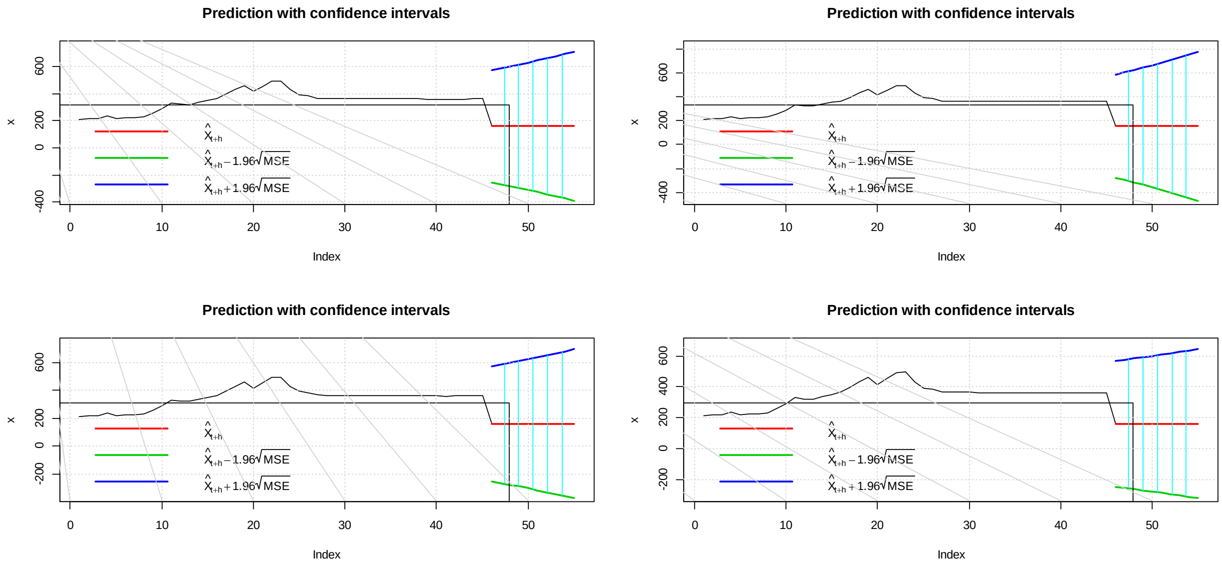

Figure 3: Forecast for Future Occurrence of the Pounds exchange rate using the four models

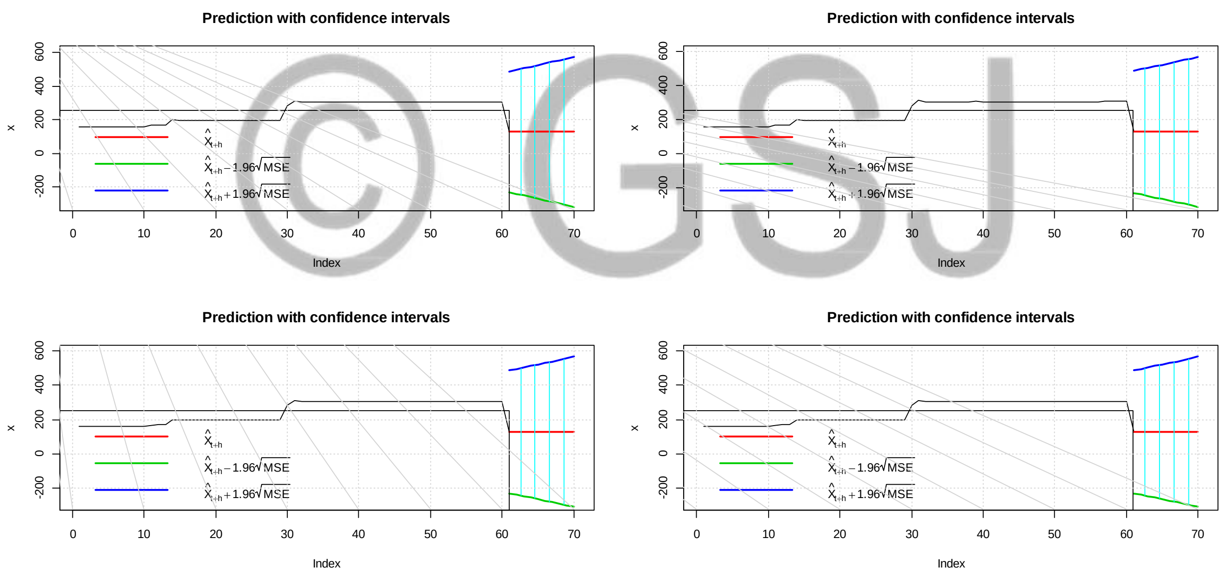

Figure 4: Forecast for Future Occurrence of the Euro exchange rate using the four models

It can be seen from Figure 2, 3 and 4 that the forecast is quite accurate. It seems that GARCH (1,1) and GARCH (1,2) have respectively efficient in capturing the dynamic nature of the data and forecasting. The forecast performance is seems to be accurate over time and their estimates are within the confidence limits.

4. Conclusion

The data were found to be stationary and hetereoscedastic after the first differenced. The GARCH (1,1) model is the best to capture the three exchange rates (US Dollar, Pound Sterling and Euro) with respect to Naira, since their estimated AIC, BIC and HQIC are smaller as compared to other models. Indeed, based on the parameter estimates and the criteria, GARCH(1,1) is chosen as the best model to capture the three exchange rate data. The tests are significant for GARCH (1,1), therefore, the residuals appear to be uncorrelated. This indicates that the residuals of the fitted GARCH (1,1) model are white noise, as such, the model fits the series quite well (the parameters of the model are significantly different from zero), so we can use this model to make forecasts. Ljung-Box Test (R^2) of GARCH (1,1) indicates that all the past observations of both exchange rate contribute significantly to the present response and the model is well fitted.

Furthermore, the normality is not significant; hence, the Shapiro-Wilk test suggests that the standardized residuals are normal. This also supports the fact that the residuals of the fitted GARCH models are white noise, and the model fits the series quite well (since one of the assumptions of the residual being white noise is normality). Hence the model is stationary due to the presence of white noise. The p-values of LM Arch Test also indicate the fitted model capture the hetroscedasticity in the data over time

References

Adeoye, B. W. and Atanda, A. A. (2011). Exchange Rate Volatility in Nigeria: Consistency, Persistency & Severity Analyses. CBN Journal of Applied Statistics, 2(2); 29 – 49.

Aliyu, S. U. R. (2009a). Exchange Rate Volatility and Export Trade in Nigeria: An Empirical zz Investigation. MPRA paper No. 13490. Retrieved from http://mpra.ub.unimuenchen.de/13490/

Aliyu, S. U. R. (2009b). Impart of Oil Price Shock and Exchange Rate Volatility on Economic Growth in Nigeria: An Empirical Investigation. MPRA paper NO. 16319. Retrieved from http://mpra.un.unimuenchen.de/16319/

Ayodele, T. D. (2014). An Empirical Evaluation of the Impact of Exchange Rate on the Niherian Economy, Journal of Economics and Sustainable Development, 5(8); 24 – 28

Ashley, R (2012). On the Origins of Conditional Heteroscedaticity in Time Series. The Korean Economics Review, 28(1); 5-25.

Bala D. A. and Asemota J. O. (2013). Exchange Rates of Volatility in Nigeria: Application of GARCH Models with Exogenous Break. CBN Journal of Applied Statistics, 4(1); 89-116.

Black, F. (1976). Studies of Stock Market Volatility Changes. Proceedings of the American Statistical Association. Business and Economic Statistics Section, 177–181.

Bollerslev T. and Wooldridge, T. (1992). Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time-Varying Covariances. *Econometric Reviews*, **11**; 143 – 172.

Engle, R. F.(1982) Autoregressive Conditional heteroskedasticity with estimates of the variance of U.K. Inflation. Econometrica.;50:987-1008.

Fama, E. F. (1965). The Behavior of Stock Market Prices. Journal of Business, 38; 34–105

Glosten LR, Jagannathan R, Runkle D. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. Journal of Finance. 48:1779-1801.

LeBaron, B. (1992). Some Relations between Volatility and Serial Correlation in Stock Market Returns. Journal of Business, 65; 199-220.

Nelson DB (1991). Conditional heteroskedasticity in asset returns; A new approach. Econometrica. ;59: 347–370.

Ogunleye, E. R. (2009). Exchange Rate Volatility and Foreign Direct Investment in Sub-Saharan Africa: Evidence from Nigeria and South Africa.

Olowe, R. A. (2009). Modelling Naira/Dollar Exchange Rate Volatility: Application of GARCH and Asymmetric Models. International Review of Business Research Papers, 5(3); 377 – 398.

Rydberg, T. H. (2000). Realistic Statistical Modelling of Financial Data. International Statistical Review, 68(3); 233 – 258.

Suliman, Z. S. A. (2012). Modelling Exchange Rate Volatility using GARCH Models: Empirical Evidence from Arab countries. International Journal of Economics and Finance, 4; 216-229.

Yinusa, D. O. and Akinlo, E. A. (2008). Exchange Rate Volatility, Currency Substitution and Monetary Policy in Nigeria. MPRA Paper No. 16255.