MODELING EXCHANGE RATE VOLATILITY IN SUB-SAHARA AFRICAN ECONOMIES: EMPIRICAL EVIDENCE FROM SOUTH AFRICA, NIGERIA AND GHANA

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Abstract

The study modeled the series of exchange rates returns in three African economies-South-Africa, Nigeria and Ghana- over the period Jan 2 2002 to June 25 2015. Specifically, the study considered seasonal breaks under the assumption of student-t distribution to examine the underlying properties of these emerging FOREX markets. It was discovered that the three markets exhibit heavy tails and serial correlations. In view of these, the study employed battery of GARCH identifications to model these features and discovered that there are ARCH and GARCH effects, January effects and presence of volatility clustering in the three markets. However, leverage effects were refuted by the GJR model while the EGARCH supports the effects. This discrepancy warranted carrying out conventional diagnostic tests that lent credence to a conclusion that GJR performed better for South-Africa while GARCH takes the lead in Nigeria and Ghana respectively.

Jel Classification Code: E440; F1; F2
Keywords: Keywords: Exchange Rates, Volatility, Sub-Sahara Africa, January Effects, GJR, GARCH, EGARCH

INTRODUCTION

Unequivocally, the adoption of market driving exchange rate system in 1973 till date has accounted for unprecedented swings in daily exchange rate returns or volatility. The African emerging economies especially Nigeria, Ghana and South-Africa are seriously beleaguered with these swings thereby a-waiting striking investigations to uncover the underlying characteristics of exchange rate returns and uncertainty in these economies. Even Kamal, Ghani and Khan (2012) said "increasing role of foreign exchange (FOREX) rate in corporate decision making is becoming famous in the developing economies, where FOREX rate volatility occupied a central position all over the world in investment decision". They concluded that there was asymmetric behavior of volatility in Pakistan.

It is seemingly realistic that a floating exchange rate system is presumably more volatile than its counterpart fixed system. Therefore, investment decision made in a regime of floating system is comparably more prone to risk and uncertainty than that taken in fixed regime. With respect to today's investment decision, quantification, prediction and estimation of volatility have become a concern to both professionals and researchers in foreign exchange market. In the light of these, Kemal (2005) emphasized that foreign exchange volatility is capable of increasing the volume of international market sales, procurement of government policy and allocation of resources for investment purposes which alternatively influences investment decision. Taylor (2005) explicitly stressed on the impact of volatility on financial decisions raging from portfolio optimization, risk management, hedging to derivatives pricing. In the same token, the study of Poon and Granger (2003) essentially confirmed that volatility has significant impact on an economy; therefore policy makers vehemently depend on volatility modeling to forecast the risk exposure of the economy together with the financial market. In view of this, modeling volatility is an indispensible tool in formulating policy.

It is a stylized fact that extensive works on volatility modeling started with the development of Autoregressive Conditionally Heteroskedastic (ARCH) model and its subsequent versions. ARCH type family allows the estimation of latent volatility in a series. Greene (2008) suggested that uncertainty of exchange rates is a latent variable with economic implications. Alam and Rahman (2012) observed that "Volatility models are important to the policy makers, since they use to observe the effect of economic factors on foreign exchange rate as well as to formulate the policies related to the money supply in the economy and the policies associated with the government expenditures and incomes". The investigation of Kama et al (2012) pointed out that economic growth of countries dealing in international transactions is significantly influenced by exchange rate volatility.

In spite of the excessive fluctuations of exchange rates, only few studies on this subject have been dedicated to African emerging foreign exchange markets in comparable manners. For example the recent study by Bala and Asemota (2013) focused on Nigerian FOREX market only; Thereby providing no evidence on other markets with similar or sometimes dissimilar characteristics. Investors in Nigeria may want to know the shocks and variations in other neighboring markets when taking decisions. Therefore, we are driving with the limitations inherent in the study of Bala and Asemota to model volatility clustering and asymmetry in three African emerging economies; Nigeria, Ghana and South-Africa which appear to be the commercial nubs of the continent. Our GARCH type models are modified to account for structural breaks and their performances are tested using appropriate loss functions and trading mechanisms. With these our GARCH estimations further differ to those of Bala and Asemota but in some respects similar to Alam and Rahman's tests in Bangladesh. The rest of the paper is arranged as follows: literature review, data characteristics, methodology, results, conclusion and recommendations.

LITERATURE REVIEW

Within the purview of Finance and Macroeconomics, ARCH-GARCH models are generally quoted to describe the basic characteristics of a financial market; especially the foreign and stock exchange markets (Kamal et al). For instance, Zivot (2009) employed practical issues related to specification, estimation, diagnostics, and forecasting to provide a thorough empirical description of GARCH models for financial time series. Hansen and Lunde (2005) have compared the potential abilities of about 330 ARCH–type equations on exchange rates conditional variance and reported that GARCH (1,1) model was outperformed by sophisticated models.

More than a decade now volatility models have been modeled to contain breaks. Hammoudeh and Li (2008) quoted GARCH (1, 1) to describe the sudden changes in stock market volatility for five Gulf areas. They accounted for breaks or large shifts in volatility for the model and found significant decline in volatility persistence that characterized these markets. Lange and Rahbek (2008) documented that regime–switching models based on conditional heteroscedasticity were peculiar type of nonlinear volatility models that provided an alternative way of modeling volatility process with breaks. The reviews of Teräsvirta (2009) on several univariate conditionally heteroscedastic models indicated that GARCH models tend to exaggerate persistence of volatility over time. Kasman, Vardar and Tunc (2011) provided overwhelming evidence in support of the preposition that interest rate and exchange rate volatility were the major determinants of the conditional bank stock return volatility.

In Pakistan, Ellahi (2011) provided strong evidence that exchange rate volatility and foreign direct investment maintained non monotonic short run association; conversely they supported positive relationship in the long run. In the European Union, Ngouana (2012) demonstrated that the union nominal effective exchange rate over the past decade that associated with hard pegged system was two times as volatile as it would have been under a hypothetical basket peg. Balg and Metcalf (2010) persuasively argued that the volatility of the money supply was a distinct determinant of foreign exchange rate variations

Also in most recent time, Bala and Asemota (2013) applied the GARCH models to Naira-US Dollar for the period of 1985 to 2011; Naira-British Pound and Nair-Euro over the period of 2004 to 2o11 in Nigeria. They reported presences of volatility for the three exchange rates and no leverage effects except for the models with volatility breaks. While, Kamal, Ghani and Khan (2012) adopted the GARCH candidate specifications but without breaks in Pakistan and they confirmed asymmetric behavior of exchange rates. In a study by Alam and Rahman (2012), attention was paid to in sample and out of sample analyses. In both samples, their findings revealed that previous exchange rate volatility significantly influenced current volatility and that EGARCH and TARCH models outperformed all the GARCH models as per in sample and out of sample with transaction costs. Narayan, Narayan and Prasad (2009) employed EGARCH model to investigate the pertinent characteristics of foreign exchange rate and documented evidence in support of positive nexus between foreign exchange rate volatility and conditional shock.

In view of the forgoing empirical stances, we have identified that the exchange rate volatility of Nigeria, Ghana and South-Africa has not been unanimously examined based on heteroskedastic frameworks with shifts. Therefore, we have made an attempt to develop hierarchy of these models using their statistical and trading performances with the aim of selecting the most appropriating forecasting models for each of the three countries.

METHOD OF STUDY

Data Characteristics

We employed daily exchange rate prices of Naira, Cedi and Rand quoted against U S Dollar over a window that ranged from January 2nd 2001 to June 25th 2015. This gives rise to about 5288 observations for each of the countries. Data on Naira and Cedi exchange rates were collected from https://www.oanda.com while Rand prices were obtained from https://www.resbank.co.za. These data are characteristically very noisy and therefore at raw level they appeared not stationary, not applicable and needed to be transformed. In this regards, we construct the long price relative (LPR) index given by the following function:

$$\mathrm{LPR}_t = In\left\{Exc_t \times (Exc_{t-1})^{-1}\right\} \equiv InExc_t + \frac{1}{In(Exc_{t-1})} \qquad 1$$

Where: $\mathrm{LPR}_t = \mathrm{R}_t; R_t$ is the return at time t; Exc_t denotes exchange rate at time t and Exc_{t-1} represents exchange rate at time $\mathrm{t}-1$. In fitting the return data into the volatility models the series must exhibit serial correlation, stationarity and display heavy tail. The serial correlation of the series is examined based on autocorrelation function (ARF) which is defined as follows:

$$p_k = \frac{\sum_{t=1+k}^{n}\left[(R_t - \overline{R})(R_{t-k} - \overline{R})\right]}{\sum_{i=1}^{n}(R_t - \overline{R})^2}; 0 \le k \le n-1 \qquad 2$$

Where: p_k is the coefficients of the autocorrelations (that is the ARF), the number of observation is n and k is the lag time of the series (see, Tsay, 2005). Here, we assume that the ARF decays very rapidly or geometrically for GARCH model to be established. Our test results based on this assumption are reported in tables1 (a, b & c) and corresponding figures1 (a, b & c).

TABLE 1A:
Autocorrelation Coefficients for Rand-Dollar Exchange Rates

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>| |</td><td>| |</td><td>1</td><td>-0.035</td><td>-0.035</td><td>4.5587</td><td>0.033</td></tr>
<tr><td>| |</td><td>| |</td><td>2</td><td>0</td><td>-0.002</td><td>4.5589</td><td>0.102</td></tr>
<tr><td>| |</td><td>| |</td><td>3</td><td>-0.029</td><td>-0.029</td><td>7.634</td><td>0.054</td></tr>
<tr><td>| |</td><td>| |</td><td>4</td><td>0.004</td><td>0.002</td><td>7.6989</td><td>0.103</td></tr>
<tr><td>| |</td><td>| |</td><td>5</td><td>-0.042</td><td>-0.042</td><td>14.231</td><td>0.014</td></tr>
<tr><td>| |</td><td>| |</td><td>6</td><td>0.029</td><td>0.025</td><td>17.184</td><td>0.009</td></tr>
<tr><td>| |</td><td>| |</td><td>7</td><td>0.045</td><td>0.047</td><td>24.643</td><td>0.001</td></tr>
<tr><td>| |</td><td>| |</td><td>8</td><td>-0.024</td><td>-0.023</td><td>26.77</td><td>0.001</td></tr>
<tr><td>| |</td><td>| |</td><td>9</td><td>-0.006</td><td>-0.006</td><td>26.899</td><td>0.001</td></tr>
<tr><td>| |</td><td>| |</td><td>10</td><td>-0.018</td><td>-0.018</td><td>28.136</td><td>0.002</td></tr>
</table>

TABLE 1B
Autocorrelation Coefficients for Naira-Dollar Exchange Rates

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>*| |</td><td>*| |</td><td>1</td><td>-0.163</td><td>-0.163</td><td>139.78</td><td>0</td></tr>
<tr><td>*| |</td><td>*| |</td><td>2</td><td>-0.128</td><td>-0.159</td><td>226.95</td><td>0</td></tr>
<tr><td>*| |</td><td>*| |</td><td>3</td><td>-0.144</td><td>-0.204</td><td>336.62</td><td>0</td></tr>
<tr><td>*| |</td><td>*| |</td><td>4</td><td>-0.088</td><td>-0.196</td><td>377.6</td><td>0</td></tr>
<tr><td>*| |</td><td>**| |</td><td>5</td><td>-0.113</td><td>-0.268</td><td>445.71</td><td>0</td></tr>
<tr><td>|* |</td><td>*| |</td><td>6</td><td>0.081</td><td>-0.128</td><td>480.21</td><td>0</td></tr>
<tr><td>|** |</td><td>|* |</td><td>7</td><td>0.247</td><td>0.127</td><td>802.94</td><td>0</td></tr>
<tr><td>| |</td><td>| |</td><td>8</td><td>0.028</td><td>0.061</td><td>807.16</td><td>0</td></tr>
<tr><td>*| |</td><td>| |</td><td>9</td><td>-0.082</td><td>-0.008</td><td>842.71</td><td>0</td></tr>
<tr><td>*| |</td><td>| |</td><td>10</td><td>-0.087</td><td>-0.026</td><td>882.78</td><td>0</td></tr>
</table>

TABLE 1C
Autocorrelation Coefficients for Cedi-Dollar Exchange Rates

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>**| |</td><td>**| |</td><td>1</td><td>-0.229</td><td>-0.229</td><td>277.07</td><td>0</td></tr>
<tr><td>*| |</td><td>*| |</td><td>2</td><td>-0.125</td><td>-0.187</td><td>359.61</td><td>0</td></tr>
<tr><td>*| |</td><td>*| |</td><td>3</td><td>-0.087</td><td>-0.179</td><td>399.88</td><td>0</td></tr>
<tr><td>| |</td><td>*| |</td><td>4</td><td>-0.036</td><td>-0.15</td><td>406.63</td><td>0</td></tr>
<tr><td>| |</td><td>*| |</td><td>5</td><td>-0.064</td><td>-0.187</td><td>428.15</td><td>0</td></tr>
<tr><td>| |</td><td>*| |</td><td>6</td><td>0.001</td><td>-0.152</td><td>428.15</td><td>0</td></tr>
<tr><td>|* |</td><td>|* |</td><td>7</td><td>0.213</td><td>0.113</td><td>668.56</td><td>0</td></tr>
<tr><td>| |</td><td>| |</td><td>8</td><td>-0.012</td><td>0.044</td><td>669.32</td><td>0</td></tr>
<tr><td>*| |</td><td>| |</td><td>9</td><td>-0.066</td><td>-0.008</td><td>692.61</td><td>0</td></tr>
<tr><td>| |</td><td>| |</td><td>10</td><td>-0.038</td><td>-0.01</td><td>700.12</td><td>0</td></tr>
</table>

We have examined the serial correlations for the series of Rand-Dollar, Naira-Dollar and Cedi-Dollar exchange rates respectively in tables 1a, 1b and 1c up to lag 10. The observed Q-statistics are very large and p-values are less than critical alpha value at 5 percent for the three series except at lags 2 and 4 for the series of Rand-Dollar exchange rate return. Therefore, the series are found to exhibit serial correlation. The figures below also jouster post this fining.

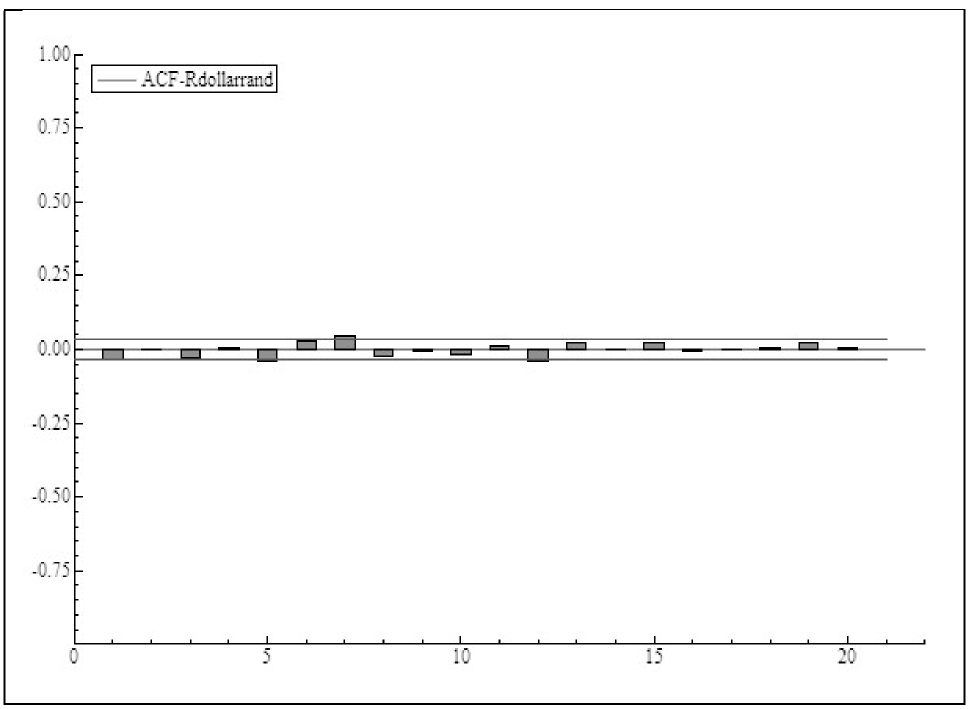

FIGURE 1 A: Rand-Dollar Autocorrelation Function

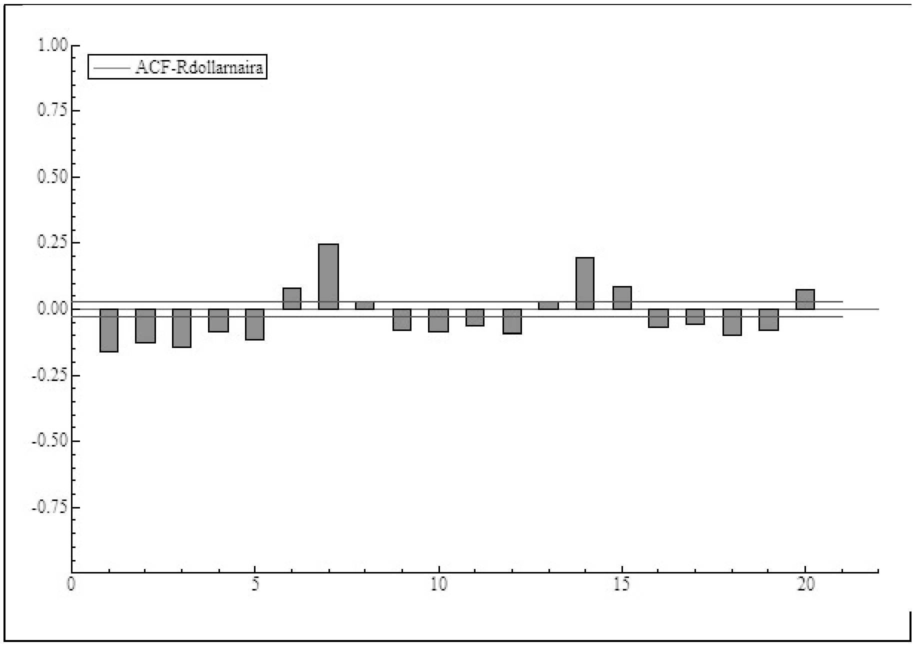

FIGURE 1 B: Naira-Dollar Autocorrelation Function

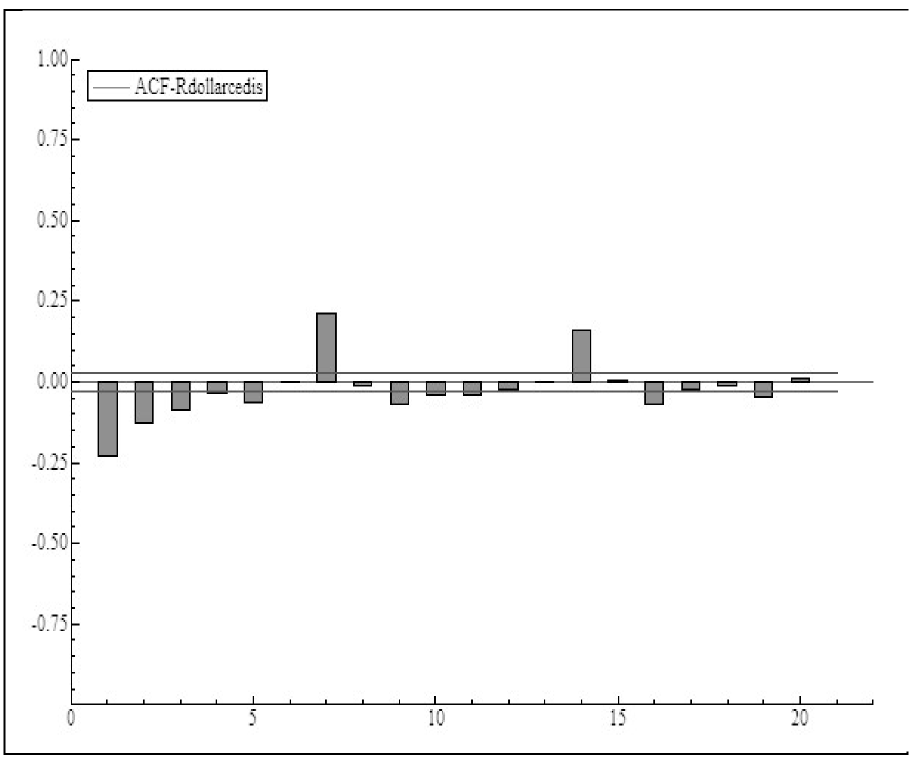

FIGURE 1 C: Cedi-Dollar Autocorrelation Function

A visual view of the figures above shows that the ARFs display both positive and negative coefficients for the three series. There is evidence that in all the three cases, the functions decay geometrically in both sides (i.e. positive and negative) which is synonymous to stationarity. However, further test on stationarity is carried out using the ADF technique. The specification of this technique is described as:

$$R_t = c + T + ADF_1 R_{t-1} + \sum_{i=1}^{P} ADF_{i+1} \triangleright R_{t-i} + \varepsilon_t \text{ ;i=1,2,..,p} \qquad 3$$

Where: C is the intercept, T is the trend, p is the lag length and ADF is the observed Augmented Dickey Fuller coefficient (statistic). By a-priori it must be different from zero at first deference or change to reject the hypothesis of a unit root. The test result is shown in table2.

TABLE 2
ADF Test Results on the Series of Rand/Dollar, Naira/Dollar & Cedi/Dollar

Series	Rand/Dollar	Naira/Dollar	Cedi/Dollar
ADF test statistic	-62.30517	-14.23226	-15.74497
1% Critical level	-3.431971	-3.431412	-3.431411
5% Critical level	-2.862141	-2.861894	-2.861894
10% Critical level	-2.567134	-2.567001	-2.567001

As shown in table 2, the ADF statistics are in absolute values larger than the critical statistics for the three series. Thus, the Rand/Dollar, Naira/Dollar and Cedi/Dollar exchange rates are stationary and in conformity with a priori. Another pertinent characteristic of these series is the structure of their distribution which can model as follows:

$$jb = N\left[\frac{(\mathrm{sk})^2}{6} + \frac{(\mathrm{kt}-3)^2}{24}\right] \qquad 4$$

Where:

$\mathbf{sk} = \dfrac{E(R^3)}{(\sigma^2)^{\frac{2}{3}}}$; that is the sknewness; $\mathbf{kt} = \dfrac{E(R^4)}{(\sigma^2)^2}$ that kurtosis and jb is the Jarque-Bera statistic. The estimation of equation 4 is reported in table 3.

TABLE 3:
Normality Test Results on the Series of Rand/Dollar, Naira/Dollar & Cedi//Dollar

Series	Rand/Dollar	Naira/Dollar	Cedi/Dollar
Skewness	0.567751	-0.031298	0.381776
Kurtosis	7.646199	24.07203	45.17959
Jarque-Bera	3449.591	97835.58	392127.5
Probability	0	0	0

The results depicted in table 3 show strong evidences of asymmetry and heavy tail. The p-value of the Jarque-Bera statistic is less alpha value at 5 percent, indicating the rejection of the normality hypothesis. Therefore, the series of the three exchange rates are asymmetric, leptokurtic and not normally distributed in natures. These results are also confirmed in the figures 2 a, b & c below: The figures show visual evidence of positive skewness for Rand/Dollar and Cedi/Dollar exchange rates; then negative skewness for the series of Naira/Dollar exchange rate. The stylized fact remains that the three series display heavy tails with asymmetries. In view of this, there are possibilities of detecting ARCH effects, outliers and clustering. The tables and figures below show the results of these possible characteristics in time series.

TABLE 3
The result of ARCH Effects for Rand/Dollar, Naira/Dollar & Cedi/Dollar Exchange Rates

Series	Rand/Dollar	Naira/Dollar	Cedi/Dollar
	ARCH	ARCH	ARCH
Coefficient	0.219872	0.064235	0.145381
Std. Error	0.014896	0.005049	0.011171
z-Statistic	14.76044	12.72326	13.01423
Prob.	0	0	0

Obviously, it becomes clear from table 3 that the three exchange rate series are characterized with ARCH affects. And these effects are pooling in nature as revealed in the proceeding figures: We have discovered from the figures and tables' results that the three exchange rate series are clustering with occasional outliers, heavy tailed and serially correlated; thereby fulfilling the assumptions of GARCH model specifications. Therefore, the next sub-section is devoted to modeling the structure of GARCH type relations.

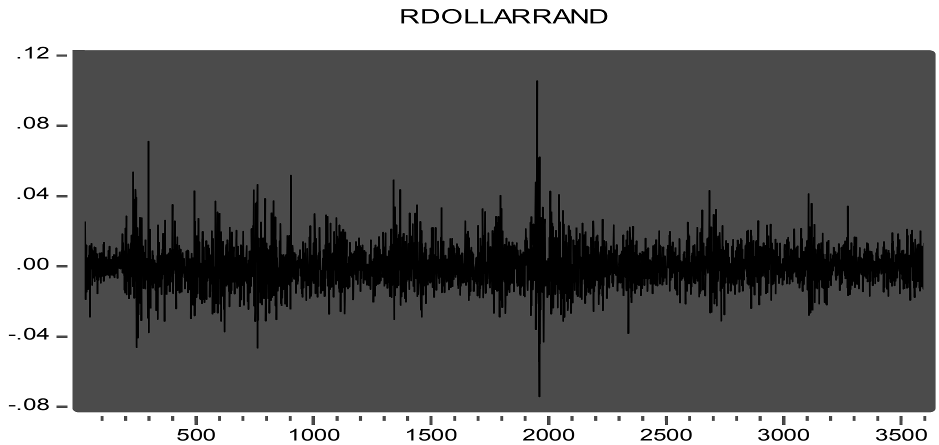

FIGURE 3A: Pooling of Rand/Dollar Exchange Rate

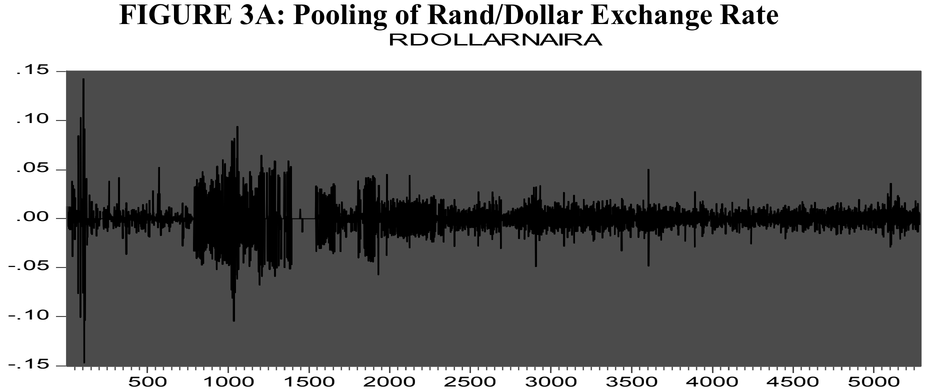

FIGURE 3B: Pooling of Naira/Dollar Exchange Rate

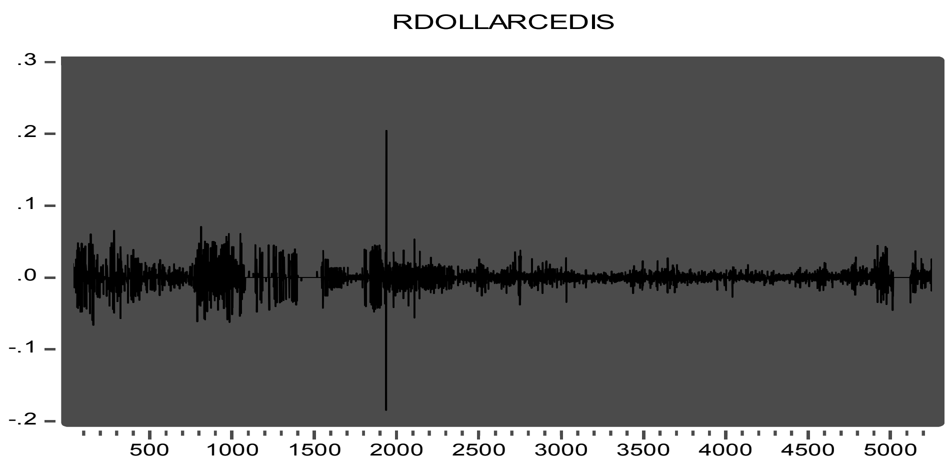

FIGURE 3C: Pooling of Cedi/Dollar Exchange Rate

The Model

We have shown in table2 that the exchange rate return series (R_t) is stationary at first order. In the light of the Wold Decomposition Theorem (WDT), any covariance or weakly stationary process can be decomposed into the sum of two uncorrelated processes-deterministic and indeterministic (Wold, 1938). That is:

$$R_t = d_t + \nu_t \qquad 5$$

Where: d_t is the deterministic process and ν_t represents the indeterministic process. ν_t can be expressed as a linear combination of past innovations (ε_{t-i}) up to lag q. Therefore:

$$\nu_t = \sum_{i=1}^{q} \psi_i \varepsilon_{t-i} \qquad 6$$

While d_t is a linear combination of historical information about R_t (F_{t-1}) and F_{t-1} is defined as ($F_{t-1} = R_{t-1}, R_{t-2},,, R_{t-p}$). Accord to Box and Jenkins (1976), equation 5 can be generalized as:

$$R_t = \lambda + \sum_{i=1}^{p} o_i R_{t-i} + \sum_{i=1}^{q} \psi_i \varepsilon_{t-i} +_i \varepsilon_t \qquad 7$$

$$(1 - o_1 L - o_2 L^2 + \ldots + o_P L^P) R_t = \lambda + (1 + \psi_1 L + \psi_2 L^2 + \ldots + \psi_q L^q) \varepsilon_t \qquad 8$$

$$o(L) R_t = \lambda + \psi(L) \varepsilon_t \qquad 9$$

Where: $o(L)$ and $\psi(L)$ are the AR and MA polynomials and their roots must lie within the unit circle for the process represented in equation 8 to be stationary and egodic. That is $o(L) = 1 - \sum_{i=1}^{p} o_i L^i < 0$ and $\psi(L) = 1 + \sum_{i=1}^{q} \psi_i L^i < 0$. In fulfilling this condition of egodicity, one of the assumptions underlying the formulation of GARCH type models has been achieved. Another pertinent assumption is that the error term (ε_t) is heteroskedastic as against the classical assumption of homoskedasticity. Thus, we look at the ε_t as a product of two components which is defined as follows:

$$\varepsilon_t = u_t \sqrt{h_t} \qquad 10$$

Where: u_t is the time invariant component and h_t is the time variant conditional variance that was expressed by Eagle (1982) as:

$$h_t = \lambda + \sum_{i=1}^{q} \rho_i \varepsilon^2_{t-i} \qquad 11$$

Equation 11 is the ARCH specification and it is fitted on the squared of return. Therefore, the model is structurally synonymous to a moving average process that only shows the impact of past innovations on variance. It fails to capture volatility clustering and heteroskedasticity. To account for these properties Bollerslev (1986) developed the Generalized ARCH (GARCH) model by introducing the lags of the conditional variance to Eagles' specification. Thus:

$$h_t = \lambda + \sum_{i=1}^{q} \rho_i \varepsilon^2_{t-i} + \sum_{j=1}^{p} \phi_j h_{t-j} \qquad 12$$

The study is restricted to GARCH (11) specification which is quoted as:

$$h_t = \lambda + \rho_1 \varepsilon^2_{t-1} + \phi_1 h_{t-1} \qquad 13$$

Where: ε^2_{t-1} and h_{t-1} are ARCH and GARCH terms at lag 1 or where p=q=1 respectively. λ, ρ_1 and ϕ_1 are the parameters with the following restrictions: $\lambda > 0; \rho_1 \geq 0 \,\&\, \phi_1 \geq 0$. To examine how seasonality inter-moves with variance, we introduce a dummy variable to represent January effects. These effects take value between 1 and 0; 1 every January when investors' expectation is to make high return because of the excessive demands on the FOREX market and 0 orderwise. Then equation 13 is augmented to include this dummy.

$$h_t = \lambda + \rho \varepsilon^2_{t-1} + \phi h_{t-1} + \eta dum \qquad 14$$

The most essential weakness of GARCH models is that they do capture leverage effects. Since these effects are integral parts of market phenomenon, Glosten, Jagannathan and Runkle (1993) introduced the Threshold GARCH (TGARCH) model which was eponymously tagged after names as GJR. This model provides a framework that explains how volatility responds to asymmetric information. It is generally believed that volatility increases with bad information but decreases with good information. Thus, the TGARCH (1 1) can be defined as:

$$h_t = \lambda + \rho_1 \varepsilon^2_{t-1} + \rho_2 \kappa_{t-1} \varepsilon^2_{t-1} + \phi_1 h_{t-1} \qquad 15$$

Where: $\kappa_{t-1}\varepsilon^2_{t-1}$ is the asymmetric term, κ_{t-1} is the dummy variable that takes value 1 when the residual is positive meaning bad news but 0 when the residual is negative indicating good news and ρ_2 is the unobserved asymmetric parameter that must be estimated. We also bring in the January effects into the TGARCH (1 1) model to examine the volatility shift in the model as shown in equation 16:

$$h_t = \lambda + \rho_1 \varepsilon^2_{t-1} + \rho_2 \kappa_{t-1} \varepsilon^2_{t-1} + \phi_1 h_{t-1} + \chi dum \qquad 16$$

Another early version of the Asymmetric GARCH-class models was developed by Nelson (1991). These models are based on the standardization of the residual term which gives rise to exponential equations. Basically, these equations are called Exponential GARCH (EGARCH) models. In this study, we propose the first order of EGARCH model with seasonal breaks and it is defined as:

$$\ln h_t = \lambda + \alpha_1 \varepsilon_{t-1}(h_{t-1})^{-0.5} + \alpha_2 \left[\varepsilon_{t-1}(h_{t-1})^{-0.5} - E\left(\varepsilon_{t-1}(h_{t-1})^{-0.5} \right) \right] + \phi_1 \ln h_{t-1} + \Omega dum \qquad 17$$

Removing the breaks gives rise to equation 18 as:

$$\ln h_t = \lambda + \beta_1 \varepsilon_{t-1}(h_{t-1})^{-0.5} + \beta_2 \left[\varepsilon_{t-1}(h_{t-1})^{-0.5} - E\left(\varepsilon_{t-1}(h_{t-1})^{-0.5} \right) \right] + \beta_1 \ln h_{t-1} \qquad 18$$

The Nelson's factor or asymmetric term is given as $\varepsilon_{t-1}(h_{t-1})^{-0.5} - E\left(\varepsilon_{t-1}(h_{t-1})^{-0.5} \right)$ and its parameter is β_2. Since these models are fitted in exchange rate series that exhibit heavy tail which is not normally distributed; we discard the assumption of Gaussuality. Therefore, we give preference to student-t distribution in the estimation procedure.

Estimation Procedure

The maximum likelihood estimation technique is employed in this study under the assumption of student-t distribution. And it is given as follows: First let state the probability density function for the student-t distribution as:

$$f(x) = \frac{v\,\mathrm{e}\left(-0.5\left|\frac{x}{\phi h}\right|^{v}\right)h^{-1}}{\phi 2^{(1+1/v)}\Gamma\left(v^{-1}\right)} \qquad 19$$

$$\phi = \left\{2^{-\frac{2}{v}}\Gamma\left(v^{-1}\right)/\Gamma\left(3v^{-1}\right)\right\}^{0.5} \qquad 20$$

Where: $v > 0$ which is the measure of the fatness of the tail, x is an integer and the gamma function $\Gamma(.)$ is expressed as:

$$\Gamma(x) = \int_0^\infty y^{x-1}e^{-y}dy \equiv (1+x) \qquad 21$$

Therefore, the likelihood function is expressed as the function of the parameter given the data and it defined as:

$$like\left(\square, \mu, v \middle| R_1, R_2,,, R_T\right) = \prod_{i=1}^{T}\frac{V}{\phi}2^{\left(-1+V^{-1}\right)}/\Gamma\left(v^{-1}\right)\sqrt{h_T}e^{\left[\frac{-R_i-\mu}{2\phi^2 h_i}\right]^{\frac{v}{2}}} \qquad 22$$

$$\log like\left(\square, \mu, v \middle| R_1, R_2,,, R_T\right) =$$

$$T\left[\log V - \log\phi - 1 + V^{-1}\log 2 - \log\Gamma\left(v^{-1}\right) - \frac{1}{2}\right]$$

$$\sum_{i=1}^{T} h_i - \frac{1}{2}\sum_{i=1}^{T}\left[\frac{R_i-\mu}{\phi^2 h_i}\right]^{\frac{v}{2}} \qquad 23$$

Where: $\square = \lambda, \rho \,\&\, \phi$ for the GARCH $\square = \lambda, \rho_1, \rho_2 \,\&\, \phi_1$ for the TGARCH $\square = \lambda, \beta_1, \beta_2 \,\&\, \beta_3$ for the EGARCH. Equation 23 is maximized with respect to these parameters to obtain their values.

In a bid of analyzing the theoretical//statistical and trading performances of the models, we estimated the loss functions and the trading measure functions for the models. These functions are discussed below:

Statistical Performance Measure

The Mean Error (ME), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE) and Theil-U (TU) are the selected statistics to evaluate the forecasting ability of the models. The smaller the values of these statistics the better the forecasting performances of the models; therefore, in competitive models the one with the smallest statistic has the best forecasting power. These statistics are defined as follows:

$$\text{ME} = \frac{1}{n}\sum_{T=1+t}^{t+n}\left(\sqrt{h_T} - \sqrt{h_T}\right) \qquad 24$$

$$\text{MAE} = \frac{1}{n}\sum_{T=1+t}^{t+n}\left|\sqrt{h_T} - \sqrt{h_T}\right| \qquad 25$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{T=1+t}^{t+n}\left(\sqrt{h_T} - \sqrt{h_T}\right)^2} \qquad 26$$

$$\text{MAPE} = \frac{1}{n}\sum_{T=1+t}^{t+n}\left|\left(\sqrt{h_T} - \sqrt{h_T}\right) \Big/ \sqrt{h_T}\right| \qquad 27$$

$$TU = \frac{\sqrt{\frac{1}{n}\sum_{T=1+t}^{t+n}\left(\sqrt{h_T} - \sqrt{h_T}\right)^2}}{\sqrt{\frac{1}{n}\sum_{T=1+t}^{t+n}\left(\sqrt{h_T}\right)^2} - \sqrt{\frac{1}{n}\sum_{T=1+t}^{t+n}\left(\sqrt{h_T}\right)^2}} \quad 28$$

Where: n is the number of out of sample forecast and is taken as 20 percent of the overall observation.

The Trading Performance of the Models

The trading performance of the models is based on the annualized return (AR), annualized volatility (Ah) and Sarpe Information Ratio (SIR). The higher the value of AR and SIR the better is the performance of the model. Conversely, the smaller the Ah the better is the trading performance of the model. These function presented as follows:

$$AR = 252 * \frac{1}{N}\sum_{t=1}^{N} R_t \quad 29$$

$$Ah = \sqrt{252} * \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(R_t - \overline{R}\right)^2} \quad 30$$

$$SIR = \frac{252 * \frac{1}{N}\sum_{t=1}^{N} R_t}{\sqrt{252} * \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(R_t - \overline{R}\right)^2}} \quad 31$$

We use OXmetric window 6 software packages for the computation of the log likelihood functions with relevant parameters and loss functions in this study. The results are discussed in the proceeding section.

RESULTS

The results of GARCH (1 1) without January effects in respects of the three exchange rates- Rand/Dollar, Naira/Dollar and Cedi/Dollar –are reported in table 4.

Table 4 provides summarized results on the test of volatility clustering and heteroskedasticity for Rand/Dollar, Naira/Dollar and Cedi/Dollar exchange rate series. The ARCH and GARCH parameters in each of the three panels are significantly different from zero because their corresponding probability values which are 0.00 through the three cases are less than the alpha value at 5 percent level. We therefore establish that there are ARCH and GARCH effects in the exchange rate of Rand, Naira and Cedi with respect to dollar. By implication, previous innovations/shocks or changes and volatility significantly influence current volatility. Also, the sums of the coefficients of ARCH and GARCH parameters are approximately 0.87, 0.87 and 0.86 for Rand/Dollar, Naira/Dollar and Cedi/Dollar exchange rates respectively. This suggests that large shocks are follow by large shocks of opposite signs while small shocks follows small shocks of opposite signs. Thus, the three exchange rates essentially exhibit volatility clustering in their distribution processes. Investors can utilize this opportunity to predict the volatility in the markets and then take advantage of exchange rate differentials to make riskless gains. In view of this, investors are on daily basis interested to know the effects of seasonality on current volatility. To investigate this we bring in the January effects into the GARCH (1 1). The results are depicted in table5.

TABLE 4
Results of GARCH (1 1) without January Effects for the Series of
Rand/Dollar, Naira/Dollar and Cedi/Dollar Exchange Rate Volatility

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Panel One: Rand/Dollar				
ARCH(Alpha1)	0.078167	0.011821	6.613	0.0000
GARCH(Beta1)	0.789085	0.036333	21.72	0.0000
Student(DF)	6.008818	0.65986	9.106	0.0000
Log Likelihood	20916.489			
Panel Two: Naira/Dollar				
ARCH(Alpha1)	0.075741	0.011067	6.844	0.0000
GARCH(Beta1)	0.787405	0.035485	22.19	0.0000
Student(DF)	6.008792	0.88532	6.787	0.0000
Log Likelihood	39365.662			
Panel Three: Cedi/Dollar				
ARCH(Alpha1)	0.075731	0.0097061	7.802	0.0000
GARCH(Beta1)	0.787416	0.029245	26.93	0.0000
Student(DF)	6.008802	0.52663	11.41	0.0000
Log Likelihood	41044.448			

The parameters of the January effects as indicated in table 5 are statistically significant and negative for the three exchange rates. This means that there are January effects in the three emerging markets and these effects have negatively influenced volatility. Therefore, the markets are predictable based on seasonal

TABLE 5.
Results of GARCH (1 1) with January Effects for the Series of
Rand/Dollar, Naira/Dollar and Cedi/Dollar Exchange Rate Volatility

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Panel One: Rand/Dollar				
Jan-Effect	-0.006809	0.00053722	-12.67	0.0000
ARCH(Alpha1)	0.072584	0.016457	4.410	0.0000
GARCH(Beta1)	0.779909	0.067264	11.59	0.0000
Student(DF)	6.006919	1.0306	5.829	0.0000
Log Likelihood	17797.587			
Panel Two: Naira/Dollar				
Jan-Effects	-0.028012	0.00084127	-33.30	0.0000
ARCH(Alpha1)	0.088231	0.0057285	15.40	0.0000
GARCH(Beta1)	0.793986	0.010406	76.30	0.0000
Student(DF)	6.017657	1.6086	3.741	0.0002
Log Likelihood	35241.201			
Panel Three: Cedi/Dollar				
Jan-Effects	-0.027974	0.00060164	46.50	0.0000
ARCH(Alpha1)	0.088618	0.0068051	13.02	0.0000
GARCH(Beta1)	0.794195	0.0080190	99.04	0.0000
Student(DF)	6.017655	0.55616	10.82	0.0000
Log Likelihood	36670.691			

occurrences of large prices changes that take place in January, and an increase in such predictability reduces uncertainty. Also, it evident in table 5 that there are still ARCH and GARCH effects and volatility clustering after the inclusion of the January effects dummy variable. However, we are now more interested to examine if there are asymmetric properties in the markets. Table 6 provides the results of the test conducted on asymmetric or leverage effects.

The results in table 6 still indicate that there are ARCH and GARCH effects except in case of the third panel that associate with the Cedi/Dollar exchange rates. But the asymmetric term parameters denoted by GJR are not significant for the three exchange rates.

Hence, the estimation of the GJR specification is in support of no leverage effects in the three markets and volatility is not driven by asymmetric information. Let us see table7 for further evidence based on EGARCH model. The results of the EGARCH specification reported in table 7 are completely opposite to those of the GJR in table6. Even though, the two techniques report that ARCH and GARCH effects are found in Naira/Dollar exchange rate, yet they show some

TABLE 6.
Results of Asymmetric Effects based on GJR (1 1) for the Series of *Rand/Dollar, Naira/Dollar and Cedi/Dollar Exchange Rate*

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Panel One: Rand/Dollar				
ARCH(Alpha1)	0.078005	0.013031	5.986	0.0000
GARCH(Beta1)	0.789004	0.038233	20.64	0.0000
GJR(Gamma1)	0.010095	0.037589	0.2686	0.7883
Student(DF)	6.008801	1.1911	5.045	0.0000
Log Likelihood	20901.310			
Panel Two: Naira/Dollar				
ARCH(Alpha1)	0.075741	0.028792	2.631	0.0085
GARCH(Beta1)	0.787405	0.036344	21.67	0.0000
GJR(Gamma1)	0.010095	0.083101	0.1215	0.9033
Student(DF)	6.008792	2.6607	2.258	0.0240
Log Likelihood	39463.619			
Panel Three: Cedi/Dollar				
ARCH(Alpha1)	0.075731	0.56327	0.1345	0.8931
GARCH(Beta1)	0.787416	0.49077	1.604	0.1087
GJR(Gamma1)	0.010095	1.0741	0.009398	0.9925
Student(DF)	6.008802	13.953	0.4306	0.6667
Log Likelihood	41130.461			

differences. Firstly there are no ARCH and GARCH effects for the series of Cedi/Dollar based on GJR; whereas EGARCH declares these effects for the series.

Secondly, ARCH effects are not found using EGARCH for the series of Rand/Dollar but they are found using GJR for the same series. Lastly and the most appealing difference is that the GJR rejects the asymmetric effects hypothesis, but the EGARCH validates the hypothesis for the three series. Therefore, according to the findings deriving by the EGARCH estimation, volatility or uncertainty increases with bad news but decreases with good news in the three markets.

In this study the authors also account for volatility shift or seasonality represented by January effects. The plausible reason for doing this is to find the middle ground between GJR and EGARCH models if there are seasonal breaks. The results are found in tables 8 and 9 respectively. The results reported in table8 show that after accounting for seasonality using the GJR model. The asymmetric parameters still remain insignificantly different from zero while the January effects are significant for the three exchange rates. This imply there is January effect as revealed by the model.

TABLE 7.
Results of Asymmetric Effects based on EGARCH (1 1) for the Series of *Rand/Dollar, Naira/Dollar and Cedi/Dollar Exchange Rate*

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Panel One: Rand/Dollar				
ARCH(Alpha1)	0.047251	0.050888	0.9285	0.3532
GARCH(Beta1)	1.234799	0.018974	65.08	0.0000
EGARCH(Theta1)	0.985688	0.10953	8.999	0.0000
EGARCH(Theta2)	0.993622	0.16015	6.204	0.0000
Student(DF)	25.477328	1.5404	16.54	0.0000
Log Likelihood	11121.573			
Panel Two: Naira/Dollar				
ARCH(Alpha1)	0.086265	0.035722	2.415	0.0158
GARCH(Beta1)	1.001712	0.00068052	1472.	0.0000
EGARCH(Theta1)	0.314271	0.039901	7.876	0.0000
EGARCH(Theta2)	0.999858	0.031813	31.43	0.0000
Student(DF)	31.104071	4.1588	7.479	0.0000
Log Likelihood	33963.557			
Panel Three: Cedi/Dollar				
ARCH(Alpha1)	0.116559	0.021807	5.345	0.0000
GARCH(Beta1)	1.000808	0.0019765	506.4	0.0000
EGARCH(Theta1)	0.320135	0.042125	7.600	0.0000
EGARCH(Theta2)	0.999040	0.019675	50.78	0.0000
Student(DF)	31.016275	4.9479	6.269	0.0000
Log Likelihood	34599.873			

We now have clear evidence in table 9 that seasonality does not change asymmetric effects. The competing models give different positions about asymmetry in the markets. Therefore, there is need to test the forecasting ability of the model in order to determine the most appropriate one. From the table above GJR has the smallest MSE, ME, RMSE and TIC; while, GARCH has the smallest MAR. It means that GJR is nominated four times, GARCH only one time and EGARCH is not nominated at all. We can suggest that GJR is the best performing model for South-African emerging FOREX market.

Table 11 shows that GJR is the best perfuming model based on forecasting ability; the model has the smallest values of MSE, MAE, RMSE and TIC. In view of this it is recommended as the best foresting model in Nigerian FOREX market. The results in table12 are somewhat different because both the GARCH and GJR models are nominated five times; EGARCH is not nominated at all. However, our nomination based on statistical performance of the models need to be verified with the trading performance measures

TABLE 8.
Asymmetric Effects based on GJR (1 1) with January Effects for the Series of *Rand/Dollar, Naira/Dollar and Cedi/Dollar Exchange Rates*

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Panel One: Rand/Dollar				
Jan-Effects	-0.010290	0.00060378	-17.04	0.0000
ARCH(Alpha1)	0.071609	0.0056599	12.65	0.0000
GARCH(Beta1)	0.785626	0.016722	46.98	0.0000
GJR(Gamma1)	0.017593	0.055007	0.3198	0.7491
Student(DF)	6.008620	1.4289	4.205	0.0000
Log Likelihood	18935.720			
Panel Two: Naira/Dollar				
Jan-Effects	-0.028012	0.0020453	-13.70	0.0000
ARCH(Alpha1)	0.088231	0.024852	3.550	0.0004
GARCH(Beta1)	0.793986	0.015032	52.82	0.0000
GJR(Gamma1)	0.010187	0.12843	0.079	0.9368
Student(DF)	6.017657	1.8853	3.192	0.0014
Log Likelihood	35280.525			
Panel Three: Cedi/Dollar				
Jan-Effects	-0.027975	0.00091267	-30.65	0.0000
ARCH(Alpha1)	0.088618	0.011699	7.575	0.0000
GARCH(Beta1)	0.794195	0.0082586	96.17	0.0000
GJR(Gamma1)	0.010187	0.12921	0.079	0.9372
Student(DF)	6.017655	0.67575	8.905	0.0000
Log Likelihood	36679.585			

In the first panel of table 13, GARCH has the highest annualized return and volatility; while GJR exhibits the lowest volatility and the highest Sharpe information ratio. It means that GRJ is nominated two times, GARCH once and EGARCH is not nominated. We discover that on the bases of statistical and trading performance measures, GRJ outperforms the GARCH and EGARCH in South-African FOREX market.

In panel two, EGARCH has the lowest annualized volatility; while GARCH and GJR have the same and highest annualized return. But the GARCH outperforms the other two models because it has the highest Sharpe information ratio. In Nigerian FOREX market GARCH takes the lead. Also, GARCH is the best trading performance model in Ghana because it is nominated two times in the third panel as the model with highest annualized return and Sharpe information ratio.

TABLE 9
Asymmetric Effects based on EGARCH (1 1) with January Effects for the Series of *Rand/Dollar, Naira/Dollar and Cedi/Dollar Exchange Rates*

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Panel One: Rand/Dollar				
Jan-Effects	-0.002904	0.00036647	-7.925	0.0000
ARCH(Alpha1)	4.900231	0.045814	107.0	0.0000
GARCH(Beta1)	0.941216	0.00049306	1909.	0.0000
EGARCH(Theta1)	-0.028018	0.0040868	-6.856	0.0000
EGARCH(Theta2)	0.202768	0.0017560	15.5	0.0000
Student(DF)	21.630624	2.7577	7.844	0.0000
Log Likelihood	16563.145			
Panel Two: Naira/Dollar				
Jan-Effects	-0.00331	22.9648e-006	-1117.	0.0000
ARCH(Alpha1)	0.082625	0.92542	0.089	0.9289
GARCH(Beta1)	1.039784	0.017912	58.05	0.0000
EGARCH(Theta1)	-0.254265	0.0086216	-29.49	0.0000
EGARCH(Theta2)	0.024337	0.074374	0.3272	0.7435
Student(DF)	8.598505	1.8039	4.767	0.0000
Log Likelihood	19182.147			
Panel Three: Cedi/Dollar				
Jan-Effects	-0.016564	0.0021067	-7.863	0.0000
ARCH(Alpha1)	-0.870135	0.0046620	-186.6	0.0000
GARCH(Beta1)	0.990582	0.00040398	2452.	0.0000
EGARCH(Theta1)	0.107739	0.063570	1.695	0.0902
EGARCH(Theta2)	1.000000	0.013757	72.69	0.0000
Student(DF)	10.291667	0.34900	29.49	0.0000
Log Likelihood	11956.374			

TABLE 10
Forecasting Ability of the Competing Models based on Rand

Particulars	Model		
	GARCH	GJR	EGARCH
MSE	1.889e-008	1.811e-008	4.357e-006
ME	3.481e-005	2.073e-005	0.002083
MAE	6.552e-005	6.813e-005	0.002083
RMSE	0.0001375	0.0001346	0.002087
TIC	0.7167	0.6537	0.9659

TABLE 11
Forecasting Ability of the Competing Models based on Naira

Particulars	Model		
	GARCH	GJR	EGARCH
MSE	3.834e-010	3.832e-010	2.18e-008
ME	-1.44e-005	-1.439e-005	0.000147
MAE	1.784e-005	1.783e-005	0.000147
RMSE	1.958e-005	1.958e-005	0.0001476
TIC	0.3931	0.393	0.9712

TABLE 12
Forecasting Ability of the Competing Models based on Cedi

Particulars	Model		
	GARCH	GJR	EGARCH
MSE	3.179e-008	3.179e-008	5.195e-008
ME	0.0001198	0.0001198	0.0001858
MAE	0.0001255	0.0001255	0.0001858
RMSE	0.0001783	0.0001783	0.0002279
TIC	0.8799	0.8799	0.9502

TABLE 13
Trading Performance Measure of the Competing Models

Particulars	Model		
	GARCH	GJR	EGARCH
Panel One: Rand/Dollar			
Annualized Return	0.058	0.027	0.019
Annualized Volatility	0.013	7.320E-17	8.933E-17
Sharpe Information	4.442	3.66E+14	2.16E+14
Panel Two: Naira/Dollar			
Annualized Return	7.46E+03	7.46E+03	-3.32E-02
Annualized Volatility	5.884E-08	6.466E-08	2.48E-16
Sharpe Information	1.27E+05	1.15E+05	-1.34E+14
Panel Three: Cedi/Dollar			
Annualized Return	3.62E-03	3.62E-03	-1.30E-02
Annualized Volatility	1.856E-07	2.04E-07	1.5E-17
Sharpe Information	1.95E+04	1.78E+04	-8.66E+14

CONCLUSION AND RECOMMENDATIONS

In this study, the researchers examined the characteristics of the foreign exchange markets of South-Africa, Nigeria and Ghana respectively with the aim of modeling these features using array of GARCH specifications fitted with or without seasonal breaks. Our findings show that volatilities are serially and significantly related over the sampling period for the three markets. This was confirmed in the study of Alam and Rahman (2012). Also, Kamal, Ghani and Khan (2012) revealed that there was asymmetric behavior of exchange rate in Pakistan; our test of asymmetry using EGARCH model is in tandem with this finding. We also discover that after accounting for volatility breaks the likelihood ratio decreased implying that selected model performance do improve with seasonal effects. This is contrary to the position of Bala, and Asemota (2013) in Nigeria. The GJR performs best in South-Africa on the basis of trading performance measures. This model was also selected in the study of Alam and Rahman (2012); but on the contrary, GARCH was nominated the best model for Nigeria and Ghana. We therefore recommend that investors should employ GJR in South-Africa and GARCH in Nigeria and Ghana.

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