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Forecasting Volatility of USDNGN Exchange Rate using Distributional Based Asymmetric GARCH (1, 1) Models

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Abstract: In this paper the generalized autoregressive conditional heteroscedastic models are applied in modeling exchange rate returns voltility of the USDNGN exchange rate using daily observations spanning the period from December 29, 2010 to December 27, 2015(1, 825 observations). The paper applies and compares two asymmetric models: eGARCH(1, 1) and gjr-GARCH(1, 1) models with different error distributions to data. The most adequate models for estimating USDNGN exchange rate volatility in terms of in-sample using information criteria and loglikelihood are eGARCH(1, 1) -GED and gjr-GARCH(1, 1)-GED.While for the out-of -sample estimate using error functions of MSE and MAE eGARCH(1, 1) –SNORM and eGARCH(1, 1)-GED models which have the minimum MSE and MAE respectively and gjr-GARCH(1, 1)-snorm produced minimum MSE and MAE each are preferred.

Key words: AIC · Garch models · Normal Distribution · Student-t distribution · Volatility

INTRODUCTION

The properties of financial time series usually referred to as “stylized features” have become very important in applied economic analysis [1]. Stylized statistical properties of asset returns, common to a wide set of financial assets; such as heavy tails, leptokurtic distribution, volatility clustering, excess of autocorrelations and leverage effect was examined [2]. First, [3] introduced Autoregressive Conditional Heteroscedasticity (ARCH) model with Normal innovations that captured some of “stylized” characteristics of financial time series (FTS) returns. Consequently [4] introduced generalized ARCH model (GARCH) to further improve the modeling process. But, usually, stock returns were modeled by time series with normal error distributions. Unfortunately, such models still failed to sufficiently capture the main “stylize facts” about financial time series (i.e. the heavy tails, leptokurtic and skewness). The need for accurate forecasting of volatility in financial markets is critical with respect to “investment, financial risk management and monetary policy making” [5]. The relevance of volatility forecasting in risk management on the short term Was pointed out [6]. The Nigerian economy is very sensitive to fluctuations in the USDNGN exchange rate given the fact that Nigerian economy is generally import dependent and majority of the imports are usually in US dollars. More so, banks as well as other financial institutions usually invest in foreign exchange instruments, hence the need for accurate modeling and forecasting of volatility. The main objective of this study is to fit volatility models to USDNGN Exchange return rates and investigate whether the best fitting model, in terms of the Akaike information criterion (AIC) also provides the best volatility forecasts of the underlying series in terms of the mean squared error (MSE) criteria the Mean Absolute Error (MAE) and the Root mean square error (RMSE). Since the introduction of ARCH and GARCH models by [3] and [6] respectively, many researches hence applied the ARCH (GARCH) models in modeling FTS volatilities. [7] argue that no reasonable evidence can be found that would allow us to conclude the inferiority of the GARCH (1, 1) as compared to more complicated models. In fact the GARCH (1, 1) model outperforms other models considered, not including asymmetric models, in estimating volatility of foreign exchange rate. [8] Considered a GARCH model with skewed- student-t distribution to capture the skewness and excess kurtosis. [9] proposed GARCH models with skewed generalized error distribution (SGED).

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[10] compared the performance of volatility forecasting of GARCH (1, 1) model versus EGARCH (1, 1) model using the monthly stock market returns of seven emerging economies. It was found that the GARCH (1, 1) model outperforms the EGARCH model, even if the stock market return series exhibit skewed distributions. [11] investigated the volatility forecasting performance of GARCH (1, 1) model with various distributional assumption on stock market indices and exchange rate markets. Their results show that a GARCH (1, 1) model combined with the logistic distribution, the scaled student's - t distribution or the Risk metrics model is preferred both in stock markets and foreign exchange markets. [12] have shown that a GARCH model with an underlying leptokurtic asymmetric distribution outperforms one with an underlying normal distribution, for modeling volatility of the Chinese stock market. Similar studies by [13] have demonstrated that the use of fat tailed error distributions within a GARCH (1, 1) framework leads to improved volatility forecasts. The former uses nine possible error distributions to model the volatility of the standard & poor's 50 with the leptokurtic distributions working out best. The author uses the mean Absolute Error Heteroscedassicity-adjasted MAE to evaluate the forecasts. An extension of the GARCH model, the GARCH in mean is used by Ryan and [14]to assess the impact of market, interest rate and foreign exchange rate risks on sensitivity of Australian bank stock returns. [15] investigated the volatility of Nigeria Naira/us dollar exchange rate by fitting six univeriate GARCH models using monthly data and concludes that the best performing models are the Asymmetric power ARCH and TS-GARCH, under student's - t innovation. The impact of Exchange rate volatility on the Ghana local stock Exchange was examined [16]. The study used an exponential GARCH model and observed the negative relationship between the exchange rate volatility and stock market returns. [17] Compared the forecast – ability of symmetric and asymmetric GARCH models. The author fitted us Dollar/Deutsche mark returns series using an AR(1) process and the GARCH (1, 1), G.JR-GARCH (1, 1) and EGARCH (1, 1) volatility equations and concluded that the EGARCH performs better in producing out of sample forecasts with the GARCH (1, 1) closely following , whereas the GJR-GARCH fares worst. The list of work on the forecast ability of asymmetric GARCH models include the research by [18] where the authors compare the performance of classical GARCH (1, 1) versus other asymmetric variations using the out of sample. The study found that asymmetric models are found to produce better forecasts. However, the GARCH (1, 1) is seen to outperform other GARCH models not taking into account the asymmetric properties. [19] Considered asymmetric GARCH models for volatility measurement for AUD/USD, GBP/USD and JPY/USD exchange return rates. This study following [18] focuses on the asymmetric GARCH(1, 1) volatility models forecasting of USDNGN exchange rate using the Normal, Skewed Normal, Student-*t*, Skewed Student-*t*, Generalized Error distribution and Skewed Generalized Error as underlying distributions for the innovations of the variance equation and comparing the forecasting ability of the models, both in-sample and out-of-sample using the AIC, Loglilihood, Mean Square Error(MSE) and Mean Absolute Error(MAE) as matrices. The rest of the article is structured as follows The data and empirical properties are presented in section 2, while the volatility models are given in section 3.Section 4 discusses forecast evaluations and section 5 presents the conclusions.

MATERIASL AND METHODS

Variance and standard deviation which are the traditional methods of measuring volatility are conditional and as such cannot capture stylize features usually exhibited by financial time series(FTS) data, such as excess kurtosis, volatility clustering , time varying, leverage effect, long memory, heavy tailed distribution etc. Engle (1982) first introduced the Autoregressive Conditional Heteroscedasticity (ARCH) model with Normal innovations that captured some of "stylized" characteristics of financial time series (FTS) returns. Bollerslev (1986) later generalized ARCH model (GARCH) to further improve the modeling process. In this paper, the role of volatility asymmetry and alternative distribution assumptions in forecasting of exchange rate returns volatility using Garch models are investigated. Two asymmetric univariate GARCH specifications:eGARCH(1, 1) and gjr-GARCH(1, 1) and Normal, Student-t and Generalized Error distributions are applied to model USDNGN exchange rate return volatility.We briefly review two distinct equations , the conditional mean and the conditional variance for these models.

Condition Mean Equation: The exchange rate return moving pattern might be an autoregressive (AR) process, moving average (MA) process or a combination of AR and MA processes i.e. (ARMA) process. For the purposes of this study the mean equation is modified to include appropriate AR and MA terms to control for autocorrelation in the data. Example, ARMA (1, 1) process is given as:

$$Y_t = \sum_{i=1}^{p} \varnothing Y_{t-i} + \sum_{j=1}^{q} \theta \in_{t-j} \quad (1)$$

where Y_t, is a time series under study

The GARCH Volatility Models: The statistical package used in this study is R version 3.1.2 (2014-10-31) for the purpose of this study make use of a GARCH (1, 1) model for conditional variance and ARMA (1, 1) model for the mean equation the ARMA (1, 1) model is used as a filter for the returns series. We define the following:

$$r_t = \mu + \epsilon_t + \epsilon_{t-1} \quad (2)$$

$$\epsilon_t = z_t\sigma_t \quad (3)$$

$$\sigma_t^2 = \alpha_0 + \alpha \in_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (4)$$

where ϵ_t is the innovation, σ_t is the volatility measure and z_t is an i.i.d variable such that $z_t \sim F$ where F is some distribution with mean zero. In this study, F will be the normal, skewed normal, students – t, skewed student's -t, GED and skewed GED error distributions.

Asymmetric GARCH Models: In practice, the price of financial assets often reacts more pronouncedly to "bad" news than "good' news. Such a phenomenon leads to a so called leverage effect, as first noted by Black (1976). The term "leverage" stems from the empirical observation that the volatility (conditional variance) of a stock tends to increase when its returns are negative. The leverage effect causes the asymmetries of variance dynamics and points out the drawbacks of GARCH model because of its symmetric effect towards the conditional variance. In order to capture the asymmetry in return volatility ("leverage effect"), a new class of models was developed, termed the asymmetric GARCH models. This paper uses the following asymmetric GARCH models; EGARCH and GJR-GARCH model for capturing the asymmetric phenomena.

The Exponential GARCH(eGARCH) Model: The general form of the Exponential GARCH (p, q) model introduced by Nelson (1991) is given by;

$$X_t = z_t\sigma_t$$

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{j=1}^{q} \beta_j \ln(\sigma_{t-j}^2) + \sum_{i=1}^{p} \alpha_i \left| \frac{X_{t-i}}{\sigma_{t-i}} \right| + \gamma_i \frac{X_{t-i}}{\sigma_{t-i}} \quad (5)$$

where γ is the asymmetric response parameter that can take a positive or negative sign depending on the effect of the future uncertainty. The term $\frac{X_{t-i}}{\sigma_{t-i}}$ in the above equation represents the asymmetric effect of shocks.

A special case of EGARCH (p, q) model is EGARCH(1, 1) model which is given by:

$$\ln(\sigma_t^2) = \alpha_0 + \beta_1 \ln(\sigma_{t-1}^2) + \alpha_1 \left| \frac{X_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{X_{t-1}}{\sigma_{t-1}} \quad (6)$$

For a positive shock $\frac{X_{t-1}}{\sigma_{t-1}} > 0$, (6) becomes

$$\ln(\sigma_t^2) = \alpha_0 + \beta_1 \ln(\sigma_{t-1}^2) + \alpha_1 \left| \frac{X_{t-1}}{\sigma_{t-1}} \right| + (\alpha_1 + \gamma) \frac{X_{t-1}}{\sigma_{t-1}} \quad (7)$$

But for a negative shock $\frac{X_{t-i}}{\sigma_{t-i}} < 0$, (6) becomes

$$\ln(\sigma_t^2) = \alpha_0 + \beta_1 \ln(\sigma_{t-1}^2) + \alpha_1 \left| \frac{X_{t-1}}{\sigma_{t-1}} \right| + (\alpha_1 + \gamma) \frac{X_{t-1}}{\sigma_{t-1}} \quad (8)$$

The Glosten, Jagannathan and Runkle GARCH (gjr-GARCH) Model: The GJR-GARCH model is another type of asymmetric GARCH models, which was proposed by Glosten, Jagannathan and Runkle (1993). The variance equation of GJR-GARCH (p, q) is given by:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i X_{t-i}^2 + \sum_{j}^{q} \beta_j \sigma_{t-j}^2 + \gamma_i I_{t-i} X_{t-i}^2 \quad (9)$$

where α, β and γ are constant parameters and I is the indicator function that takes the values one or zero. I= 0; if $\epsilon<0$ and I=1; if $\epsilon>0$ It is necessary to restrict the parameters of the model in order to ensure positivity of the conditional variance .Hentschel (1995) shows that σ_t^2 is positive if $\alpha\ 0 > 0$, $\alpha, \beta, \gamma \geq 0$.

The Distribution of Error: This paper considered six different types of error distributions.

Normal Distribution:

$$f(z) = \frac{1}{\sqrt{2\pi}} \exp^{\frac{-z^2}{2}}, -\infty < z < \infty$$

Skewed Normal Distribution:

$$f(z)=\frac{1}{\omega\pi}\exp^{\frac{-(x-s)^2}{2\omega^2}}\int_{-\infty}^{a\frac{z-s}{\omega}}\exp\frac{-t^2}{2}dt,-\infty<z<\infty$$

where ξ denotes the location; ω denotes the scale and α denotes the shape of density

Student-t distribution:

$$f(z)=\frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{v\pi}\Gamma\left(\frac{v}{2}\right)}(1+\frac{z^2}{v})^{-(\frac{v+1}{2})}$$ $-\infty<z<\infty$ where v denotes the number of degrees of freedom and Γ denotes the Gamma function.

- Skewed Student–*t* Distribution:

$$f(z:\mu,\sigma,v,\lambda)=bc(1+\frac{1}{v-2}(\frac{b\left(\frac{z-\mu}{\sigma}\right)+a}{1-\lambda})^{2})^{-(\frac{-v+1}{2})},$$

if $z<\frac{-a}{b}$

or

$$f(z:\mu,\sigma,v,\lambda)=bc(1+\frac{1}{v-2}(\frac{b\left(\frac{z-\mu}{\sigma}\right)+a}{1+\lambda})^{2})^{-(\frac{-v+1}{2})}$$

if $z\geq\frac{-a}{b}$

where v is a shape parameter with $2<v<\infty$ and λ is a skewness parameter with $-1<\lambda<1$. The constants a, b and c are given as: $a=4\lambda c(\frac{v-2}{v-1})$, $b=1+3\lambda^2-a^2$, $c=\frac{\Gamma(\frac{v+1}{2})}{\sqrt{\pi(v-2)}\Gamma(\frac{v}{2})}$ μ and σ^2 are the mean and variance of the Skewed Student–*t* distribution.

Generalized Error Distribution (GED): $f(z,\mu,\sigma,v,)=\frac{\sigma^{-1}v\exp\left(-0.5|(\frac{z-\mu}{\sigma})/\lambda/|^{v}\right)}{\lambda 2^{(1+\frac{1}{v})}\Gamma(\frac{1}{v})}$, $1<z<\infty$, $v>0$ is the degree of freedom or tail thickness parameter and $\lambda=\sqrt{2^{(-\frac{2}{v})}\Gamma\left(\frac{1}{v}\right)/\Gamma\left(\frac{3}{v}\right)}$ If v=2 , the GED yields the normal Distribution. If v<1 , the density function has thicker tails, than the normal density function, whereas for i>2 it has thinner tails.

Skewed Generalized Error Distribution (SGED):

$$f(z,v,\xi)=v\left[2\theta\Gamma\left(\frac{1}{v}\right)\right]^{-1}Exp(-\frac{|z-\delta|^{v}}{[1-sign(z-\delta)\varepsilon]^{v}\theta^{v}})$$

where,

$$\theta=\Gamma\left(\frac{1}{v}\right)^{-0.5}\Gamma\left(\frac{3}{v}\right)^{-0.5}S(\varepsilon)^{-1},\qquad \delta=2\xi AS(\xi)^{-1},$$

$$S(\xi)=v(1+3\xi^2-4A^2\xi^2)\quad A=\Gamma\left(\frac{2}{v}\right)\ \Gamma\left(\frac{1}{v}\right)^{-0.5}\Gamma\left(\frac{3}{v}\right)^{-0.5}$$

where v>0 is the shape parameter controlling the height and heavy – tail of the density function, while ξ is a skewness parameter of the density with $-1<\xi<1$ in the empirical section of this study, all parameter in the above distribution are that default values in R package, location, scale and skewness parameter are equal to 0, 1 and 1.5 respectively shape parameter is equal to 5 for students –t and skewed student's –t distributions and equal to 2 for GED and skewed GED distributions the parameters of the model in (4) α_0, α_1 and β are non-negative with $\alpha+\beta<1$ to ensure stationarity. The parameters of the model are estimated using the R package 3.1.2, the set of 1825 returns is estimation sample comprising 1725 observations for in-sample evaluation and 100 forecasting sample called out of sample data used to investigate the performance of volatility forecasting. The parameters mean and variance equations are estimated for each distribution. The values of the parameters robust T statistics and p-values are shown in Tables 2 to 7 using the p-values obtained; we may deduce that parameters of the models are significant at the 5% level of significance.

Data and Empirical Properties: The data used in this study are the daily closing values of Nigerian naira/US Dollar exchange rate. The data were collected from OANDA SOLUTIONS FOR BUSINESS webservices@oanda.com. The data span the period from 29th December, 2010 to 27th December, 2015 and comprise 1825 observations of the spot price and are converted for the needs of fitting the model to a logarithmic return series. If the price series is denoted by $\{X_t\}$

$$r_t=\ln\left(\frac{x_t}{x_{t-1}}\right)$$

Fig. 1: displays the time series of prices, log returns and acf of USDNGN exchange rates . The plot of the returns series suggests the presence of heteroscedasticity. In fact, we observe clusters of periods of high volatility as well as those of low volatility.

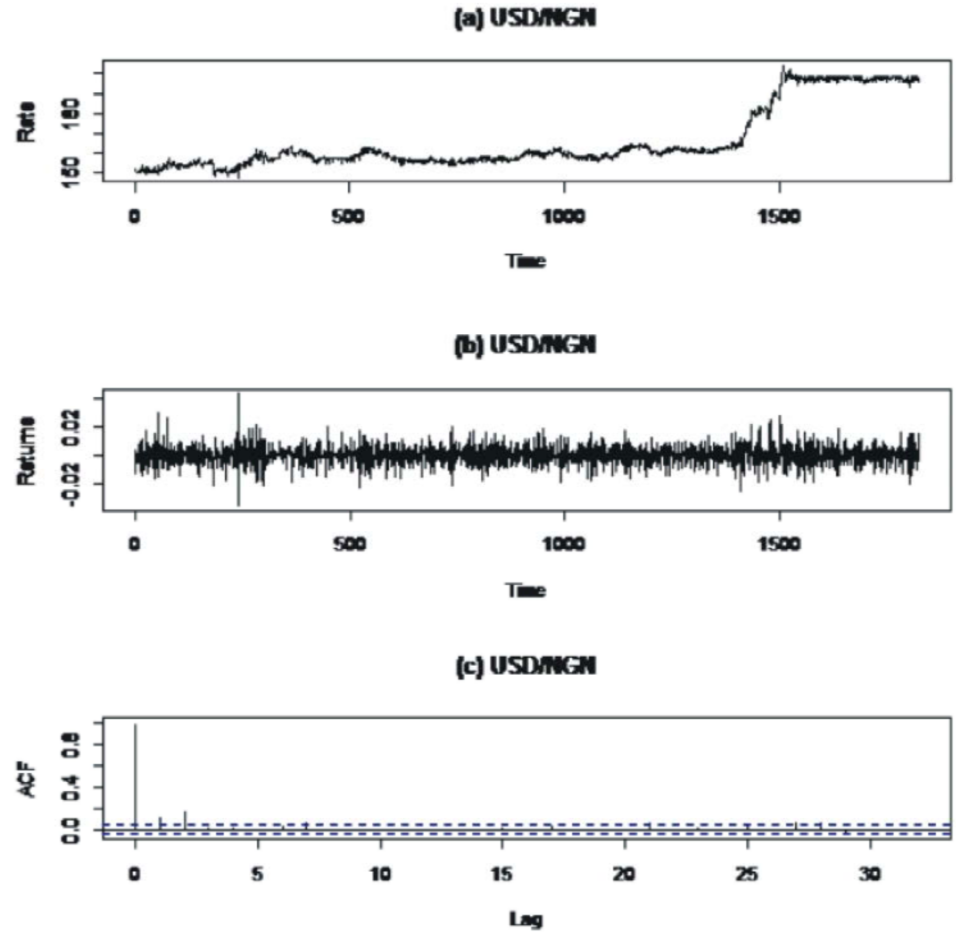

Fig. 1: Exchange rates, corresponding log Returns and acf for the period 29/12/2010 to 27/12/2015

Table 1: Descriptive statistics

Statistic	value
Mean	0.000151
Standard deviation	0.0067
Range	0.079011
Skewness	0.08378
Kurtosis	5.22672
Jarque-Bera	12.321
LBP	119.2
ARCH -test	11.458

From Table 1, it is observed that the mean is 0.000151 which is very close to zero. It may be seen also that the returns exhibit positive skewness and excess kurtosis. The Jarque-Bera test performed at 5% level of significance rejected the null hypothesis test of zero skewness and zero excess kurtosis ($\chi_{test}^2 = 12.321 > 5.99$). This suggests departure from normality assumption.

The Ljung-Box-Pierce test at 5% significance level and with up to lags allows us to deduce the lack of randomness in the data (presence of autocorrelation). The critical value for the test is 11.0705. In the same vain Engle's ARCH test at 5% level of significance with up to five lags also rejected the null hypothesis that returns form a random sequence of normal disturbances thus, the presence of heteroscedasticity with the critical value-11.0705. These features support the use of a GARCH model for capturing the time varying volatility.

The constant omega is significant for eGARCH(1, 1)-norm and eGARCH(1, 1)-SNORM and insignificant for rest of the distributions. Alpha1 is not significant for all the models. Beta1, gamma1, shape and skew parameters are all significant at 5% level of significant. One of the major advantage of the EGARCH model is that it incorporatee the asymmetries in financial market volatilities. Alpha α and gamma γ parameters help to capture two important asymmetries in conditional variances. If parameter gamma $\gamma < 0$, fall in exchange rate increases the volatility more than rise in exchange rate of the same magnitude. This phenomenon is called leverage effect. For all the distributions, $\gamma > 0$ and since $\gamma \neq 0$ it means that there

Table 2: Parameter Estimation of the eGARCH (1, 1)

Model	Dist	Parameter	omega	alpha1	beta1	gamma1	skew/shape
eGARCH	norm	Estimate	-1.54884	0.021065	0.846994	0.25082	
		P-value	0.016611	0.280273	0	0.000034	
eGARCH	snorm	Estimate	-1.50551	0.020838	0.85126	0.248526	0.989725
		P-value	0.02193	0.29817	0	0.000051	0
eGARCH	std	Estimate	-1.64877	0.034836	0.837761	0.261038	7.785652
		P-value	0.09244	0.161182	0	0.002209	0
eGARCH	sstd	Estimate	-1.61725	0.033768	0.840864	0.259994	0.989451
		P-value	0.089978	0.17173	0	0.002202	0
eGARCH	ged	Estimate	-1.66787	0.028061	0.836047	0.258954	1.415876
		P-value	0.080926	0.261384	0	0.001767	0
eGARCH	sged	Estimate	-1.66787	0.026477	0.84166	0.256677	0.988617
		P-value	-1.61081	0.299656	0	0.007636	0

Table 3: Parameter Estimation of the gjr-GARCH (1, 1)

Model	Dist	Parameter	omega	alpha1	beta1	gamma1	skew/shape
eGARCH	norm	Estimate	0.000006	0.14029	0.734398	-0.03035	
		P-value	0.020538	0.000095	0	0.315723	
eGARCH	snorm	Estimate	0.000005	0.135431	0.748542	-0.02837	0.979104
		P-value	0.029861	0.000104	0	0.336932	0
eGARCH	std	Estimate	0.000006	0.157299	0.721602	-0.04976	8.427905
		P-value	0.021271	0.00038	0	0.177704	0
eGARCH	sstd	Estimate	0.000006	0.155921	0.724738	-0.04754	0.980613
		P-value	0.021055	0.000329	0	0.196734	0
eGARCH	ged	Estimate	0.000006	0.045193	0.722872	-0.04141	1.454612
		P-value	0.036184	0.000866	0	0.263964	0
eGARCH	sged	Estimate	0.000006	0.147764	0.728076	-0.03869	0.981208
		P-value	0.04113	0.000824	0.000824	0.292077	0

exists asymmetric impact in the USDNGN exchange rate returns but no leverage effect. The parameter beta β helps to determine the persistence of volatility in the exchange rate returns. The values for β are all close to 1 , this means that USDNGN is highly persistent for the periods under study. The sum of the coefficients on the lagged squared error and lagged conditional variance is close to 1 in all the eGARCH(1, 1) models for different distributions considered. This suggests that shocks to the conditional variance will be highly persistent.

The constant omega, alpha1, beta1 and skew parameters are all significant at 5% level of significance. The negative values observed in gamma1 indicate existence of leverage effect in USDNGN exchange rate data for the period under study.

Forecast Evaluation: We make use of 2 metrics for forecast evaluation both in and out of samples. We consider mean square error (MSE) and Mean Absolute Error (MAE) defined as follows:

$$MSE = \frac{1}{n} \times \sum_{t=1}^{n} (r_t^2 - \sigma_t^2)^2 \quad (5)$$

$$MAE = \frac{1}{n} \sum_{t=1}^{n} | r_t^2 - \sigma_t^2 | \quad (6)$$

where r_t^2 is used as a substitute for the realized or actual variance [12] and [20] employed r_t^2 as proxy for realized volatility and σ_t^2 is the forecasted variance.

The sign bias tests for USDNGN exchange rate returns are all not significant at 5% level for the six models considered. However, Negative sign bias test is significant at 10% level of significant.Also eGARCH(1, 1)-norm and eGARCH(1, 1)-snorm are significant at 10% level.

Table 5 shows significant Negative sign Bias for gjr-GARCH(1, 1)-snorm .

The two symmetric statistical loss functions MSE and MAE are among the most popular methods for evaluating the forecasting power of a model given their simple mathematical structure.Also AIC, loglikilihood are used to assess the in-sample forecasting accuracy. Tables 6 and 7 show the AIC, loglikelihood, MSE and MAE for the forecasted volatility. We observe that the six models seem to produce relative accurate forecasts given the quite

Table 4: Sign Bias Test for USDNGN exchange return rates:eGARCH(1, 1)

Model	Dist	Parameter	SignBias	Negative Sign Bias	Positive Sign Bias	Joint Effect
eGARCH	norm	Estimate	0.136	1.727	1.65	5.709
		P-value	0.8918	0.08427 *	0.09918*	0.12667
eGARCH	Snorm	Estimate	0.1332	1.7569	1.6698	5.877
		P-value	0.89406	0.07911 *	0.09514*	0.11775
eGARCHH	std	Estimate	0.3226	1.6731	1.0181	3.8473
		P-value	0.74706	0.09449 *	0.30877	0.27843
eGARCH	sstd	Estimate	0.3053	1.6677	1.039	3.8723
		P-value	0.76018	0.09555 *	0.29896	0.27559
eGARCH	ged	Estimate	0.9738	1.7517	0.6671	3.8118
		P-value	0.3303	0.08 *	0.5048	0.2825
eGARCH	sged	Estimate	0.8009	1.6792	0.7902	3.6268
		P-value	0.42331	0.09329 *	0.42949	0.30469

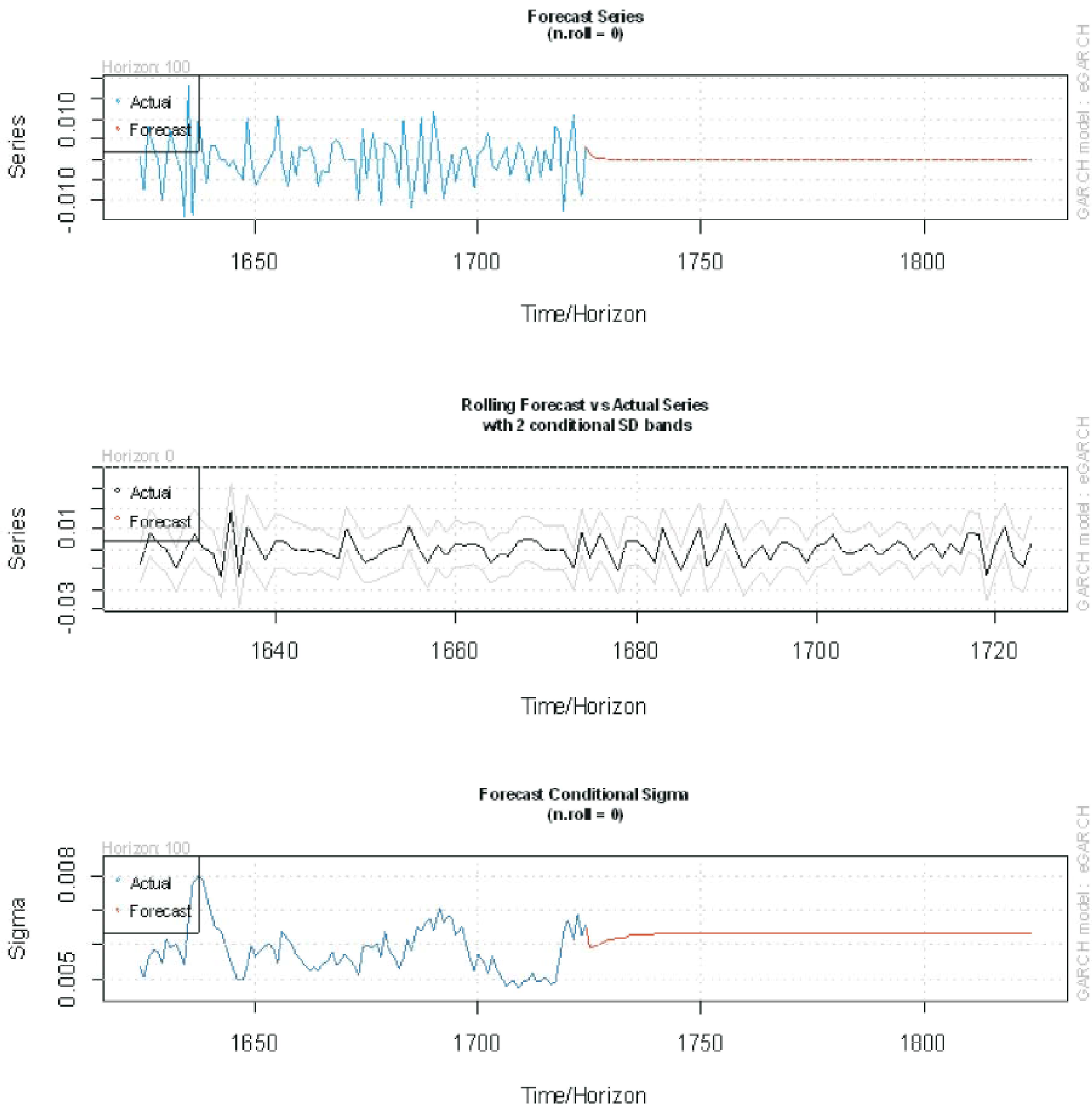

Fig. 2: Forecasted volatility versus Actual Return series eGARCH(1, 1) -ged

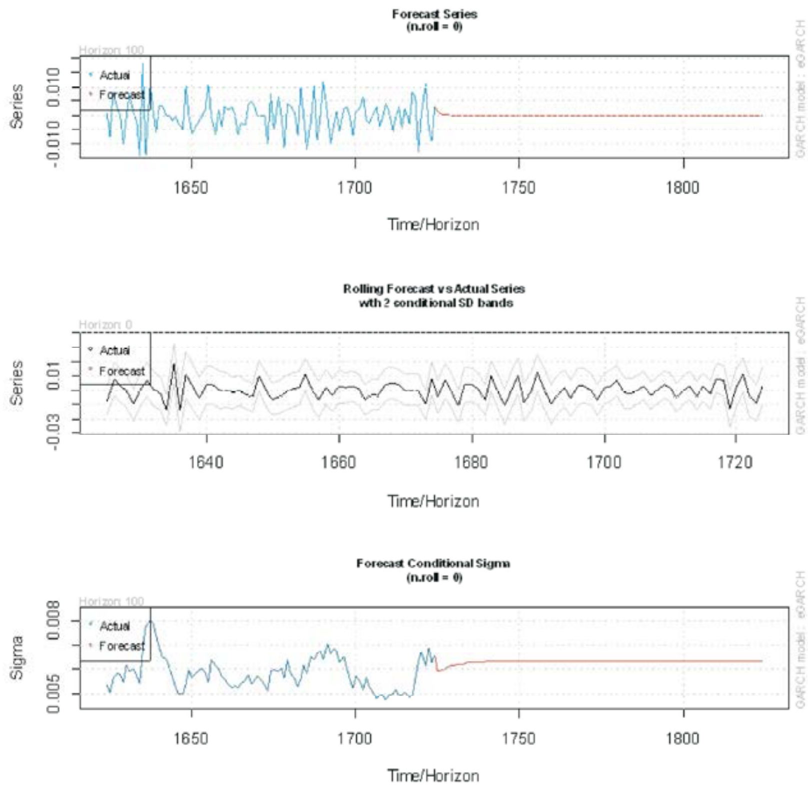

Fig. 3: forecasted volatility versus Actual Return series gjr-GARCH(1, 1) -std

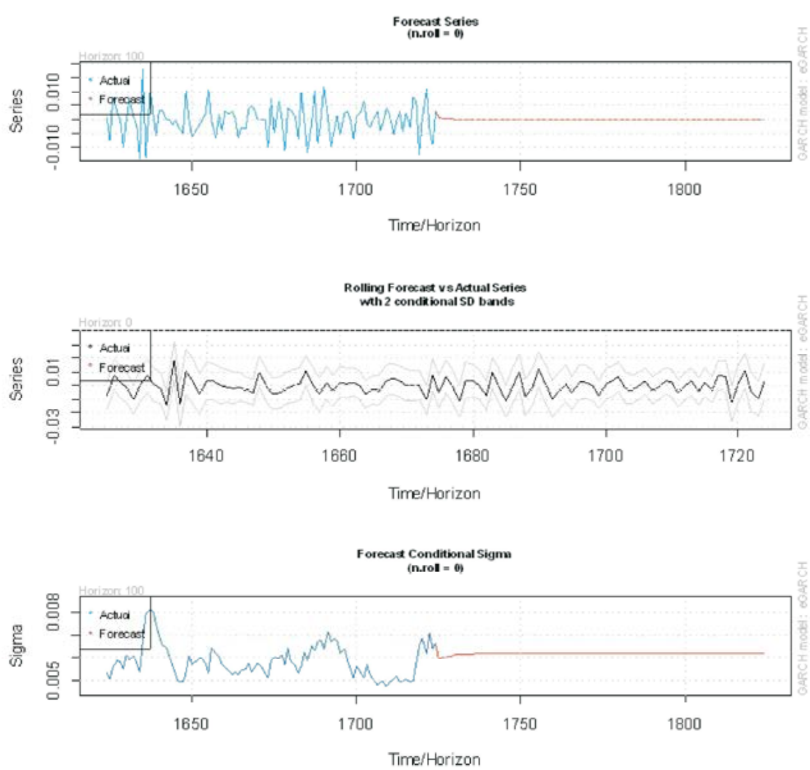

Fig. 4: forecasted volatility versus Actual Return series eGARCH(1, 1) -snom

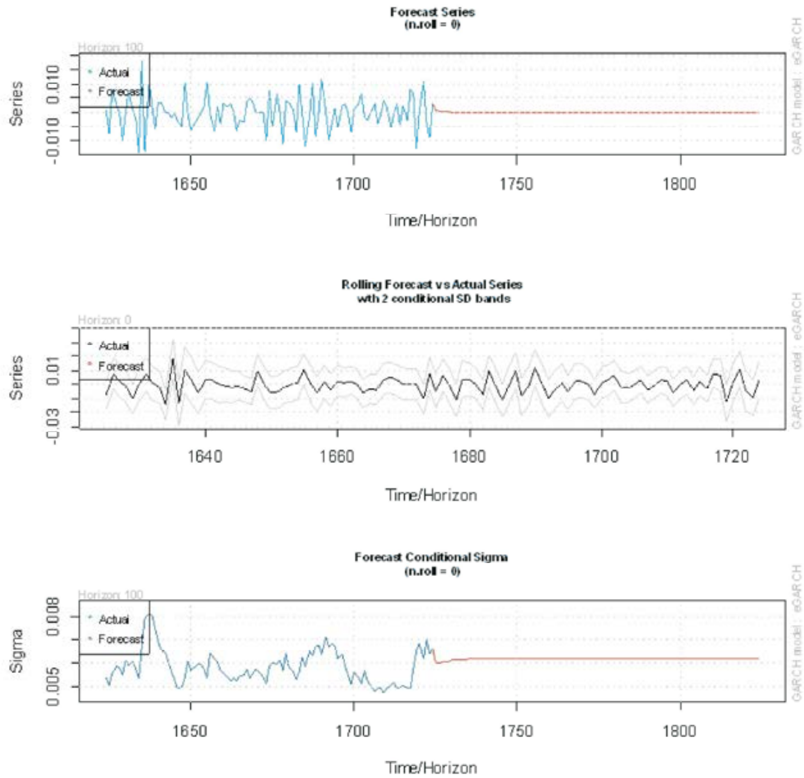

Fig. 5: Forecasted volatility versus Actual Return series eGARCH(1, 1) -norm

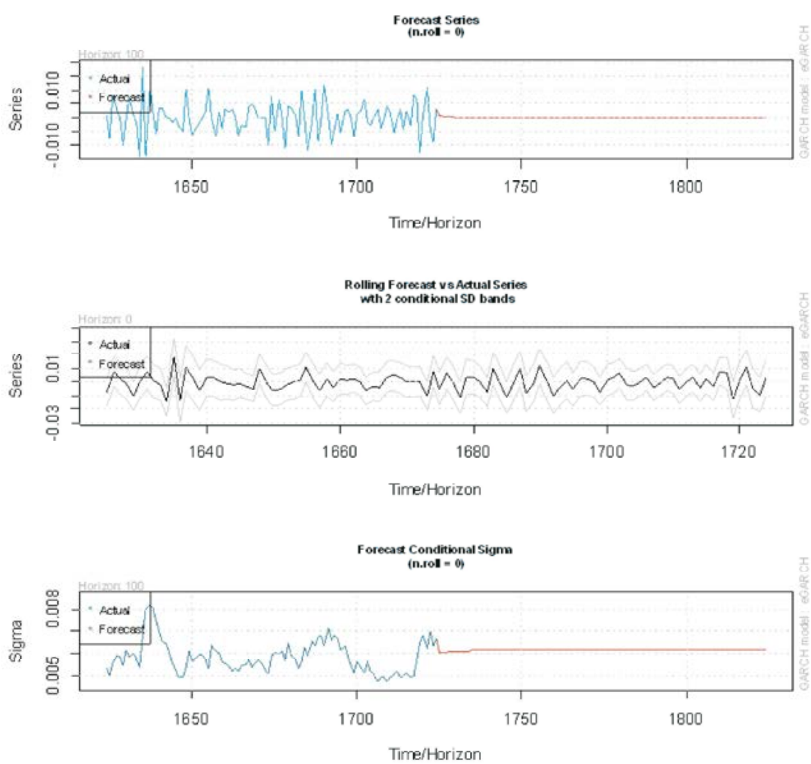

Fig. 6: Forecasted volatility versus Actual Return series gjr-GARCH(1, 1) -snorm

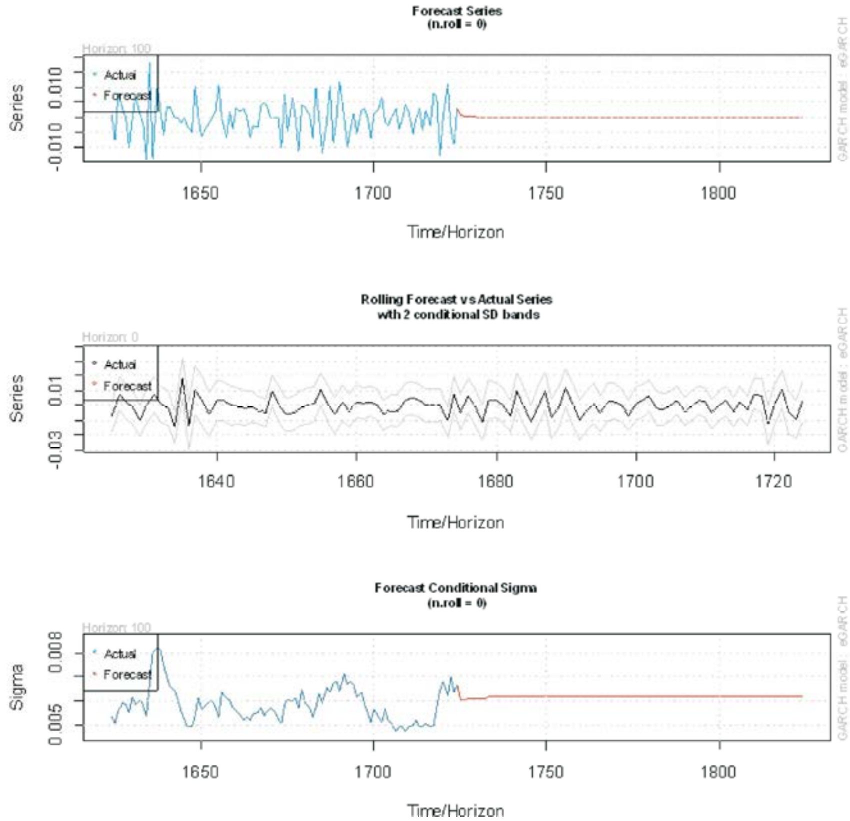

Fig. 7: Forecasted volatility versus Actual Return series gjr-GARCH (1, 1) -norm

Table 5: Sign Bias Test for USDNGN exchange return rates:gjr-GARCH(1, 1)

Model	Dist	Parameter	SignBias	Negative Sign Bias	Positive Sign Bias	Joint Effect
eGARCH	norm	Estimate	0.4782	1.6279	1.042	3.7708
		P-value	0.6326	0.1037	0.2976	0.2873
eGARCH	snorm	Estimate	0.4153	1.6616	1.1366	4.0719
		P-value	0.67795	0.09677*	0.25381	0.2558
eGARCH	std	Estimate	0.3399	1.3717	0.6559	2.3233
		P-value	0.734	0.1703	0.512	0.5081
eGARCH	sstd	Estimate	0.5188	1.4629	0.5685	2.4639
		P-value	0.604	0.1437	0.5698	0.4819
eGARCH	ged	Estimate	0.772	1.41	0.4715	2.3414
		P-value	0.4402	0.1587	0.6373	0.5046
eGARCH	sged	Estimate	0.6128	1.3515	0.587	2.2376
		P-value	0.5401	0.1767	0.5573	0.5246

Table 6: AIC, LOGLIKELIHOOD, MSE and MAE for the fitted distributions eGARCH(1, 1)

	Dist					
	norm	snorm	std	sstd	ged	sged
AIC	-7.3282	-7.3271	-7.3526	-7.3515	-7.3539	-7.3529
MSE	0.000049043	4.87E-05	0.000050895	5.08E-05	6352.73	5.16E-05
MAE	6.08E-03	6.13E-03	7.06E-03	7.10E-03	6.01E-03	6.18E-03
LOGLIKE	6323.9	6323.958	6345.935	6345.986	6347.172	6347.085

Table 7: AIC, LOGLIKELIHOOD, MSE and MAE for the fitted distributions gjr-GARCH(1, 1)

	Dist					
	norm	snorm	std	sstd	ged	sged
AIC	-7.3394	-7.3384	-7.3605	-7.3595	-7.3503	-7.3596
MSE	4.53E-05	4.48E-05	4.75E-05	4.75E-05	4.77E-05	4.77E-05
MAE	6.73E-03	6.70E-03	6.90E-03	6.89E-03	6.91E-03	6.91E-03
LOGLIKE	6333.523	6333.725	6353.018	6352.902	6352.789	6352.73

small values of AIC, MSE, RMSE and MAE and large value of loglikilihood. From Tables 6 and 7, we can see that the true model is always the best fitted model in terms of the AIC but the true model does not necessarily provide the minimum values of MSE and MAE and might not produce the best forecasting volatility. Our result seems to agree with Shamiri and Isa (2009) argument that there are several plausible models that we can select to use for our forecast and we should not be fooled into thinking that the one with the best fit is the one that will forecast the best. For the two distributional asymmetric GARCH(1, 1) models considered, eGARCH(1, 1)-ged and gjr-GARCH(1, 1)-ged produced the smallest AIC and largest scores of log-likelihood respectively, thereby proving superior to rest of other distributional asymmetric GARCH(1, 1) models considered in this work. Table 6, for eGARCH(1, 1) model , eGARCH(1, 1)-snorm , eGARCH(1, 1)-ged recorded the minimum MSE and MAE respectively. Also in table 7 gjr-GARCH(1, 1)-snorm produced minimun MSE and MAE respectively.

CONCLUSION

The accurate measurement and forecasting of exchange rate returns is very important for the Nigerian economy. Firstly, Nigeria depends heavily on imported goods, secondly, there is significant increase in the amount of foreign investments into the country and lastly, important national reserves are held in foreign currencies, mostly in US dollars. This is the reason the study of fluctuations in foreign exchange rates in Nigeria are a key issue. R package was used to find the best fitted asymmetric GARCH models among the different error distributional assumptions considered for in-sample data and out-sample estimation of paramters in the model. The study considered two asymmetric GARCH(1, 1) models :eGARCH(1, 1) and gjr-GARCH(1, 1) under error distributions such as the Normal, Skewed Normal, Student-t distribution, Skewed Student-t distribution, Generalized Error distribution (GED) and Skewed Generalized Error distribtion. The results obtained indicate that all the models performed fairly well in capturing the volatility fluctuation of Nigerian exchange rate returns with slight advantage to eGARCH(1, 1)- GED and gjr-GARCH(1, 1)- GED for the in-sample fit . The two models have the lowest AIC and the highest log-likelihood values. The AIC and log-likelihoood values given by different models with different error distributions are reported in Tables 6 and 7.For out -of -sample forecasting using the statistical error functions, eGARCH(1, 1) -snorm and eGARCH(1, 1)-ged models have the minimum MSE and MAE respectively.While gjr-GARCH(1, 1)-snorm produced minimum MSE and MAE each. Again Tables 6 and 7. The empirical results of this study reveal evidence of leverage effect in USDNGN exchange return rates for the periods under study.

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