

Exchange Rate Volatility Analysis of the Rwandan Franc (1990-2010)

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ABSTRACT

This study analyses the volatility of foreign exchange rate and its causes in the Rwandan Economy and then derives appropriate statistical models for forecasting the foreign exchange rate of that economy. Univariate volatility and conventional time series models are applied to the exchange rate data and their forecasting powers compared using a set of accuracy measures like AIC, Log Likelihood and BIC. The study also sought to investigate whether News affect exchange rates of Rwanda. The News include the genocide of 1994 and the country's joining of EAC in July 2007. Significant volatility models are obtained for Rwandan exchange rate data implying that the concept of volatility has relevance in this particular economy. The models both symmetric and asymmetric used in this research are GARCH and its family of models like EGARCH. The EVIEWS statistical package is used in the analysis. The models obtained indicated that the Rwanda exchange rate is highly volatile and is affected by news. The 1994 genocide was found to increase the exchange rate volatility while the integration of the economy into the East African Community was found to reduce the exchange rate volatility. The country was therefore encouraged to open up its economy to the outside markets especially those in the region. This will not only reduce the exchange rate volatility but also encourage both local and foreign investors.

Keywords: Exchange rate; Foreign exchange rate volatility; Symmetric and asymmetric models; News; Forecasting.

1. INTRODUCTION

Though volatility of financial data has been broadly analyzed for a variety of developed and developing countries, to my knowledge, the concept has not been done for Rwanda especially using the GARCH family of models. Therefore this research serves to bridge this gap by examining the volatility properties of this country.

Most of the financial markets like exchange rate markets, stock exchange rates and interest rates are uncertain, improbable and not easy to predict. This is because they are highly influenced by any local or global events that affect the economy. These events are what we call NEWS. In Rwanda the major local event that could alter the movement (variations) of the exchange rates of the Rwandese Francs are the Genocide of 1994 and the joining the East African community in July 2007. Usually the joining of major trading markets affects the

new comer economies due to the fact that their economies are opened to external market variations .A common market group like the East African community could help Rwanda reduce on volatility as the financial risks are shared among the member economies hence it can be regarded as harmonizing market behavior. Furthermore, integration usually increases volatility especially for new members of the group due to cross border contagion.

A country's variation in its exchange rate could be explained by some variations in international events for example the Asian Crisis, acts of terrorism like the September 11th terrorist attack on the major World Trade Centre sometimes called the Twin towers, the crumple of firms and industries, the stock market crash among others. The impacts of some of these international events have not been felt so much like the national one. The exchange rate of the Rwandese Franc has been found to react quickly to the shocks in the market possibly because it's not pegged to any big currency like the US Dollar. Usually pegging of low value currencies to major currencies helps the country to overcome abrupt shifts in the rates. The events that have affected the financial market situations of Rwandan economy either take place for a long time and some others are short lived. To be precise, the effect of the genocide of 1994 in Rwanda affected the country up to the third quarter of 1995. The extent and length of the effect or impact on the financial situation depends on the magnitude and the causes of the event.

The uncertainties of financial markets are very important areas through which most scholars and financial experts have based their studies to come up with means through which predictions can be made for development. Volatility is thus a good and very important concept to study because it has got wide applications especially in business where the decision on whether to invest more or less greatly depends on how volatile the financial markets like that of exchange rates are. Most of the business units and companies that do not take fluctuations into consideration usually over or under estimate the risks depending on the market situations.

This study has been occasioned by the fact that Rwanda's financial data has not been analyzed using the GARCH family of models. This study which is supposed to fill this gap is guided by the following objectives;

1. To determine which of the GARCH family of models fits Rwanda's foreign exchange rate data for the period 1990-2010. The selected model will then be used for forecasting the country's future exchange rate volatility. The selection of the best model is done by use of Akaike Information Criterion (AIC) as it ensures that such a model is a parsimonious one (Akaike 1973). AIC penalises each of the competing model for every extra parameter it uses. Hence the more parameters that the model contains, the less its suitability for being chosen as a good model.

- 77 2. To establish whether volatility periods exist in the exchange rate data of Rwanda.
78 These volatility periods are said to exist depending on whether significant volatility
79 models are obtained for the exchange rate data of the country in question.
80 3. To examine the impact of news on the exchange rates of Rwanda. The news may
81 be bad news or good news that leads to either negative or positive volatility of
82 exchange rates. The news to be considered are the genocide that took place in
83 1994 and the country's joining of the East African Community in 2007.

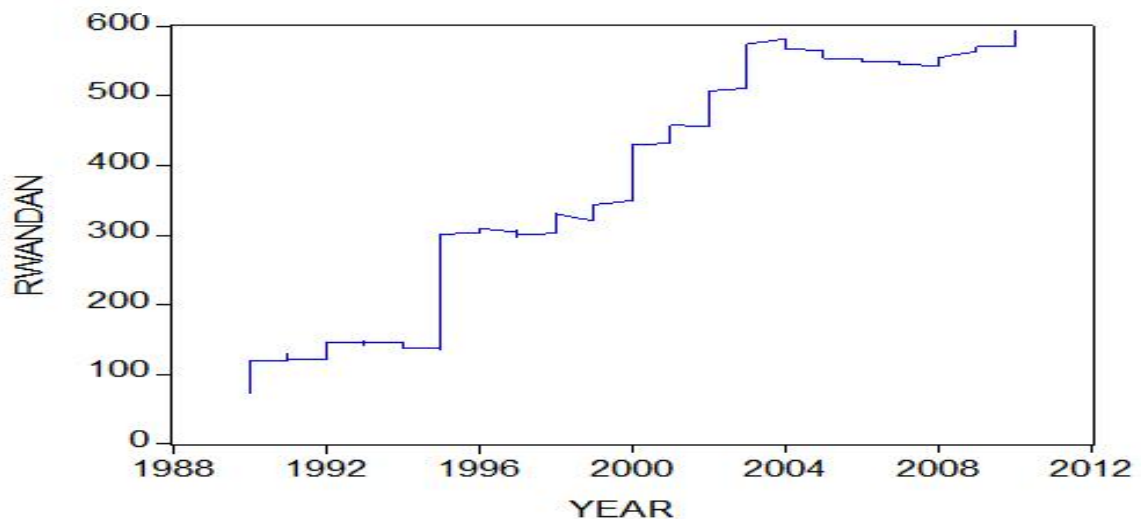
84 2. METHODOLOGY

85 2.1 Data

86 To achieve the objectives of this study, monthly data of the exchange rates of the Rwandan
87 Franc against the US Dollar for a period of 20 years from 1990M1 to 2010M12 has been
88 used. Eviews7 package has been used because it is user friendly and doesn't require use of
89 any programming. Data used was collected from International monetary Fund (IMF) data
90 base. The time series graphical representation of the data that has been used for the period
91 of up to 2010M12 is shown in Figure 1.

92

FIG 1: Plot of the exchange rate data (1990-2010)



93

94 The exchange rate movement of the Rwandese Franc is seen to have an upward trend.
95 Other than the periods during the genocide in 1994, the magnitude of the variations in the
96 data points at different months is not very big indicating fairly stable exchange rate behavior
97 for the country. The upward trend as portrayed by Figure 1, tells us that the data we have
98 used is non-stationary.

99

100 2.2 Modeling Procedure.

101 The GARCH model is applied through the following procedures;

102

2.2.1 Making the data stationary

This involves removing the trend and seasonality if they exist from the data. Removing the trend involves taking successive differences of the data and testing if the resulting data has a unit root by the use of the Augmented Dickey-Fuller test.

2.2.2 Lag determination

The determination of how far back we have to take the data (Lag order) to obtain a more meaningful model that is parsimonious is one of the key issues of any statistical modeler. The larger the significant lags P and Q the longer and more complicated the model is. The longer the model equation the more the parsimony of the model is compromised. Engle (1982) highlights that the ARCH model that can be used to capture all the aspects of financial data would require it to have very many terms which would make it less parsimonious. Furthermore, the more terms the model has, the more likely it is to have possibility of negative variance which is nonsensical. The possibility of negative variance arises from any possible big negative coefficient. Nelson (1992) states that for an ARCH(q) given by $\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \alpha_3 \varepsilon_{t-3}^2 + \dots + \alpha_q \varepsilon_{t-q}^2$, then the existence of high values of α_i would render the RHS of the equation negative which would mean a negative variance that does not make sense since the variance is always positive.

The use of GARCH tries to solve this issue. In fact Bollerslev (1986) suggested GARCH which includes past variance terms into the original ARCH model. The Generalised ARCH

model is of the form $\sigma_t^2 = \alpha_0 + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2$. This solves the problem of negative variance but it has a drawback of failure to cater for the asymmetries i.e impact of news since it takes error(perturbations) to be positive yet some negative shocks exist in the market.

Never the less GARCH is widely used in contemporary statistical analysis. Chen and Lian (2005) found that GARCH order as low p=1 and q=1 which is GARCH (1,1) captures most of the aspects of data which makes it highly parsimonious. Therefore we don't have to bother with lags which are very big for example p>=5 and q>=5 because of this. For the Rwandese Data it was found that lags of p,q<4 was able to show relatively very accurate model for forecasting the exchange rate of this country. The partial autocorrelation function and the autocorrelation function of the data shown below highlights that ARIMA (3,1,4) would be a fair model to think of a good representative of the Rwandese data. The lags greater than 6 would be telling us that the values of the rates six months ago affect the present value of the exchange rate which is spurious.

138 **2.2.3 Modeling process.**

139 The Data analysis will involve obtaining the volatility model equation which is a combination
 140 of the men and variance model equations. The general form of the volatility model ARIMA
 141 (P,d,Q):GARCH(P,Q) which used is of the form;

$$142 \quad Z_t = \mu + \sum_{i=1}^p \phi_i Z_{t-i} - \sum_{j=1}^q \phi_j \varepsilon_{t-j} + u_t \quad u_t \sim (0, \sigma_t^2) \dots \dots \dots (1)$$

$$143 \quad \sigma_t^2 = \alpha_0 + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2 \dots \dots \dots (2)$$

144 Where equation 1 is the mean model(ARIMA) and 2 is the variance model(GARCH family)
 145 with μ and α_0 being the intercepts, P and Q being equal monthly lags of Rwandese
 146 exchange rates, ϕ_i , ϕ_j , α_i and β_j are the coefficients to be determined . $\alpha_i \geq 0$, $\beta_j \geq 0$ and also $\sum$
 147 $(\alpha_i + \beta_j) < 1$.
 148

149 In equation 1, Z_t is the current exchange rate and u_t is the stochastic error term which is
 150 assumed to be normally distributed ie $E(u_t)=0$ and Variance (σ_t^2) shown by equation 2 which
 151 is taken to be constant (Homoscedastic).

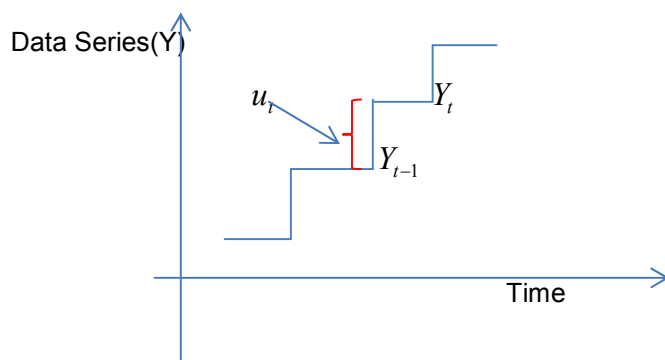
152 **2.2.4 Formal tests on the Data**

153 **2.2.4.1 The Unit root tests**

154 This is the test for stationary of a data series. It is also known as the Augmented Dickey
 155 Fuller test. The general idea behind this test is that; suppose our data series can be
 156 represented by the model $Y_t = \rho Y_{t-1} + u_t \dots \dots \dots (3)$

157 obtained by regressing the value Y_t against its immediate previous lagged value Y_{t-1} . When
 158 the value of $\rho = 1$ model 1 becomes a random walk model which is non-stationary as in the
 159 fig. 2

160 Fig.2: Simple illustration of data following a random walk



168 From this random walk model, it is sufficient to test if the coefficient is statistically equal to 1.
 169 If this is true, then the series in question is non-stationary.(Gujarati 2000).Suppose we
 170 subtract Y_{t-1} both sides of equation (3) we obtain the first difference equation (4) as follows

$$171 \quad Y_t - Y_{t-1} = \rho Y_{t-1} - Y_{t-1} + u_t$$

$$172 \quad \Delta Y_t = (\rho - 1)Y_{t-1} + u_t$$

173 Let $(\rho - 1) = \sigma$ then we obtain

$$174 \quad \Delta Y_t = \sigma Y_{t-1} + u_t \dots \dots \dots (4)$$

175 For equation (4) to be stationary, then σ must be equal to zero. For it to be a random walk ,
 176 then σ must be equal to 1.

177 When $\sigma = 0$,

$$178 \quad \Delta Y_t = u_t$$

$$179 \quad Y_t - Y_{t-1} = u_t \text{ which is stationary.}$$

180 We note that when $\sigma = 0$ then $\rho = 1$ showing that though the original data series is not
 181 stationary, the first difference of the data is trend free. However if σ is negative, then

$$182 \quad \Delta Y_t = -Y_{t-1} + u_t$$

$$183 \quad Y_t - Y_{t-1} = -Y_{t-1} + u_t$$

184 $Y_t = u_t$ which shows that the original data series is stationary. Therefore if we obtain σ as
 185 negative it would mean that we would obtain $\rho = 0$ showing that the original series is trend
 186 free. The process of finding a stationary data therefore involves taking successive
 187 differences while testing whether the obtained differenced data has got a unit root until a
 188 trend free data is obtained.(Coshall2008). This process is done by making use of the
 189 Augmented Dickey-Fuller test that has a null hypothesis H_0 : data is trend stationary. The null
 190 is rejected when the probability for the test is less than 5%. The ADF test has been
 191 employed in the test for the stationarity of the exchange rates of Rwanda used in this study.

192 **2.2.4.2 Normality test**

193 In the search for the optimal model, it is always necessary that we test whether the residuals
 194 of the model are normally distributed i.e Residuals $\sim N(0, \sigma^2)$. To determine whether the
 195 residuals are normal, we use any of the following procedures:

- 196 1. Drawing the histogram of the residuals .This is a rough estimate method because
 197 when the histogram is drawn, one mentally superimposes the normal curve and
 198 judges whether it fits onto this histogram or not.
- 199 2. Drawing a Normal Probability Plot (NPP) of the residuals. This graphical method
 200 involves plotting the residual's values on the x- axis and their corresponding values

from the normal distribution on the y-axis. If the residuals are normally distributed then most of the points should lie on a straight line. Furthermore, equal number of points should lie to the left and right of zero showing a mean of zero as illustrated in Figure 3.

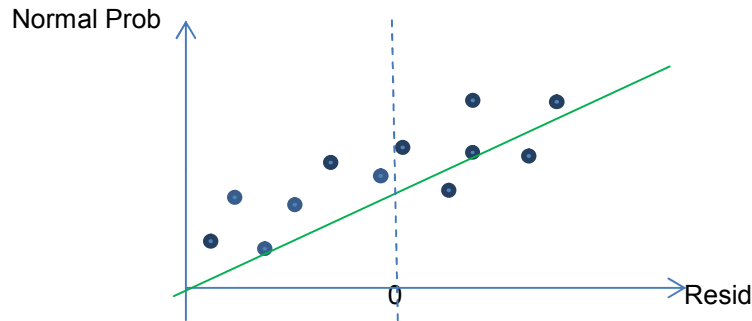


Fig. 3: Normal Probability plot of residuals

3. Testing the normality of the residuals by use of the Jaque Bera Test.

This test has the null hypothesis H_0 : Residuals are normally distributed. The test statistic for the test is given by

$$JB = n \left\{ \frac{S^2}{6} + \frac{(K - 3)^2}{24} \right\}$$

Where n = sample size of the residuals

S = Skewness coefficient

K = Kurtosis coefficient.

For a perfectly normally distributed data, $S=0$ and $K=3$. Therefore in the JB test, we are testing the hypothesis that $S=0$ and $K=3$. Under the Null hypothesis H_0 : Residuals are normally distributed, the two friends Jacque and Bera showed that asymptotically(for large samples) the JB statistic is chi-square distributed with 2 degrees of freedom. If the probability is very low which happens when the computed value of JB statistic is far away from zero, then we reject the null and the reverse is true. The JB test is the one that has been employed in the testing for normality of the residuals of all the models in this study.

2.2.4.3 Autocorrelation test

Usually we require that there is no auto correlation or serial correlation of the residuals of the optimal model. This therefore forces the statistical modeler to check whether it is a problem in any model. Checking for autocorrelation of the residuals depends on the type of the original data. Usually when the data is cross sectional, there is no reason as to why the modeler may think of the residuals from different cross sections to be correlated. However if

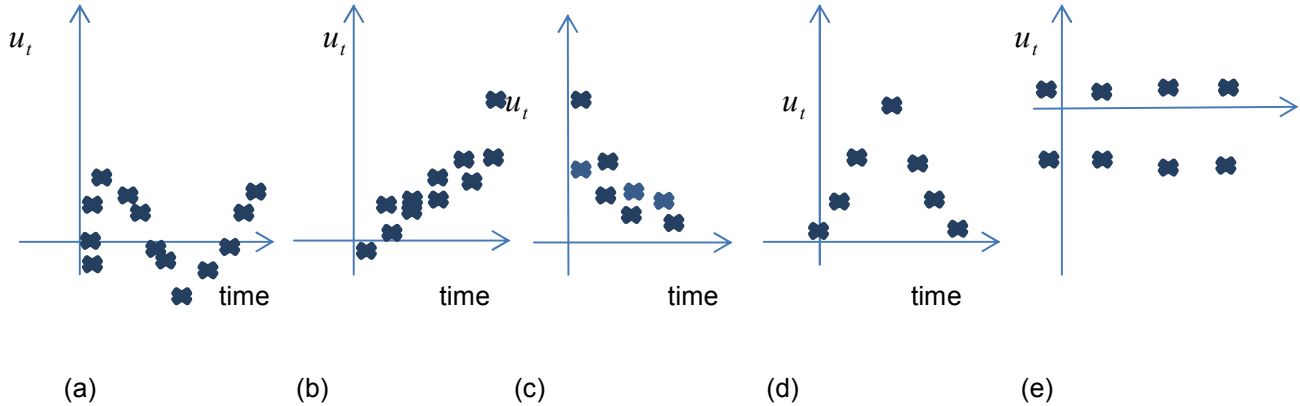
we are looking at time series data, it is useful to think of this problem arising since the errors at successive time intervals may be related (correlated) especially if the time intervals are small. For small time intervals like a day, week and a month, autocorrelation is a potential problem. However, as the time lags become big for example yearly data, five years data, ten years data and so on, the errors may be assumed to be uncorrelated.

There are many ways of checking for autocorrelation of residuals some of which include the following.

1. Use of residual plots over time.

When the residuals are plotted against time, different patterns may be exhibited which give us an idea of whether autocorrelation is or is not a problem in the residuals under consideration. Suppose the residuals exhibit the plots in Figure 4

Fig. 4: Graphs showing autocorrelation of residuals



Graphs a-d in figure 4 shows that the residuals are correlated while graph e shows that the residuals are not correlated. From the graphs, it is evident that residual autocorrelation can either be negative or positive.

2. Use of the Durbin- Watson test

Testing for autocorrelation can also be done by use of the D-W test. The test makes use of the coefficient of auto covariance or simply coefficient of autocorrelation ρ .

The first order autocorrelation is related to D-W test statistic d by the relation

$$d = \frac{\sum_{t=2}^n (e_t - e_{t-1})^2}{\sum_{t=1}^n e_t^2} \approx 2(1 - \rho)$$

269 Therefore
 270 $d = 2(1 - \rho)$; $-1 \leq \rho \leq 1$
 271 Where ρ and e_t are the coefficient of autocorrelation and the errors of the model
 272 respectively. Given the error series e_t , then $\rho = \frac{\sum e_t e_{t-1}}{\sum e_t^2}$
 273 Since $-1 \leq \rho \leq 1$, then $0 \leq d \leq 4$
 274 When $\rho = 1$ and $d = 0$ then we conclude that there is perfect positive correlation. On
 275 the other hand when $\rho = -1$ and $d = 4$ we have perfect negative correlation of the
 276 residuals.
 277 We recall that our major concern does not lie on the autocorrelation; we most
 278 concerned with no autocorrelation. This only happens when $\rho = 0$ and $d = 2$
 279 In the modelling process when we obtain the value of D-W statistic hovering around
 280 2 we conclude that there is no autocorrelation of the residuals.
 281 There are two intervals within which the value of d can lie $0 \leq d \leq 2$ and $2 \leq d \leq 4$.
 282 When the value of d lies in any of these ranges, D-W derived critical lower bounds
 283 d_L and critical upper bounds d_U based on the number of observations n and
 284 number of explanatory variables k tabulated at a given level of significance. If the
 285 computed value of $d < d_L$ we reject the null and when $d > d_U$ then we accept the null
 286 hypothesis and conclude that the residuals are not auto correlated. If $d_L \leq d \leq d_U$
 287 then no conclusion is made about whether the residuals are correlated or not.
 288 Once autocorrelation is judged to be a major problem, then some remedies can
 289 made some of which include;
 290 i. Including neglected variables
 291 ii. Improving the model specification by even including higher order powers.
 292 iii. Use of a'laprais transformation of data.

293 **2.2.4.4 Homoscedastic test**

294 In addition to making sure the residuals are not correlated, the optimal model should have
 295 residuals that have a constant spread (variance) a phenomenon that we refer to as
 296 homoscedasticity. There are various tests available in most contemporary statistical
 297 packages. However, this research zeroed on the use of the White's test. The test has a null
 298 hypothesis H_0 : residuals are not heteroscedastic.

299 The test relies on the knowledge of number of observations n and the coefficient of
 300 determination R^2 . Given the knowledge of these two values, then the
 301 value $n * R^2 \sim \chi_{df}^2$ where df = number of regressors in the auxiliary model.

302 Suppose we have a model $Y = \beta_1 + \beta_2 X_{2i} + \beta_3 X_{3i} + u_i$, then we run an auxiliary model
 303 of the squared residuals given by

304 $Y = \alpha_1 + \alpha_2 X_{2i} + \alpha_3 X_{3i} + \alpha_4 X_{2i}^2 + \alpha_5 X_{3i}^2 + \alpha_6 X_{2i} X_{3i} + v_i$ and get the value of R^2 of
 305 this auxiliary model. We compute the value $n * R^2$ which is approximately chi-square with 5
 306 degrees of freedom.

307 If the value of $n * R^2$ is greater than the chi-square value at a chosen level of significance,
 308 we reject the null hypothesis and conclude that the residuals are homoscedastic. The
 309 converse is also true for heteroscedastic residuals. The white's test has been used in testing
 310 for homoscedasticity of the residuals exhibited by the volatility models in this paper.

311

312 3. RESULTS AND DISCUSSION

313

314 Fig. 1 shows a clear upward trend. It is therefore evident by inspection that the Rwanda's
 315 exchange rate data used is not stationary because of this trend. In fact Augmented Dickey-
 316 Fuller test on the non-differenced data indicates that the data has a unit root. ADF test has a
 317 Null Hypothesis H_0 : Data contains a unit root. We reject H_0 when the probability for the test is
 318 less than a set level of significance (e.g 1%, 5% etc).

319 When ADF test is carried out on non-differenced and successive differenced data, the output
 320 in table 1 is obtained.

Data	ADF test statistic	Probability
Non-differenced	-1.272661	0.6427
1 st Difference	-15.97257	0.0000

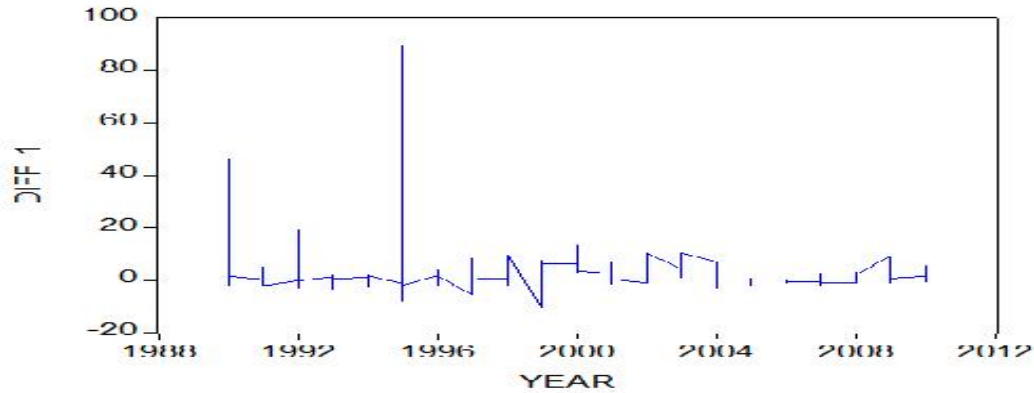
321 Table 1: Results of ADF test on exchange rate data

322

323 The results for the test on the non-differenced data in table 1 tell us that we accept the null
 324 hypothesis and conclude that the data has got a unit root because the probability for the test
 325 is 0.6427. When the same test is carried out on the first differences of the same data we
 326 obtain the value of prob.=0.0000<0.05. The graph for the differenced data is shown in fig. 5

327

Fig.5: Plot of the first difference of the Rwanda's foreign exchange data



328

329 The ADF test tells us to reject the Null hypothesis since the probability for the test is
 330 $0.00000 < 5\%$ and therefore conclude that the first difference of the Rwandan exchange rates
 331 is stationary. This leads us to the choice of the mean (ARIMA) model of the form ARIMA
 332 $(p,1,q)$ since we require just one differencing to get rid of the trend. The correlograms (PACF
 333 and ACF) of the Rwandese exchange rate data given in table 2 in the appendix leads us to
 334 choose ARIMA(3 1 4) as the mean model for this data from the significant spikes. The
 335 Eviews outputs for these tests are given by Table A and B in the appendix. Furthermore,
 336 from the serial autocorrelation test results in table 3 of the appendix, it can be deduced that
 337 the residuals for this mean model are not serially correlated because there are no significant
 338 spikes on the correlograms of the squared residuals. This is also confirmed from Breusch
 339 Geoffrey test for serial autocorrelation with the Null H_0 : residuals are not serially correlated.
 340 The prob. for the test is 0.004 hence we accept the null at 5% level of significance and
 341 therefore there is no correlation of the residuals. Furthermore, the D-W statistic given by this
 342 model is $2.001572 \approx 2$ implying that the residuals are not correlated which satisfies the
 343 assumption of the optimal model. The assumption of normality of the residuals is violated
 344 since the Jaque bera test in fig 6 yields the output with probability $0.0000 < 5\%$ which makes
 345 us to reject the null.

346

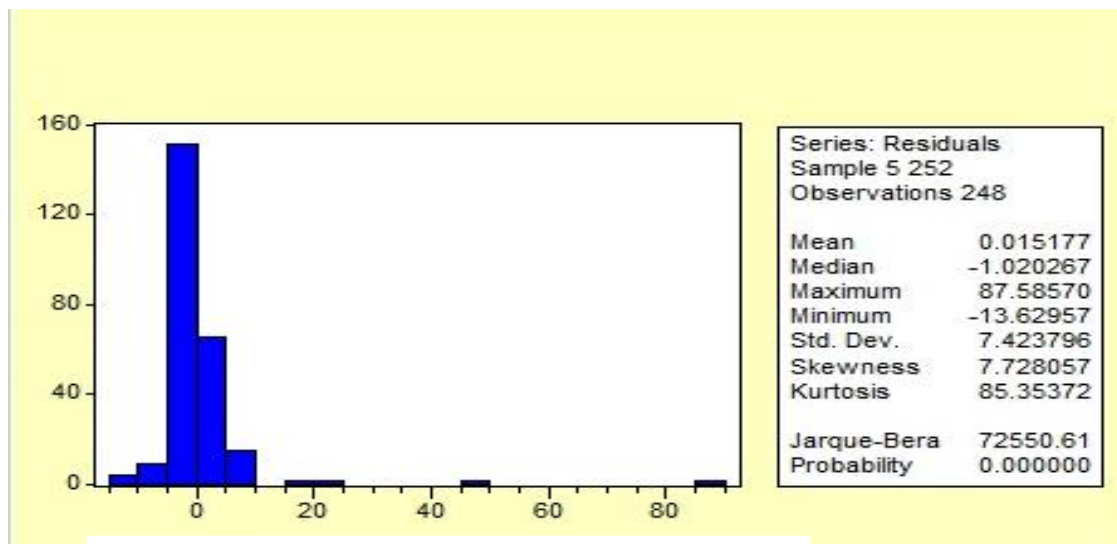


Fig 6: Normality test on the residuals of the mean model

Various GARCH models both symmetric and asymmetric were fitted for the $p[1,3]$ and $q[1,4]$ and the best model for this data was found to be GARCH(1,2). Therefore, the volatility model for the data in question is of the form ARIMA (3,1,4):GARCH(1,2). Table 4 shows the parameters for this model.

The volatility model is of the form			
$GARCH = C(4) + C(5) \cdot RESID(-1)^2 + C(6) \cdot RESID(-2)^2 + C(7) \cdot GARCH(-1)$			
Parameters	Coefficient	Standardized Errors	Probability
MEAN EQUATION			
C	1.167408	0.398733	0.0034
AR(3)	0.235789	0.050396	0.0000
MA(4)	0.236131	0.028756	0.0000
VARIANCE EQUATION			
C	-0.066004	0.0202275	0.0011
RESID(-1)^2	-0.048330	0.003553	0.0000
RESID(-2)^2	-0.056905	0.003544	0.0000
GARCH(-1)	1.008626	1.48E-05	0.0000

Table 4: Optimal volatility model for the Rwandese exchange rate data

4.. FORECASTING

4.1. Forecasting using the GARCH (3,4) model

4.1.1 Static forecasts

362 The static forecast for the fitted data of the exchange rate of Rwanda is given by the figure
 363 7

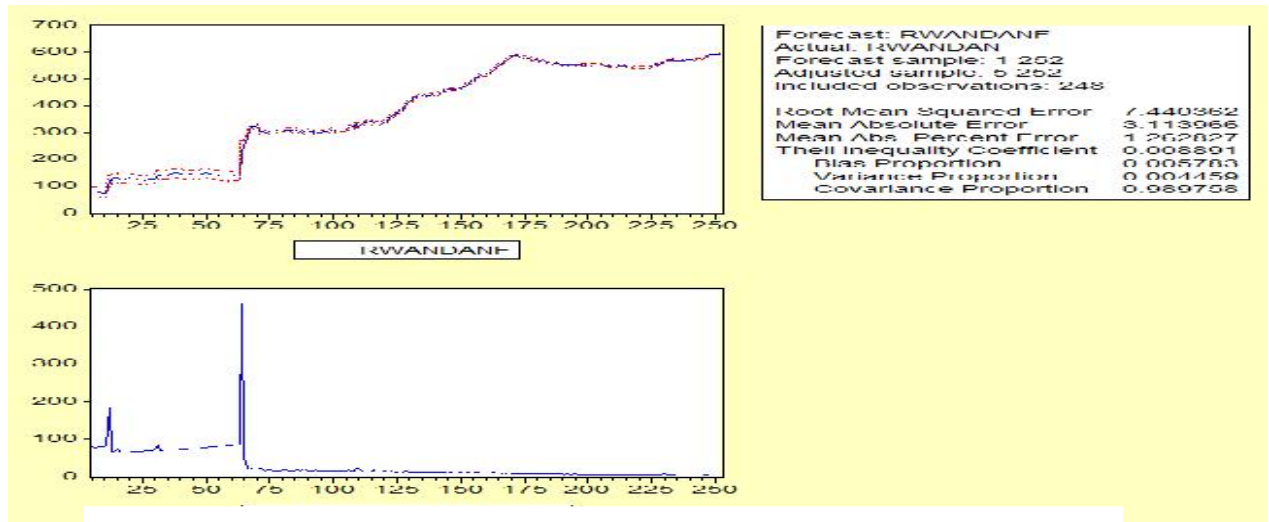


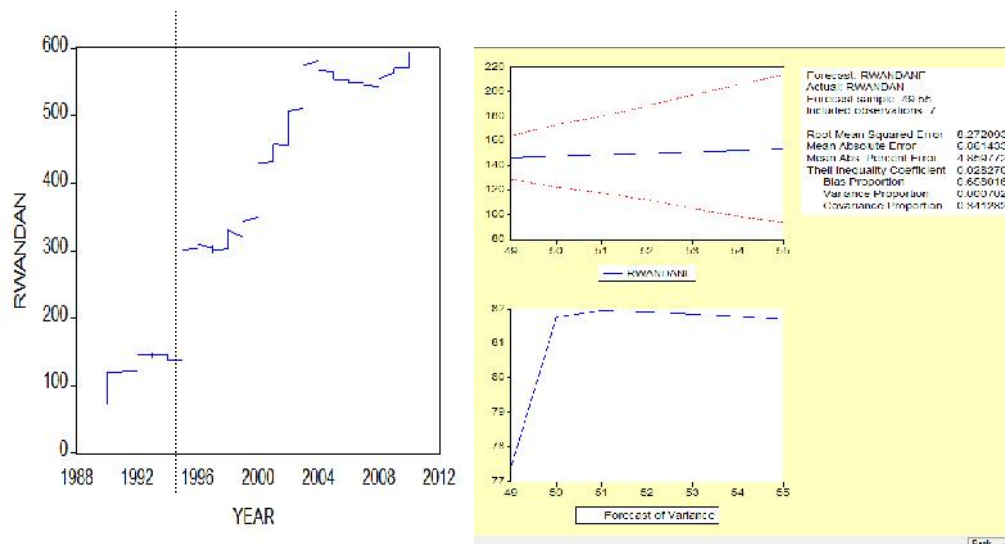
Fig. 7: Static forecasts for the exchange rates using the fitted volatility model

The MAPE of this forecast is 1.25% implying that this model fits the data well. The graph of the static forecast of the Rwanda's exchange rates where the red lines are taken to be confidence limits shows that the error margins from the blue line (mean) is very small. Furthermore, the variance proportion of 0.004 means that there is a small variation of the forecasted values by the model and the actual values. This therefore means that the model fits the data pretty well.

4.1.2 Dynamic forecasts

When we analyzed what happened to the movement of the exchange rate data in Rwandese Franc during the period of genocide in 1994, the result was the plot of the data shown in fig 8.

Fig.8: Volatility of exchange rate during the period of genocide



378 The forecast of variance shows that the rate was persistently increasing during the period of
 379 1994 which could be due to the unrest during the genocide that was taking place. However
 380 the variance was mean reverting because the variance was tending to the constant
 381 unconditional mean of variance. Engle and Andrew (2001) highlights that the volatility nature
 382 of most economic variables is always in such a way that they are mean reverting.
 383 In 2007 the country joined the EAC and the movement of the data during that period is
 384 shown by the plot of the data in fig. 8. The forecast of variance from the year 2007M6 to
 385 2008M6 is shown in fig.9

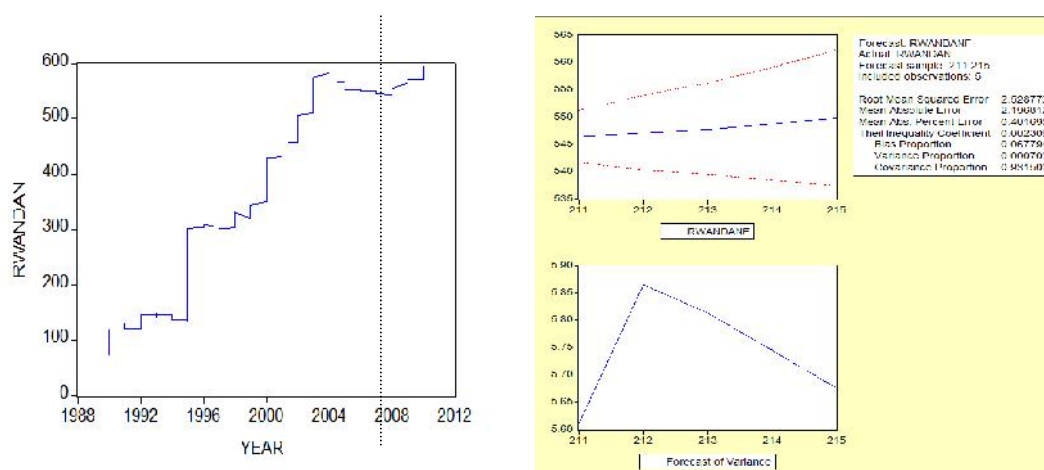


Fig.9: Volatility of the Rwandese data after joining EAC

388 A close look at the exchange rate movements before and after 2007 shows that the currency
 389 volatilities after are less than those before. Furthermore, the forecast of variance shows that
 390 the variance was increasing in the first month of joining EAC but it tremendously decreased
 391 for all other months. This shows that joining EAC has helped Rwanda to increase the value
 392 of the franc or reduce the volatility of this data set hence joining EAC harmonized its
 393 currency. The government policies which have been adopted to cater for each of the
 394 member country's interests in this market group have favoured the exchange rate of
 395 Rwanda. The comparison of means of the data points of the two separate periods by use of
 396 the t- test can also give an idea of the differences in the volatilities of the Rwandan franc
 397 during the two periods.

402 5 CONCLUSION AND POLICY IMPLICATIONS

403 5.1 Conclusions.

404 The exchange rate volatility analysis of the Rwanda's financial data led to the selection of
 405 GARCH (1,2) as the most appropriate forecasting model for the economy. The application of
 406 this model to the exchange rate of the Rwandese Franc was found to exhibit high volatility

407 and also susceptible to News as found in the forecasts of the variances during the period
408 under study.

409 **5.2 Policy Implications.**

410 The above results should therefore be an eye opener for economic policy makers in the
411 country to peg the currency of the country to big currencies such as the dollar, the pound or
412 the euro to avoid unnecessary shocks in the currency market. The country should also open
413 the economy to the various regional market groupings especially those that are in its
414 immediate neighborhood like the COMESA etc. Opening up the economy would reduce the
415 exchange rate volatility hence encouraging both local and international investors to invest in
416 the economy thus helping in the development of the country.

417 **5.3 Recommendation for further Research**

418 Further research should be done using the regression based approach in order to find out
419 the effect of macro and micro economic factors like inflation, interest rate etc. on the volatility
420 of the exchange rate.

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425 paper.

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427 **AUTHORS' CONTRIBUTIONS**

428 Warren Tibesigwa carried out the statistical modeling with Eviews, managed the literature
429 searches, organized (typed) the first draft of the manuscript. William Kaberuka proof read
430 and edited the draft to come up with the present version and did the interpretation of the
431 output obtained from Eviews. Both authors read and approved the final manuscript

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450 DEFINITIONS, ACRONYMS, ABBREVIATIONS

451 **COMESA**:Common Market for East and Southern Africa

452 **EAC** : East African Community

453 **GARCH** : Generalised Auto Regressive Conditional Heteroscedasticity

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456 APPENDIX

457

Augmented Dickey-Fuller Unit Root Test on RWANDAN		
Null Hypothesis: RWANDAN has a unit root		
Exogenous: Constant		
Lag Length: 3 (Automatic based on SIC, MAXLAG=15)		
	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-1.272661	0.6127
Test critical values:		
1% level	-3.456622	
5% level	-2.872998	
10% level	-2.572951	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RWANDAN)
Method: Least Squares
Date: 07/22/13 Time: 17.11
Sample (adjusted): 5 252

Table A: Results of ADF test on the non-differenced exchange rate data

Augmented Dickey-Fuller Unit Root Test on D(DIFF_1)		
Null Hypothesis: D(DIFF_1) has a unit root		
Exogenous: Constant		
Lag Length: 2 (Automatic based on SIC, MAXLAG=15)		
	t-Statistic	Prob *
Augmented Dickey-Fuller test statistic	-15.97257	0.0000
Test critical values:		
1% level	-3.456730	
5% level	-2.873045	
10% level	-2.572976	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DIFF_1,2)
Method: Least Squares
Date: 07/21/13 Time: 09:57

Table B: Results of ADF test on the first-difference exchange rate data

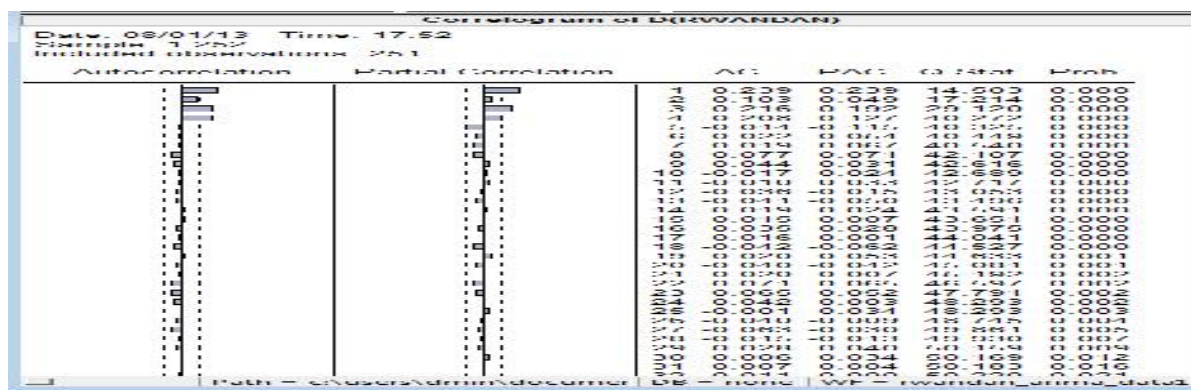
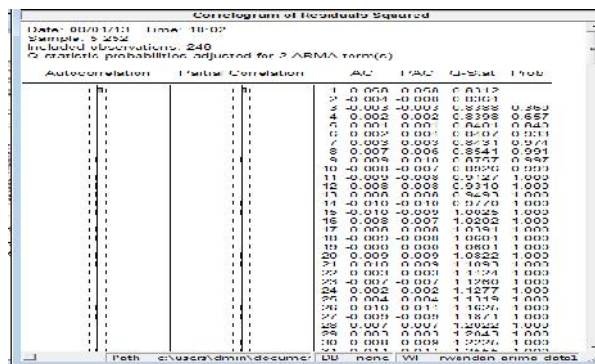


Table 2. Results of test on the significance of lags



Breusch-Godfrey Serial Correlation LM Test				
F statistic:	5.636382	Probability	0.004048	
Obs*R squared:	10.99368	Probability	0.004100	
Test Equation:				
Dependent Variable: RFSID				
Method: Least Squares				
Date: 08/01/13 Time: 18:08				
Presample missing value lagged residuals set to zero.				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000912	0.700477	-0.001303	0.9990
AR(1)	-0.015316	0.064246	-0.238398	0.8118
MA(4)	0.004442	0.062176	0.071214	0.9433
RFSID(1)	0.203350	0.064128	3.171003	0.0017
RFSID(2)	0.028855	0.065376	0.441373	0.6593
R squared	0.044329	Mean dependent var	0.016177	
Adjusted R squared	0.028598	S.D. dependent var	7.423796	
S.E. of regression	7.218873	Akaike info criterion	6.838198	
Sum squared resid	13009.40	Schwarz criterion	6.909034	
Log likelihood	-342.9386	F-statistic	2.817924	
Durbin-Watson stat	2.001572	Prob(F-statistic)	0.025863	

Table 3: Correlograms of squared residuals and Breusch-Geofrey Serial Correlation test