RWANDA CURRENCY MARKET RISK ANALYSIS: EVIDENCE FROM ASYMMETRY EFFECTS

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Abstract

This study evaluates the presence and characteristics of the asymmetric effects and volatility clustering in Rwanda currency market. Under GARCH types model, Value at Risk models are estimated by assuming that the residuals follow normal, student t and skewed student t distributions. Backtesting results for symmetric and asymmetric models have been done based on Kupiec and Christoffersen test. The results from Backtesting show that most accurate VaR estimate are obtained from asymmetry GARCH models and provide evidence on the existence of the asymmetric effect in the Rwanda currency market and the other currencies.

Keywords: `currency market, GARCH, asymmetric effects, Value at Risk, Backtesting`

1. Introduction

Prior 2000's, different countries in Africa had noticeably the reduction of international competitiveness as a result of flow oriented within the economy [1]. The foreign exchange rate found to adversely affect not only the market or production of goods and services, but also the behaviour of exchange rate in these

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economies fluctuate everyday [2]. Using volatility models, the exchange rate markets should show the accuracy of absorption and reflection of all relevant information which influence the significance of financial stabilities or changed the exporting behaviour for any macroeconomic perspective ([3], [4], [5]). However, the deviation of exchange rate from its equilibrium value cause misallocation of resources towards financial and economic dynamics. If it is persistently misaligned currency market, the economy risk to be destabilized face to the degree of the official exchange rate which may guide to sustain the resiliency for the external position. Most of the time, the economy may not reflect the value of an economic reality due to lack of exchange rate flexibility ([6], [4], [5]). Moreover, the country has to set up measures and policies to monitor the market risk and financial instability ([5], [7]). However, in modern financial econometrics, the statistical approaches discovered to predict and highlight the existence of leptokurtosis behaviour and volatility clustering within financial data.

Different literatures showed that most of empirical models have an isolation of quantitative effects of exchange rate on trade and lending rate from financial institutions, as an evidence for modelling volatility of the currency market model under asymmetry effects ([8], [9], [10]). While, the risk effects of exchange rate under symmetric effects revealed no difference between appreciation and depreciation on foreign currency markets ([11], [12]). In the financial time series analyses, it resulted that the existence of asymmetry risk effects increases the uncertainty of currency market. The presence of asymmetric volatility in the currencies market may be relatively scarce, but in financial forecasting, such volatility may interrupt macroeconomic policies. The diagnostics of asymmetry effects on volatility revealed smaller residual kurtosis when use asymmetric GARCH than symmetric models [13]. The asymmetry effects on exchange rates varies according to the nature of an economy and the principle ruling the nature of the exchange rate (i.e fixed vs flexible). The responses of asymmetric effects on exchange rate in United States found to have bad news than good news compared to the Europe and Asia, where the volatility affect smaller forecasting

errors using asymmetric GARCH than symmetric GARCH models ([14], [12], [15]).
Few studies have done for the African markets for providing the implications of asymmetric effects on volatility and for symmetric GARCH models were estimated with and without volatility breaks [10]. They revealed that most of the models rejected the existence of a leverage effect, except for those with volatility breaks ([2], [16], [17]). Since it was observed that results improved when the volatility models considered breaks, incorporating significant events in the GARCH model results have confirmed that asymmetric GARCH-models fit better currencies markets returns volatility for African countries.
Indeed, in Egypt, asymmetric effect was present in the Egyptian exchange rate market with positive shock increasing volatility more than the negative of the same magnitude using EGARCH [18]. While, different models have rejected the hypothesis that asymmetric effect is present in Nigerian currency market [19].
In Rwanda the price fluctuations dominate the degree of the whole economic environment and it stimuluses the unexpected fall in the exchange rate and it has reduced the business investment implementation in whole sectors including financial and economic activities [20]. Since 2014, the external shocks weakened the Rwandan economy and such vulnerabilities, rebuilding foreign exchange reserve found to be alternate for enhancing the economy's resilience [21].
Moreover, Bretton Woods agreements has brought the attention for both policy makers and academia to draw conclusion based on the facts that volatility of exchange rates risks to increase the transaction costs [22].

The exchange rate expectations and potentials play a central role in virtually all monetary models for the open economy. Given the widely documented characteristics of financial asset returns, different external shocks have affected the economy due to ineffective modelling tools for highlighting the errors over times ([13], [12]). For example, early 2017, the Rwandan francs depreciated by 9.7 percent against the US$, higher than projected under the program, and has depreciated by 14.5 percent in the 11 months since mid-2015 [21]. Hence, this study inclusively aims to evaluate the presence and characteristics of the asymmetric effects return volatility in Rwanda currency market. The paper is organized as follows: Section 2 characterize the short memory models used and their specifications. Section 3 we present backetesting VaR valuation methods. Section 4 explores results and discussions. Finally, section 5 concludes this work, summarizing our results and discussing the questions that still remain.

2. Methodology

To study the asymmetry effects on exchange rate volatility, different statistical approaches have to be applied before failing to discover the size of errors for the models under least squares and symmetry GARCH models. Hence, this study applies the GARCH extensions family to capture the asymmetric effects in the model. It is noted that modelling volatility using asymmetric GARCH model such as Exponential GARCH (EGARCH) and Glosten - Jagannathan - Runkle model (GJR GARCH) or Threshold GARCH (TGARCH) model allows good news and bad news to have different impact on volatility. It is well established that when modelling volatility using GARCH family models, the appropriate specification of the mean and variance equations are vitally important. The models are estimated using Maximum Likelihood Methods under the assumptions of Gaussian error distribution and non normal error distributions.

Autoregressive Moving Average (ARMA)

This model was introduced in order to remove the linear dependence in the series and to obtain the residuals which are uncorrelated. The time series r_t is an ARMA(p,q) process if r_t is stationary and for every t,

$$r_t = \mu + \sum_{i=1}^{p} \phi_i r_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t \tag{1}$$

where $\epsilon_t \sim \mathcal{N}(0, 1)$.

Generalised Autoregressive Conditional Heteroskedasticity (GARCH)

The GARCH models allow conditional variance to depend upon to its own lag ([23], [24]). This typically reduces the number of required ARCH lags when forecasting volatility. The process (ϵ_t) is an GARCH(p,q) process if it is stationary and if it satisfies, for all t and some strictly positive valued process $\sqrt{h_t}$, the following equations are satisfied

$$\epsilon_t = \sqrt{h_t}\eta_t \tag{2}$$

$$h_t = \omega + \sum_{i=1}^{P} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{Q} \beta_j h_{t-j} \tag{3}$$

where $\omega > 0$, $\alpha_i \geq 0$, $i = 1, \ldots, P$, and $\beta_j \geq 0$, $j = 1, \ldots, Q$.

Which is an ARMA(max(p,q),p) model for the squared innovations.

$$\epsilon_t^2 = \omega + \sum_{i=1}^{R} (\alpha_i + \beta_i)\epsilon_{t-i}^2 - \sum_{j=1}^{q} \beta_j V_{t-j} + V_t \tag{4}$$

Where $R = max(p, q)$, $\alpha_i = 0$ for $i > p$ and $\beta_i = 0$ for $i > q$, and $V_t = \epsilon_t^2 - \mathbb{E}(\epsilon_t^2 \mid F_{t-1}) = \epsilon_t^2 - h_t$. For more details see [25]

Exponential Generalised Autoregressive Conditional Heteroskedasticity (EGARCH)

In particular, we modelled the variance of the residuals from the mean equations using EGARCH and GJR-GARCH models to capture the degree of the leverage effects for each exchange rate in the market regardless the lag length in the model. The traditional implication for the lack of asymmetric volatility is that exchange rates are relative prices: good news for bidding is bad news for selling exchange rate and vice versa. The rise and fall of a currency is not measured by changes in the currency market. A better volatility measure, such as the realized volatility estimated from intraday returns, may capture the asymmetric relationship between return and volatility. This conjecture is tested using the EGARCH specification for daily realized volatility, where EGARCH (p, q) can be specified as:

$$ln(h_t) = \omega + \sum_{j=1}^{p} \left(\alpha_j \left| \frac{\epsilon_{t-j}}{\sqrt{h_{t-j}}} \right| + \gamma_j \frac{\epsilon_{t-j}}{\sqrt{h_{t-j}}} \right) + \sum_{i=1}^{q} \beta_i ln(h_{t-i}). \tag{5}$$

Where γ is the asymmetry parameter measuring leverage effect, α is the size parameter measuring the magnitude of shocks, and persistency is captured through β [26]. An important feature of the EGARCH specification is that conditional variance is an exponential function, thus there is no need for non-negativity restrictions, as in earlier GARCH specifications [27].

Glosten Jaganathan and Lunker (GJR-GARCH)

The GJR-GARCH Model takes into account the asymmetries in the volatility by adding another term to the conditional variance (GARCH) equation [28]. Unlike the EGARCH (p,q), the effect is captured in a linear fashion in the GJR-GARCH(p,q) model, for example. The asymmetry effect is captured using a dummy variable. The GJR-GARCH(p,q) model is one of the widely used models:

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \gamma_1 \epsilon_{t-1} d_{t-1} + \sum_{j=1}^{q} \beta_j h_{t-j}. \tag{6}$$

where $d_{t-1} = 1$ if $\epsilon_{t-1} < 0$, and $d_{t-1} = 0$ otherwise and hence it allows a response of volatility to news with different coefficients for good and bad news. In this model, good news are represented by $\varepsilon_\tau > 0$, and bad news by $\varepsilon_\tau < 0$, and have different effects on the conditional variance equation. The good news only has an impact of α and bad news has impact in the sum of $\alpha + \gamma$. The leverage effect of bad news exists only when $\gamma \neq 0$ in this case the news impact is asymmetric [28].

VaR (Value at Risk)

Let X_t be a log return series at a moment in time t, and F_L be a cumulative function of loss distribution given by $F_L(x) = P(L \leq x)$. Value at Risk is defined as a value such that there is a probability(P) of exhibiting a worse return over the next T days and it indicates the potential loss of asset value over a period of time where the degree of confidence is important [29]. In fact the VaR just indicates the most we can expect to lose if no negative event occurs. VaR at significance level α (most often 1% and 5%) is actually an α-quantile of the distribution function F_L, or in other words, VaR presents the smallest real number satisfying the inequation $F_L(x) \geq \alpha$, i.e.:

$$VaR_\alpha = inf(X \mid F_L(x) \geq \alpha). \tag{7}$$

ARMA(m,n)-EGARCH(p,q) model the one-step-ahead conditional mean and variance forecast

We evaluate the one-day-ahead VaR estimated at time F_t for long and short trading positions under hypothesis of Normal, Student t and Skewed student t. If the series ϵ_t is a random variable with the standardised normal distribution, then the conditional distribution of a random variable X_{t+1} for the available data with the moment t inclusive, also has a normal distribution with the mean $\widehat{X}_t(1)$ and variance $\widehat{h}_t(1)$.

$$\begin{aligned}
\widehat{X}_t(1) &= \mathbb{E}(X_{t+1} \mid F_t) = \sum_{i=1}^{m} \phi_i X_{t+1-i} + \sum_{j=1}^{n} \theta_j \epsilon_{t+1-j} \\
\widehat{\epsilon}_t(1) &= \mathbb{E}(\epsilon_{t+1} \mid F_t) = \sqrt{\widehat{h}_t}\eta_t \\
\widehat{h}_t(1) &= \mathbb{E}ln(h_{t+1} \mid F_t) = \alpha_0 + \sum_{j=1}^{p} \left(\alpha_j \left| \frac{\epsilon_{t+1-j}}{\sqrt{h_{t+1-j}}} \right| + \gamma_j \frac{\epsilon_{t+1-j}}{\sqrt{h_{t+1-j}}}\right) + \sum_{i=1}^{q} \beta_i ln(h_{t+1-i})
\end{aligned} \tag{8}$$

Therefore, it is straightforward to compute the one-step-ahead VaR forecast, since under all distributions, we can compute the corresponding quantiles, which we then multiply by our conditional standard deviation forecast:

$$\begin{aligned}
VaR_{long} &= \widehat{X}_t(1) - F(\alpha)\sqrt{\widehat{h}_t(1)} \\
VaR_{short} &= \widehat{X}_t(1) + F(\alpha)\sqrt{\widehat{h}_t(1)}
\end{aligned} \tag{9}$$

given that $F(\alpha)$ is the corresponding quantile of the assumed distribution, and $\sqrt{\widehat{h}_t(1)}$ is the forecast of conditional standard deviation at time t.

- For normally distributed standardized innovations:
  The 5% quantile of the conditional distribution, representing the estimation of VaR at a 95% confidence level and for a forecast horizon 1 step

ahead, is computed as:

$$
\begin{aligned}
VaR_{long} &= \widehat{X}_t(1) - 1.96\sqrt{\widehat{h}_t(1)} \\
VaR_{short} &= \widehat{X}_t(1) + 1.96\sqrt{\widehat{h}_t(1)}
\end{aligned}
\tag{10}
$$

- For standardized t-distributed innovations:

  with $v > 2$ degrees of freedom, the 5% quantile of the conditional distribution is:

$$
\begin{aligned}
VaR_{long} &= \widehat{X}_t(1) + \frac{t_v(\alpha)}{\sqrt{\frac{v}{v-2}}}\sqrt{\widehat{h}_t(1)} \\
VaR_{short} &= \widehat{X}_t(1) + \frac{t_v(1-\alpha)}{\sqrt{\frac{v}{v-2}}}\sqrt{\widehat{h}_t(1)}
\end{aligned}
\tag{11}
$$

  where $t_v(1-\alpha)$ is the corresponding critical value of $(1-\alpha)$ quantile from the t distribution with v degrees of freedom.

- For skewed Student-t distribution innovations:

  with v degrees of freedom, the 5% quantile of the conditional distribution is:

$$
\begin{aligned}
VaR_{long} &= \widehat{X}_t(1) + skst_{\alpha,v,\xi}\sqrt{\widehat{h}_t(1)} \\
VaR_{short} &= \widehat{X}_t(1) + skst_{1-\alpha,v,\xi}\sqrt{\widehat{h}_t(1)}
\end{aligned}
\tag{12}
$$

  where $skst_{\alpha,v,\xi}$ and $skst_{1-\alpha,v,\xi}$ are the left and right quantiles of $\alpha\%$ from the skewed t distribution with v degrees of freedom, ξ is the asymmetry (skewness) parameter.

3. Backtesting

When a VaR model is estimated it is important to check its reliability and accuracy. The statistical framework which help us to test the accuracy of the risk estimate is called backtesting. The purpose of backtesting is to evaluate whether the amount of losses predicted by VaR is valid. That process is divided into two groups; the unconditional tests check whether or not the frequency of violations, is consistent with the selected confidence level and the conditional coverage tests examine whether the number of violations is the same as the expected value, this test makes an assumption for the observations to be independent of each other; for example when exception occurs for two or more consecutive days, this should be a problematic with the model.

3.1. The Kupiec test

Kupiec proposed a test in 1995 for testing if the number of exceedances is in line with the choosen confidence level that is the unconditional coverage test. Let x be the observed number of exceedances in the sample, or, in other words, $x = \sum_{t=1}^{T} I_t$ is a number of days over a T period of time when the portfolio loss over a fixed interval $X_{t,t+1}$ was larger than the VaR estimate [30]

$$I_{t+1} = \begin{cases} 1, \text{ if } X_{t,t+1} \geq -VaR_t \\ 0, \text{ if } X_{t,t+1} < -VaR_t. \end{cases} \tag{13}$$

The failure number follows a binomial distribution where the expected exception frequency is $p = \frac{x}{T}$. The ratio of failures, x, to trials, T, under the Null hypothesis should be p. The appropriate likelihood ratio statistic is:

$$LR_u c = 2ln[(1 - \frac{x}{T})^{T-x}(\frac{x}{T})x] - 2ln[(1-p)^{T-x}p^x]. \tag{14}$$

The Kupiec test has a chi-square distribution, asymptotically, with one degree of freedom. For the confidence level of 95% the critical value is 3.84. This test fail to accept the null hypothesis of correct exceedances for both high and low failures i.e if the test statistic exceeds the critical value the model seems inaccurate.

3.2. The Christoffersen test

The conditional coverage test, under the Christoffersen approach, detects whether the exceptions occur in clusters or not; the exception happens when the actual returns exceeds the predicted number at risk value i.e. $r_t < -VaR_t$.

If the existence of clustering can be proved, the model is misspecified and needs to be recalibrated. The observations can have two indicators:

$$I = \begin{cases} 1, \ if \ violation \ occurs \\ 0, \ if \ no \ violation \ occurs. \end{cases}$$

As defined in the above indicator, the n_{10} is to be the amount of days that violation is followed by no violation, n_{01} a non violation followed by a violation and so on. The likelihood ration is computed under the null hypothesis that state that the number of exception might be independent of each other and is given by the following expression:

$$LR_\alpha = -2ln[(1-\pi)^{n_{00}+n_{10}}\pi^{n_{01}+n_{11}}] + 2ln[(1-\pi_{01})^{n_{00}}\pi_{01}^{n_{01}}(1-\pi_{11})^{n_{10}}\pi_{11}^{n_{11}}], \tag{15}$$

where the corresponding probabilities are $\pi = \frac{n_{01}+n_{11}}{n_{00}+n_{01}+n_{10}+n_{11}}$, $\pi_{01} = \frac{n_{01}}{n_{00}+n_{01}}$ and $\pi_{11} = \frac{n_{11}}{n_{10}+n_{11}}$. The test statistic is asymptotically as χ^2 with two degrees of freedom. The model is considered to have the independence problem if the null hypothesis is rejected [31].

The Christoffersen introduced the conditional coverage test, which represents an incorporated test of hypothesis of unconditional test and independance statistic test. The main advantage of this procedure is that it can reject a VaR model that generates either too many or too few clustered violations[30]. The conditional coverage is $\chi^2(2)$ distributed and the critical value at 95% is 5.99 The test statistic is as follows:

$$LR_{cc} = LR_{uc} + LR_{ind} \tag{16}$$

Where LR_{cc} is the Likelihood ratio conditional coverage test, LR_{uc} is the Likelihood ratio of the unconditional coverage test (or Likelihood ratio of the Kupiec's test) and LR_{ind} is the Likelihood ratio of independance.

4. Data and Descriptive statistics

The daily quotes of the exchange rate used to model volatility and capture volatility clustering and the asymmetric effects volatility for East Africa Countries members's currencies; Burundi Francs (Bif/Rwf), Kenyan Shillings (Ksh/Rwf), Uganda Shillings (Ugsh/Rwf) and Tanzanian Shillings (Tsh/Rwf) exchange rate. The total number of observations was 2439 within a period starting from 4^{th} January 2010 to 16^{th} October 2019 obtained from National Bank of Rwanda is used in this study. The prices are formed by taking the average of the bid and ask quotes, and the returns are computed as the difference of logarithmic daily exchange rates

$$r_t = ln\Big(\frac{P_t}{P_{t-1}}\Big), \tag{17}$$

given P_t observed as the daily average exchange rate for each currency mentioned and r_t as calculated daily return. The currency market in Rwanda are mostly slow down its activity during non-trading days i.e. week-ends and public holidays. Different literatures have accommodated filtered return series and excludes these non-trading days [32] as the same scenario for the used data in this study. It resulted for better understanding the impact of asymmetry effects on volatility and incorporated the modelling effects for forecasting purpos [33]. Findings of this study aim to evaluate the presence and characteristics of the asymmetric effects return volatility in currency market in Rwanda. Figure 2 in appendices shows that there is behaviours of movement of up and down in Ksh, Ugsh and Bif exchange rates some times this one is very fast and other time is very quite over the sample period. The plots reveal that the variances change over time and the volatility tends to be cluster. The sample has been tested for stationarity using the Augmented Dickey-Fuller test. The null hypothesis of unit root is rejected and therefore the series is stationary integrated at first order of differencing see table (1).

Table 1: Augmented Dickey-Fuller test of the daily returns

	ADF Test H_0: Series has a unit root		
	1% critical value	5% critical value	10% critical value
Bif/Rwf	-3.96	-3.41	-3.12
ADF test	-3.137	3.3148	4.9464
Ksh/Rwf	-3.96	-3.41	-3.12
ADF test	-2.7214	2.9583	4.1451
Ughs/Rwf	-3.96	-3.41	-3.12
ADF test	-3.3119	4.3435	6.3009
Tsh/Rwf	-3.96	-3.41	-3.12
ADF test	-2.8618	2.9935	4.44

Figure 1 presents log average returns for each exchange rate for the dominant currency market in Rwanda. This figure reveals that volatility clustering is present in each case as the series show the periods of low volatility tends to be followed by the periods of relatively low volatility and other period of high volatility which likewise tend to be followed by high volatility. This aspect can be thought of as clustering of the variance error term over time.

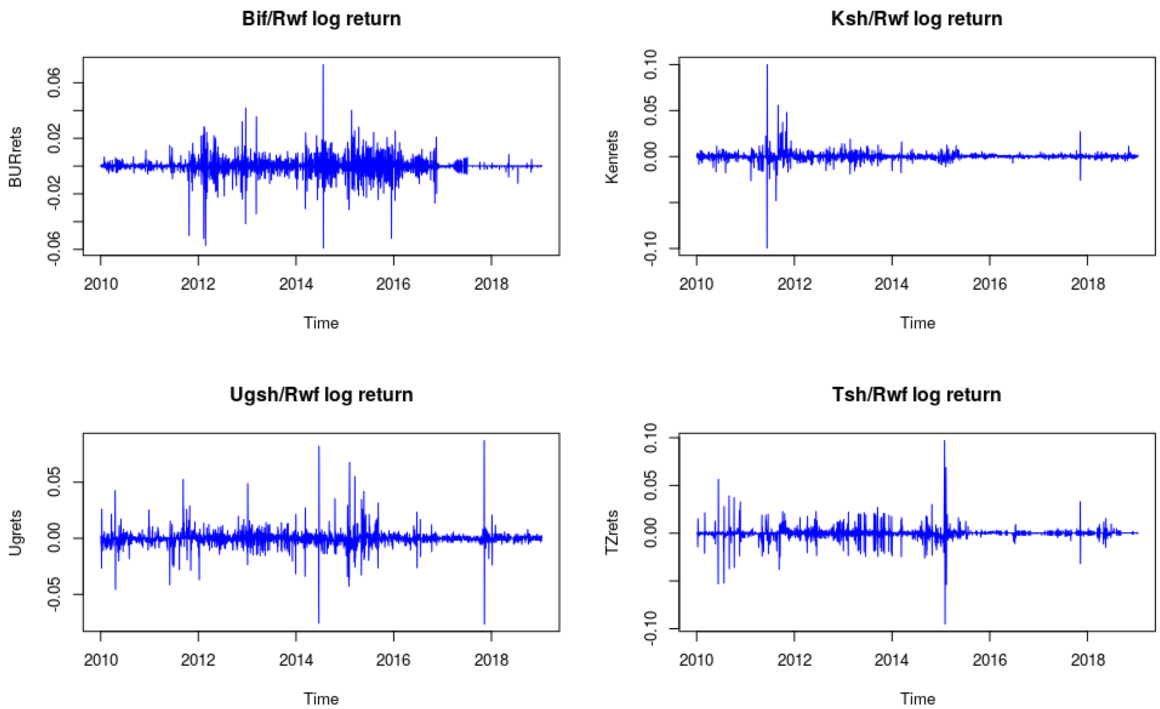

Figure 1: Plot of log average of Exchange rate with Rwandan Francs (Jan 2010-Oct 2019).

Table 2, gives an overview of the statistics of the dominant exchange rate with Rwanda from January 2010 to october 2019. The table highlights linear and average returns for each exchange rate: Burundi Francs; Kenya, Tanzania and Uganda Shilling as well as statistics testing for normality. The sample means are not statistically different from zero. The measures for skewness and excess kurtosis show that return series except Uganda Shillings are negatively skewed and highly leptokurtic with respect to the normal distribution. Likewise, Jarque-Bera test rejects normality for each of the return series at the 5 per cent level of significance. Moreover, the returns for exchange rate for each currency are approximately symmetric (most are slightly left skewed) but highly leptokurtic. The Jarque-Bera statistic indicates decisive rejection of normality in the currency market in Rwanda.

Table 2: Summary of descriptive statistics for returns with Rwandan Francs (Jan 2010-Oct 2019)

Statitics	Bif r_t	Ksh r_t	Ugsh r_t	Tsh r_t
Mean	0.0000	0.000	-0.000	-0.000017
Std.Dev	0.0063	0.0074	0.0069	0.0064
Skewness	-0.546	-0.793	1.101	-0.417
Kurtosis	23.230	165.697	42.230	60.908
J-Bera	12E05	24E04	42E02	79E03
Prob	2.2e-16	2.2e-16	2.2e-16	2.2e-16
Observation	2438	2438	2438	2438

The Lagrange Multiplier(LM) test presented in table 3 fails to accept the null hypothesis of non ARCH effect for all the exchange returns. Looking for the test of Ljung Box and LM tests it is clearly evident that the autocorrelation ARCH effect is very much present in the data. Therefore, we these facts push us to run the ARCH family models.

Table 3: ARCH-LM Test for residuals of returns series

Currencies	Bif	Ksh	Ugsh	Tsh
ARCH-LM test statistic	206.67*	193.64*	94.494*	193.99*

Notes: 1-H_0: There are no ARCH effects in the residual series

2-*Indicates that the results are statistically significant at the 1% level.

5. Empirical results and Discussion

The tables 9 to 12 in the appendix reveal that the parameter estimates of all conditional volatility models employed in the analysis and information criteria for the estimated symmetric and asymmetric GARCH models. It is well observable that though both the size and asymmetry parameter as well as the asymmetric parameter were statistically significant which implies the existence of asymmetric effect on volatility in the models evaluating the currency market in Rwanda. The asymmetry dynamics were captured in each and every exchange rate returns. The asymmetric positive parameter confirmed that positive shocks will have strong impact on future volatility than negative shocks in Rwanda currency market. Obviously, GARCH extensions family model are absolutely necessary for capturing the behaviour of volatility in Rwanda currency markets. The estimated series for comparative purpose were the GARCH, GJR-GARCH and EGARCH models under the assumptions that residuals follow a Normal, Student t and Skewed student t distribution. The results showed the presence of asymmetric effect in the returns is confirmed by the significance non zero asymmetric parameter for Kenya shilling, Uganda Shilling, Burundi Francs and Tanzania Shilling.

The ARMA(0,1)-EGARCH(1,1), ARMA(1,1)-EGARCH(1,1), and ARMA (0,1)-EGARCH (1,1) with skewed student t distribution and ARMA (2,3)-GARCH (1,1) with student t distribution are appropriate model respectively based on AIC, BIC and log-likelihood values for Kenya shilling, Burundi Francs, Uganda Shilling and Tanzania Shilling against Rwandan Francs.

In the field of statistical modeling, the AIC has been defined as an approximation of the Kullback-Leibler divergence. And by noting that the KLD is a measure of dissimilarity between two distributions and is specially used for model selection. Thus in this paper we used this measure to clarify the results of model selected using LL, AIC and BIC. Let us recall Kullback-Leibler divergence between student t and skewed student t distributions. Therefore, the Kullback-Leibler divergences are given by

$$D_1 \equiv D_{KL}(f_{Student}, f_{Skewed}) = \int_{\mathbb{R}} f_{std}(x) \ln\left(\frac{f_{std}(x)}{f_{sstd}(x)}\right) dx \tag{18}$$

$$D_2 \equiv D_{KL}(f_{Skewed}, f_{Student}) = \int_{\mathbb{R}} f_{sstd}(x) \ln\left(\frac{f_{sstd}(x)}{f_{std}(x)}\right) dx \tag{19}$$

The model selection criteria is based on D_1 and D_2. If D_1 is less than D_2, then the model under student t distribution of density $f_{Student}$ performs well than the model under skewed student t distribution of density f_{Skewed}, otherwise the model under skewed student t distribution is quite appropriate. To compute the relation 18 and 19, we consider the same data as used for LL, AIC and BIC and the results are given in the following table

Table 4: Kullback-Leibler divergence results

Currencies	Ksh	Tsh	Bif	Ugsh
D1	0.830201	0.199403	0.802813	0.847243
D2	0.189521	0.844196	0.188072	0.187481

As observed in the above table 4, the KLD results from the selected relevent distributions between student t and skewed student t. The selected distribution for Kenya, Uganda and Burundi is the skewed student t distribution while for Tanzania is the student t distribution as confirmed by our result obtained in the table 9 - 12.

Value at risk violation occurs when the actual loss exceeds the predicted VaR. In our backtesting and forecasting methodology we analysed the following approach of the sliding window of 1000 days returns data as the basis for model estimation and forecasting for one day ahead of VaR.

From table 5 - 8, The Kupiec and Christoffersen test results are presented, where the kupiec test validates whether the exceptions provided by a model are close to the expected number of exception given a backtesting period. The Christoffersen test, on the other hand confirms the presence or not of exceptions clustering. For Bundian francs, we can observed that all the models failed to pass Kupiec test with 95% except for EGARCH with heavy tailed assumptions. So the GJR EGARCH and GARCH models under student t and Skewed students t errors distributions underestimate the forecast for burundian francs. Hence the $ARMA(1,1) - EGARCH(1,1)$, under student t distribution and skewed student t distribution passed all test with 95% and 99% and seems to be the accurate model for Burundian francs. For Kenya shillings the null hy-

Table 5: Backetesting result of Bif/RwF

Models	Kupiec test 95%			Kupiec test 99%			Christoffersen test 95%		Christoffersen test 99%	
	A.N of violations(E.N is 50)	Statistic test	P value	A.N of violations(E.N is 10)	statistic test	P value	statistic test	P value	Statistic test	P value
$ARMA(1,1) - GARCH(1,1)_N$	22	20.694	0	10	0	1*	21.685	0	0.202	0.904*
$ARMA(1,1) - GARCH(1,1)_t$	75	11.484	0.01	25	16.043	0	23.503	0	16.043	0
$ARMA(1,1) - GARCH(1,1)_S$	76	12.362	0	25	16.043	0	24.72	0	17.326	0
$ARMA(1,1) - EGARCH(1,1)_N$	19	26.233	0	11	0.098	0.754*	26.969	0	0.343	0.842*
$ARMA(1,1) - EGARCH(1,1)_t$	55	0.51	0.475*	13	0.831	0.362*	0.949	0.622*	1.173	0.556*
$ARMA(1,1) - EGARCH(1,1)_s$	58	1.284	0.257*	13	0.831*	0.362*	1.438	0.487*	1.173	0.556*
$ARMA(1,1) - GRJGARCH(1,1)_N$	25	15.995	0	10	0	1*	18.055	0	0.202	0.904*
$ARMA(1,1) - GRJGARCH(1,1)_t$	75	11.484	0.001	26	17.947	0	14.883	0.001	19.336	0
$ARMA(1,1) - GRJGARCH_S$	75	11.484	0.01	26	17.947	0	14.883	0.01	19.336	0

* Statistically significance with respect to the corresponding P value; A.N= Actual Number; E.N= Expected Number.

Table 6: Backetesting result of Ksh/RwF

Models	Kupiec 95%			Kupiec 99%			Christoffersen 95%		christoffersen 99%	
	A.N of violations(E.N is 50)	Statistic test	P value	A.N of violations(E.N is 10)	statistic test	P value	statistic test	P value	Statistic test	P value
$ARMA(0,1) - GARCH(1,1)_N$	17	30.454	0	7	1.016	0.314*	35.132	0	1.114	0.573*
$ARMA(0,1) - GARCH(1,1)_t$	22	20.694	0	4	4.706	0.03*	21.138	0	4.738	0.094*
$ARMA(0,1) - GARCH(1,1)_s$	22	20.694	0	3	6.826	0.09	21.138	0	600.844	0.033*
$ARMA(0,1) - EGARCH(1,1)_N$	29	10.867	0.01	9	0.105	0.746*	12.11	0.02	3.488	0.175*
$ARMA(0,1) - EGARCH(1,1)_t$	17	30.454	0	2	9.635	0.02	31.575	0	9.635	0.008
$ARMA(0,1) - EGARCH(1,1)_s$	16	32.741	0	2	9.627	0.02	34.048	0	9.635	0.008
$ARMA(0,1) - GRJGARCH(1,1)_N$	28	12.036	0.01	8	0.434	0.51*	13.459	0.001	4.288	
$ARMA(0,1) - GRJGARCH(1,1)_t$	24	17.475	0	3	6.826	0.009	17.745	0	6.844	0.033*
$ARMA(0,1) - GRJGARCH(1,1)_s$	22	20.694	0	3	6.826	0.09	21.138	0	6.844	0.033*

* Statistically significance with respect to the corresponding P value; A.N= Actual Number; E.N= Expected Number.

Table 7: Backetesting result of Ugsh/RwF

Models	Kupec 95%			Kupec 99%			Christoffersen 95%		Christoffersen 99%	
	A.N of violations(E.N is 50)	Statistic test	P value	A.N of violations(E.N is 10)	statistic test	P value	statistic test	P value	Statistic test	P value
$ARMA(0,1)-GARCH(1,1)_N$	10	49.472	0	4	4.706	0.03*	49.675	0	4.738	0.094*
$ARMA(0,1)-GARCH(1,1)_t$	30	9.769	0.002	2	9.627	0.002	19.939	0	9.635	0.008*
$ARMA(0,1)-GARCH(1,1)_s$	25	15.995	0	4	4.706	0.03*	21.136	0	4.738	0.094*
$ARMA(0,1)-EGARCH(1,1)_N$	19	26.233	0	8	0.434	0.51*	26.969	0	0.563	0.755*
$ARMA(0,1)-EGARCH(1,1)_t$	34	6.043	0.014	5	3.094	0.079*	6.067	0.048	3.144	0.208*
$ARMA(0,1)-EGARCH(1,1)_s$	27	13.278	0	5	3.094	0.079	13.374	0.001	3.144	0.208*
$ARMA(0,1)-GRJGARCH(1,1)_N$	14	37.704	0	5	3.094	0.079*	38.102	0	3.144	0.208*
$ARMA(0,1)-GRJGARCH(1,1)_t$	30	9.769	0.002	7	1.16	0.314*	11.626	0.03	1.114	0.573*
$ARMA(0,1)-GRJGARCH(1,1)_s$	19	26.233	0	3	6.826	0.009	27.036	0	6.844	0.033*

* Statistically significance with respect to the corresponding P value; A.N= Actual Number; E.N= Expected Number.

Table 8: Backetesting result of Tsh/RwF

Models	Kupiec 95%			Kupiec 99%			Christoffersen 95%		Christoffersen 99%	
	A.N of violations(E.N is 50)	Statistic test	P value	A.N of violations(E.N is 10)	statistic test	P value	statistic test	P value	Statistic test	P value
$ARMA(2,3) - GARCH(1,1)_N$	25	15.995	0	11	0.098	0.754*	25.81	0	2.709	0.258*
$ARMA(2,3) - GARCH(1,1)_t$	58	1.284	0.257*	12	0.38	0.538*	3.216	0.2*	0.672	0.715*
$ARMA(2,3) - GARCH(1,1)_s$	50	0	1*	11	0.098	0.754*	2.201	0.333*	0.343	0.428
$ARMA(2,3) - EGARCH(1,1)_N$	21	22.441	0	14	1.437	0.231*	29.494	0	7.614	0.022*
$ARMA(2,3) - EGARCH(1,1)_t$	46	0.346	0.557*	6	1.886	0.17*	0.707	0.702*	1.959	0.376*
$ARMA(2,3) - EGARCH(1,1)_s$	44	0.788	0.375	7	1.016	0.214*	2.672	0.263*	1.114	0.573*
$ARMA(2,3) - GRJGARCH(1,1)_N$	28	12.036	0.001	15	2.189	0.139*	16.027	0	3.704	0.157*
$ARMA(2,3) - GRJGARCH(1,1)_t$	57	0.989	0.32*	12	0.38	0.538*	3.137	0.208*	0.672	0.715*
$ARMA(2,3) - GRJGARCH(1,1)_s$	53	0.186	0.666*	10	0	1*	0.688	0.709*	0.202	0.904*

* Statistically significance with respect to the corresponding P value; A.N= Actual Number; E.N= Expected Number.

pothesis of correct exceedances is rejected for all models at 95% confidence level of significance i.e. non of the analysed models have passed the Kupiec test and Christoffersen for 95% while all models do not reject the null hypothesis of exceedances are independents at 99%, therefore $EGARCH_N$ is the appropriate model for Kenyan Shillings and this is evidenced by the higher p -value among the competing models. For Uganda shilling all the models passed the kupiec test and christoffersen test for 99% and failed for 95% confidence level for both test. So $ARMA(0,1) - EGARCH(1,1)$ with normal distribution pass statistical test with 99% and is deemed to be the best model for Uganda Shillings. For Tanzania shillings all the models have passed all test at all level of significance except for the models with normal errors distributions. Based on the significance model with higher p value $ARMA(2,3) - GJRGARCH(1,1)$ with skewed student t is choosen to be a better performance in backtesting for Tanzanian shillings. Hence, we can conclude the asymmetric GARCH types models outperform better the VaR forecast model for all currencies.

6. Conclusion

This study presents the evaluation and modelling on asymmetric volatility in realized exchange rate volatilities against Rwanda Francs. The asymmetry in exchange rates is more complex than it is in exchange rates when period of data is daily. The presence of asymmetric volatility in exchange rates calls for alternative economic explanations to those based on currency markets. The presence of asymmetric effect has been found in Daily exchange rate returns for Kenya shilling, Tanzania Shilling, Burundi Francs and Uganda Shilling against Rwandan Francs. The backtesting results showed that all the models passed Kupiec and Christoffersen test for Tanzania shillings except for normality assumption. None of the models passed the Kupiec and Christoffersen test with 95% confidence level but all models passed the Kupiec and Christoffersen test with 99% confidence model for Uganda shillings. For Kenya Shillings all models failed to accept the null hypothesis of correct exceedances with 95% confidence level and EGARCH under student t and skewed student t errors distributions failed all tests. For Burundian shillings the $ARMA(1,1)-EGARCH(1,1)$ with student t and skewed student t distribution accepted the null hypothesis of all test . In general the asymmetric volatity models are accurate for capturing volatility clustering and asymmetric effects for all currencies.

This study contributes to the existing literature through the extension of the research concerning the estimation of currency market volatility using symetric and asymmetric GARCH-type models. There is a strong evidence that daily returns can be characterised by the asymmetric GARCH-type models. One possible explanation is the direction and size of central bank interventions. Another is the base-currency effect in which the base currency is used for profit and loss calculation, therefore the variations in the foreign exchange rate becomes risk of the other currency. Future research should also explore the impact of asymmetric volatility on volatility forecasting and option pricing.

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Appendices

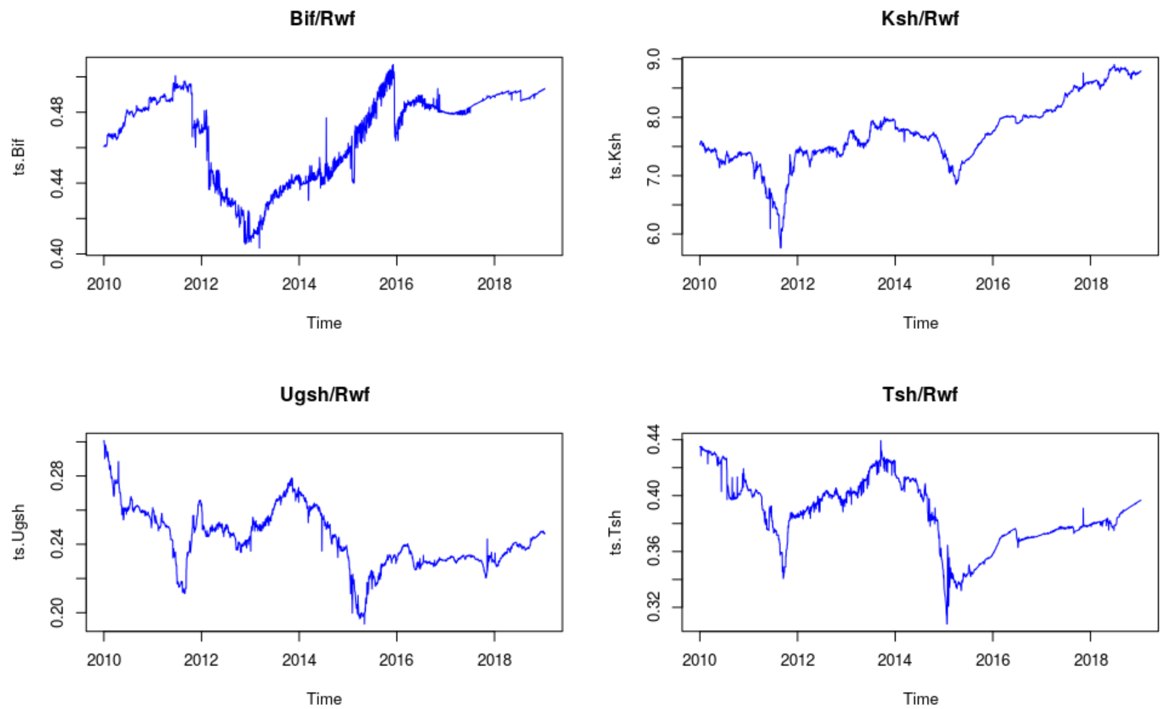

Figure 2: Plot for average of Exchange rate with Rwandan Francs (Jan 2010-Oct 2019).

Table 9: Parameter estimates of the model with different distributions of the standardised residuals for Bif/FRW

	ARMA(1,1)- GARCH(1,1)			ARMA(1,1)- EGARCH(1,1)			ARMA(1,1)- GJRGARCH(1,1)		
Distribution	Normal	Student	Skew S	Normal	Student	Skew S	Normal	Student	Skew S
Mu	0.00008	0.000137	0.000137	0.000037	0.000160	0.000164	0.000084	0.000141	0.000133
	(0.00046	(0.000000)	(0.001821)	(0.000000)	(0.000000)	(0.000000)	(0.098131)	(0.000000)	(0.000000)
Ar1	0.134	0.255005	0.247542	0.171967	0.153815	0.150293	0.133295	0.259201	0.275216
	(0.00189)	(0.001432)	(0.000235)	(0.000000)	(0.000007)	(0.000000)	(0.001474)	(0.000830)	(0.0004826)
Ma1	-0.6646	-0.477066	-0.472385	-0.692985	-0.290662	-0.282791	-0.670379	-0.420908	-0.424561
	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000001)
Omega	0.00000	0.000000	0.000000	-0.327815	-0.012117	-0.010397	0.000000	0.000000	0.000000
	(0.781673)	(0.000000)	(0.999657)	(0.000000)	(0.000001)	(0.000032)	(0.890844)	(0.999678)	(0.999203)
Alpha1	0.133272	0.162589	0.189961	0.034220	0.182658	0.407098	0.134844	0.137976	0.153859
	(0.000000)	(0.000000)	(0.000000)	(0.008146)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)
Beta1	0.865727	0.814852	0.789115	0.963875	1.000000	1.000000	0.863559	0.794866	0.798938
	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)
shape		2.856355	2.883038		2.100000	2.019020		2.755612	2.734662
		(0.000000)	(0.000000)		(0.000000)	(0.000000)		(0.0000)	(0.000000)
skew			0.984338			1.014028			0.907910
			(0.000000)			(0.000000)			(0.000000)
Gamma1				0.381129	0.316202	0.695422			
				(0.000000)	(0.000000)	(0.000000)			
eta11							-0.066498	-0.548573	-0.583187
							(0.043430)	(0.108327)	(0.000030)
LL	10090.17	11040.7	11044.61	10160.34	11152.34	11161.4	10093.93	11019.48	11037.9
AIC	-8.2725	-9.0514	-9.0538	-8.3292	-9.1422	-9.1488	-8.2748	-9.0332	-9.0475
BIC	-8.2582	-9.0348	-9.0348	-8.3126	-9.1232	-9.1274	-8.2581	-9.0142	-9.0261

Table 10: Parameter estimates of the model with different distributions of the standardised residuals for Ksh/RWFs

	ARMA(0,1)- GARCH(1,1)			ARMA(0,1)- EGARCH(1,1)			ARMA(0,1)- GJRGARCH(1,1)		
Distribution	Normal	Student	Skew S	Normal	Student	Skew S	Normal	Student	Skew S
Mu	0.000156	0.000121	0.000092	0.000166	0.000121	0.000100	0.000177	0.000117	0.000091
	(0.000259)	(0.000020)	(0.008807)	(0.036994)	(0.000017)	(.003788)	(0.000017)	(0.000039)	(0.009998)
Ma1	-0.096935	-0.054076	-0.056774	-0.128773	-0.048156	-0.049288	-0.107168	-0.052640	-0.054101
	(0.000167)	(0.004089)	(0.003871)	(0.000000)	(0.000000)	(0.004442)	(0.000014)	(0.006374)	(0.005362)
Omega	0.000000	0.000001	0.000001	0.024201	-0.542534	-0.553817	0.000000	0.000001	0.000001
	(0.783979)	(0.408911)	(0.392073)	(0.000000)	(0.000001)	(0.000000)	(0.848585)	(0.382902)	(0.364120)
Alpha1	0.061539	0.242929	0.248421	-0.041165	-0.061962	-0.063038	0.044633	0.044633	0.240371
	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000321)	(0.107325)	(0.000000)	(0.000000)	(0.000000)
Beta1	0.937332	0.756071	0.750579	1.000000	0.948037	0.947050	0.951975	0.752262	0.745697
	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)
shape		2.679076	2.680780		2.149466	2.152123		2.667903	2.679039
		(0.000000)	(0.000000)		(0.000000)	(0.000000)		(0.0000)	(0.000000)
skew			0.971963			0.984377			0.976393
			(0.000000)			(0.000000)			(0.000000)
Gamma1				0.128987	0.556301	0.558365			
				(0.000000)	(0.000000)	(0.002156)			
eta11							0.218954	0.162747	0.156241
							(0.000000)	(0.004549)	(0.000030)
LL	10645.02	11334.51	11335.44	10670.93	11360.21	11360.49	10655.39	11339.55	11340.22
AIC	-8.7285	-9.2933	-9.2932	-8.7489	-9.3130	-9.3135	-8.7362	-9.2966	-9.2963
BIC	-8.7166	-9.2790	-9.2766	-8.7346	-9.2939	-9.2969	-8.7219	-9.2799	-9.2773

Table 11: Parameter estimates of the model with different distributions of the standardised residuals for Tsh/RWFs

	ARMA(2,3)- GARCH(1,1)			ARMA(2,3)- EGARCH(1,1)			ARMA(2,3)- GJRGARCH(1,1)		
Distribution	Normal	Student	Skew S	Normal	Student	Skew S	Normal	Student	Skew S
Mu	0.000166	0.000209	0.000206	0.000170	0.000153	0.000203	0.000266	0.000213	0.000211
	(0.00296)	(0.000000)	(0.000001)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)
ar1	1.458501	1.040969	1.193969	1.485157	1.981556	1.276842	0.099846	0.871333	1.015866
	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.501023)	(0.000000)	(0.000001)
ar2	-0.488689	-0.076160	-0.221328	-0.835103	-0.981681	-0.948428	-0.569638	0.089823	-0.047754
	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000001)
ma1	-1.799873	-1.168274	-1.341253	-1.818492	-2.040155	-1.337172	-0.453558	-0.995101	-1.155913
	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.001578)	(0.000000)	(0.000001)
ma2	0.938011	0.230899	0.417240	1.269809	1.106806	1.028206	0.638724	0.045005	0.222219
	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000001)
ma3	-0.103751	-0.016030	-0.038504	-0.216197	-0.066544	-0.060328	-0.292228	0.002971	-0.021780
	(0.000000)	(0.000000)	(0.001786)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000001)
Omega	0.000000	0.000000	0.000000	-0.067491	-0.186107	-0.186107	0.000000	0.000000	0.000000
	(0.75820)	(0.99508)	(0.995780)	(0.000000)	(0.000001)	(0.000032)	(0.888351)	(0.997534)	(0.999203)
Alpha1	0.072645	0.327083	0.320224	-0.055970	0.021165	-0.010502	0.055130	0.308834	0.321574
	(0.000000)	(0.000000)	(0.000000)	(0.002146)	(0.000000)	(0.88731)	(0.000000)	(0.000000)	(0.000000)
Beta1	0.926355	0.653382	0.660365	0.988498	0.976010	0.982547	0.935996	0.670125	0.660921
	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000	(0.000000)	(0.000000)
shape		2.841121	2.888980		2.100000	2.011935		2.825056	2.830362
		(0.000000)	(0.000000)		(0.000000)	(0.000000)		(0.0000)	(0.000000)
skew			0.979452			1.011428			0.984482
			(0.000000)			(0.000000)			(0.000000)
Gamma1				0.243719	0.742997	1.592597			
				(0.000000)	(0.000000)	(0.000000)			
eta11							0.377943	0.091481	0.082317
							(0.000000)	(0.0010832)	(0.000030)
LL	9962.007	11390.84	11391.04	10122.32	11441.12	11409.64	9996.685	11389.78	11396.39
AIC	-8.1649	-9.3362	-9.3356	-8.2956	-9.3766	-9.3500	-8.1925	-9.3345	-9.3391
BIC	-8.1435	-9.3124	-9.3094	-8.2718	-9.3505	-9.3214	-8.1687	-9.3084	-9.3106

Table 12: Parameter estimates of the model with different distributions of the standardised residuals for Ugsh/RWFs

	ARMA(0,1)- GARCH(1,1)			ARMA(0,1)- EGARCH(1,1)			ARMA(0,1)- GJRGARCH(1,1)		
Distribution	Normal	Student	Skew S	Normal	Student	Skew S	Normal	Student	Skew
Mu	0.000056	0.000057	-0.000062	0.000100	0.00008	-0.000040	0.000221	0.000055	-0.000057
	0.48099)	(0.213870)	(0.317884)	(0.000000)	(0.051559)	(0.659527)	(0.000204)	(0.225108)	(0.351354)
Ma1	-0.158286	-0.031028	-0.031891	-0.200710	-0.02519	-0.025377	0.250097	-0.032888	-0.032537
	(0.000000)	(0.000000)	(0.074319)	(0.000000)	(0.008004)	(0.289904)	(0.000000)	(0.061687)	(0.067200)
Omega	0.000001	0.000003	0.000003	-0.034847	-0.39051	-0.352097	0.000000	0.000003	0.000003
	(0.20128)	(0.003771)	(0.000298)	(0.000000)	(0.000001)	(0.000002)	(0.417176)	(0.999678)	(0.000000)
Alpha1	0.118266	0.275979	0.284769	-0.076485	-0.10906	-0.145295	0.078293	0.271154	0.283398
	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)
Beta1	0.880734	0.723021	0.714231	0.992382	0.95769	0.959678	0.912559	0.720913	0.702402
	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)
shape		2.452299	2.883038		2.10000	2.060055		2.442393	2.463415
		(0.000000)	(0.000000)		(0.000000)	(0.000000)		(0.0000)	(0.000000)
skew			0.952815			0.957240			0.956015
			(0.000000)			(0.000000)			(0.000000)
Gamma1				0.205777	0.53946	0.673077			
				(0.000000)	(0.000000)	(0.000000)			
eta11							0.322584	0.159903	0.147260
							(0.000000)	(0.000000)	(0.017168)
LL	9119.545	10068.28	10071.67	9247.444	10117.55	10120.81	9155.036	10072.18	10075.05
AIC	-7.4771	-8.2545	-8.2565	-7.5812	-8.2941	-8.2960	-7.5054	-8.2569	-8.2585
BIC	-7.4652	-8.2403	-8.2399	-7.5669	-8.2775	-8.2770	-7.4911	-8.2403	-8.2394