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Modelling Volatility in the Currency Exchange Rates of The Kenya Shilling Against The U.S. Dollar

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ABSTRACT
In recent years, Foreign Exchange (FOREX) rate has had an increasing role in corporate decision making. Due to the high uncertainty in the exchange rate volatility; FOREX rate volatility has become equally helpful in many micro as well as macro-economic decision-making. The research project aimed at modelling the volatility of log-returns on Kenya shilling against US dollar exchange rate in Kenya over a period of 1st January 1976 to 15th March 2022. In this study, we applied Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model in analyzing daily data from Central Bank of Kenya (CBK). The project employed the use of Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) in order selection; utilizing maximum log-likelihood estimation method (MLE) in estimating the unknown parameters to identify the best model suited for modelling currency exchange rates. The parameters were tested by the use of Ljung-Box-Pierce Q-test to check whether the Hypothesis made on the residuals is true that is, that residuals satisfy the requirements of the White noise, zero mean and constant variance. The project further fitted in a GPD Model (Generalized Pareto Distribution Model) in which the excess distribution and the tail of the underlying distribution over a chosen threshold was obtained. VaR (Value at Risk) estimate was then being determined. The mean equation that was best fitting for the data was between GARCH (1, 1) to GARCH (4, 5). The optimal GARCH model for the returns of the KSH/USD exchange rate is the GARCH (4, 5) with student-t innovations.

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I. Introduction

Exchange rate has a risk affecting both importers and exporters in the exchange market. The collapse of the Bretton Woods agreement of Fixed Exchange rates among major industrial countries led to extensive debate about the topic of exchange rate volatility and its potential influence on welfare, inflation, international trade and degree of external sector competitiveness of the economy and also its role in security valuation, investment analysis, profitability and portfolio risk management (Suliman Zakaria Suliman Abdala). Most investors and financial analysts are concerned about the uncertainty of the returns on their investment assets caused by the variability in speculative market risk and the instability of business performance Alexander (1999). A number of econometric models have been developed to investigate the unexpected events, uncertainties in prices (and returns) and the non-constant variances in the financial markets across the world. The Autoregressive Conditional Heteroscedasticity (ARCH) by Engle 1982 and GARCH models by Bollerslev (1986).

Important characteristics within financial time series is Leptokurtic (fat tails), volatility clustering (or volatility pooling) and Leverage effect. A series with some periods of low volatility and some periods of high volatility is said to exhibit volatility clustering; the error exhibits time-varying heteroscedasticity (unconditional standard deviation are not constant) in particular the tendency for changes in stock prices to be negatively correlated with changes in stock volatility; a phenomenon is known as the leverage effect which was first noted by Black (1976), who attributed asymmetry to leverage effect and price movement are negatively correlated with volatility. In this content negative shocks increase predictable volatility in asset more that positive shocks. In financial markets leverage effect is a stylized fact that a downward movement is always followed by higher volatility. Volatility is higher after negative shocks than positive shocks of the same magnitude.

The modelling and forecasting of exchange rates and their volatility has important implications for many issues in economics and financial market. Volatility needs monitoring and presents a major risk to investors and policy makers. Many models have been applied in modelling the volatility of exchange rates in various countries and has been found that different models fit different data. In this study, we modelled the volatility of log-return on Kshs against US Dollar, Euro and Sterling Pound using data from CBK. The exchange rate volatility has implications for many issues in the arena of finance and economics. Such issues included impact of foreign exchange rate volatility on derivative pricing, global trade partners, countries balance of trade position, government policy making decisions and international capital budgeting.

Exchange Rate Policy in Kenya

The exchange rate is determined by the level of supply and demands on the international markets. Foreign exchange market rate changes, is difficult to understand and predict because the market is very volatile and large. The evolution of Kenya's foreign exchange rate policy over the past three decades, a fixed exchange rate was maintained in the 1960's and 1970's with the currency becoming overvalued, though not extremely so as most studies have shown. Exchange rate controls were maintained from the early 1970s. The basic motive behind the foreign exchange controls stemmed from the balance of payment crisis of 1971/72 in order to conserve foreign exchange and control pressure on the balance of payments. Other controls and domestic credit, interest rates, imports and domestic prices were instituted. Though the controls provided an easy response to certain balance of payments and inflationary pressure, it created major distortions in the economy that were not evident until early 1980s. The historical policy regime shifts of exchange rate can be divided in two phases; the fixed exchange rate period before 1982 and the flexible exchange rate after 1982.

The flexibility period is the most interesting for analysis, with growing peg up to 1990 and dual and floating rates in the 1990s. The growing peg mostly associated with inflationary accommodation did not however, lead to a higher inflation rate than the fixed period. But a floating rate in 1993 led to an explosive inflation rate and a huge response on interest rates. The floating exchange rate system adopted in 1990s was expected to allow a more continuous adjustment of the exchange rate to shifts in the demand for and supply of foreign exchange. It would also lead to equilibrating the demand for supply of foreign exchange by changing the normal exchange rate rather than the level of reserving; thus allowing Kenya the freedom to pursue its own monitory policy without having to be concerned about balance of payment effects. The CBK through its monitory policy committee reviews and fixes the central bank rate. The rates are applicable when carrying out overnight lending to and amongst banks. In the open market operations, buying and selling on treasuries impact on central bank rates. CBK controls the money base that is, the amount in circulation as well as commercial banks deposits, it holds by exchanging treasury bonds in open market.

Exchange Rate Volatility

From many studies done by different researchers, exchange rate volatility is defined as the measure of the fluctuations in exchange rate. It can be measured over time that is, on hourly, daily, monthly or annual basis. Since volatility of financial returns evolves over time, it provides ideas of how much the exchange rate can change within a given period. In Kenya, the Kshs has been a free fall since the start of the year 2011. Kshs lost 26% (percent) from Kshs 80.80 to the US Dollar on January 3rd, 2011, to a mean rate of Kshs 102 to the US Dollar on September 26th, 2011.

The exchange rate of Kshs. between 2003 and 2010 averaged at about 74-78 to the US Dollar. Historically, from 1993 until 2012 the US Dollar/Kshs exchange averaged 78.72 reaching an historical high of 106.85 in October 2011 and a record low of 36.23 in the January of 1993. The prevailing rate as at July 2018 is 103. Various governments have resorted to different national policies and strategies to mitigate the effects of volatility crisis.

STATEMENT OF THE PROBLEM

Currency exchange rate volatility is very important factor involved in the decision making of the investors and policy makers. In real life, financial data for instance currency exchange rate data, variance changes with time (a phenomenon defined as heteroscedasticity) which is due to the supply and demand of exchange rate resulting to fluctuation of returns, hence there is need of coming up with a model that can accommodate this possible variation in variance. Many researches have been done to model the volatility of currency exchange rate, and has been found out that different models fit different data. In this study we modelled the volatility of log-return on Kshs against US Dollar, Euro and sterling pound using data from CBK.

Exchange rate volatility affects policy makers as well as investors hence the need to study volatility which can aid in financial decision making. These kinds of fluctuations present real dangers to economic stability. A weak shilling makes Kenyan goods and services cheaper in the international market but makes imports more expensive so exporters benefit while importers lose. Conversely, a strong shilling makes Kenyan goods and services expensive in the international market and makes imports more affordable. Volatility thus brings about questioning of the stability of financial markets. Depending on the direction a government wants its economy to make, they may create monetary policies that either appreciate or depreciate their currency. Policy makers essentially rely on volatility estimations so as to enable them make decisions on what direction the currency should take.

In the Kenyan Market, Maana et al.(2010) and Latifa et al. (2013) concluded that the GARCH(1,1) model was sufficient for estimation of volatility in various currency exchange rates, the KES/USD being one of them. GARCH (1,1) is normally applied with the normal distribution. This model however, can only capture some of the skewness and fat tails in financial time series. Also financial time series tend to exhibit non-normality hence the need to explore other conditional distributional forms for the error term that can better capture the characteristics of the data. The study thus attempts to model the volatility behaviour of KES/USD exchange rates which is crucial to diverse groups of people such as governments, importers, exporters, corporate decision makers and investors.

Objectives of the study

1. To specify a volatility model for exchange rate.
2. To determine risk measure associated with the volatility.
3. To predict the volatility of forex exchange.

II. Review Of Literature

Bollerslev (1986) acknowledges the usefulness of the ARCH process in modelling several different economic phenomena. However, he noted in most of those applications, the introduction of a rather arbitrary linear declining lag structure in the conditional variance equation to take account of the long memory typically found in empirical work because estimation of a totally free lag distribution often would lead to violation of the non-negativity constraints. He then came up with GARCH, a more general class of processes which allowed for a more flexible lag structure which also permitted a more parsimonious description. In empirical applications of the ARCH model, a relatively long lag in the conditional variance equation is often required and to avoid problems with negative variance parameter estimates a fixed lag structure is typically imposed. This led to an interest in the extension of the ARCH class of models to allow for both a longer memory and a more flexible lag structure. The GARCH (p, q) process is then described followed by the simplest in this class, the GARCH (1, 1).

The usefulness of the autocorrelation and partial autocorrelation functions in identifying and checking time series behaviour in the conditional variance equation of the GARCH is shown. He also considers maximum likelihood estimation of the GARCH regression which different from Engle (1982) because of the inclusion of the recursive part. The maximum likelihood estimate is found to be strongly consistent and asymptotically normal. He also found that a general test for GARCH (p, q) is not feasible as in Godfrey (1978). Bollerslev (1986) then used the GARCH process to model the uncertainty of in fluctuation, an unobservable economic variable of major importance. He proceeded to explain the rate of growth in the implicit GNP deflator in the US in terms of its own past. The model was estimated on quarterly data, a total of 143 observations, using ordinary least squares. The model was found to be stationary and none of the first ten autocorrelations or partial autocorrelations for $_t$were significant at 5% level. Findings showed that the GARCH (1, 1) model provided a slightly better t than the ARCH (8) model in Engle and Kraft (1983) as well as exhibiting a more reasonable lag structure.

Engle (1982) noted that for conventional econometric models, the conditional variance did not depend upon its own past. He thus proposed the ARCH model which was able to capture the idea that today's variance does depend on its past as well as the non-constant nature of the one period forecast variance. He then went ahead to define the likelihood function for the ARCH processes as well as a formulation for the general ARCH process. He also found that the parameter had to satisfy the non-negativity constraints as well as some stationary conditions. Finally, he used the ARCH model to estimate the means and variances of inflation in the UK.Latifa et al. (2013) model heteroscedasticity in foreign exchange for US, UK, Euro and Japanese Yen data using GARCH models. Monthly averages for the various currency exchange rates were collected for the period from January 2001 to December 2010, a total of 120 observations per foreign currency. The period was chosen because of the two major milestones that the country underwent i. e. Election period followed by the post-election violence in 2007/2008. Their major aim is to study how these events affected the performance of the afore mentioned currencies.

Their findings show uncertainty of exchange rates between 2001 to 2005 , gaining relative stability up to 2008 where the shilling became weaker against the foreign currencies due to post election violence. They noted that the Kenyan economy undergoes a cycle of about five years approximately, from one election period to the next. The GARCH (1,1) model was found to be adequate, thus confirming the work of Bollerslev (1992). They recommended further research on whether Non-linear (N-GARCH) can be appropriate for modelling this kind of data.

Rotich (2014) models USDKES,EURKES and GBPKES exchange rate volatility using the EGARCH model under the assumption of both normal and student-t distribution for comparison purposes. He notes that the student-t EGARCH is more favourable compared to the normal distribution because of evidence of the heavy tailed nature of financial time series. According to him, the normal GARCH model could neither explain the entire fat tail nature of the data nor could it explain the asymmetric responses. He then goes ahead to describe the EGARCH model as well as to give a specification of the two error distributions i. e. normal and student-t.

From his results, the series showed volatility characteristics of returns, non-normality of the return series and presence of ARCH effects. There was also evidence of leverage effects whereby good news produced more volatility than bad news. The GBPKES and the EURKES were both fitted by an EGARCH (1,1) model while USDKES will be fitted by an AR(1)/EGARCH(1,1) with $_t$ t(0; 1;)

The rate of returns was employed to study the currency exchange rate. From the ADF and PP tests, the exchange rates were found to contain a unit root (non-stationarity). For the normality test, the Jacque Bera test showed that the exchange rate returns series departed from normality. From their summary statistics of exchange rate returns, Naira/USD is leptokurtic and negatively skewed with relative to normal distribution while Naira/UK pound sterling is platykurtic and positively skewed. They established the presence of persistent volatility in return series and suggested that the persistence could be due to the import dependence, inadequate supply of foreign exchange by the Central bank of Nigeria and activities of foreign dealers and parallel market. They suggested that further studies should be done using higher frequency data and other different volatility models and that the impact of government intervention should also be investigated.

Baba Insah (2013) in his paper, investigates the presence and nature of real exchange rate volatility in the Ghanaian economy propelled by the fact that over the years there have been intermittent spikes in volatility which indicated that Ghana's international competitiveness had deteriorated over the period of the study. The exchange rates considered in the study is the log of the real effective exchange rate. The Breusch-Pagan test was used to test for the presence of ARCH (1) effects. As much as ARCH effects were detected using the Breusch-Pagan test, the ARCH model was found not to fit the estimation. However, GARCH (1, 1) model was found to perform well in the modelling of exchange rates. Switch of regime from fixed to floating caused a spike in volatility from 1983 to 1986 but was more minimal between 2001 and 2010.

Abdalla (2011) used daily observations from 19 Arab countries and considered the GARCH approach in modelling exchange rates. Observations in the period 1st January 2000 to 19th November 2011, a total of 4341, were used. The LM test was used to test for heteroscedasticity. GARCH model was then used to investigate the volatility clustering and persistence. The model had only three parameters that allowed for an in finite number of squared errors to influence the current conditional variance (volatility). EGARCH (1, 1) was used to capture leverage effects as GARCH models are poor in capturing these effects.

GARCH (1, 1), TARCH (1, 1) and EGARCH (1, 1) model specifications are used as they sufficiently capture exchange rate behaviour. EGARCH model was used because it allows for oscillatory behaviours of the variance and requires no parameter restriction of non-negativity of coefficients like GARCH as it is modelled in log-linear form. The model also captures leverage effect. Non-normality of the exchange rate returns was confirmed by skewness, kurtosis and J-B statistics. Volatility clustering was also visible. The ADF and PP unit root tests conform non-stationarity of the data.

GARCH model results were robust based on diagnostic tests on residuals that show the absence of serial correlation and no remaining ARCH effects. The TGARCH model on the other hand revealed an asymmetry term that was insignificant at all conventional significance levels suggesting no detectable asymmetry in all exchange rate series except Kwacha/Swiss franc. This evidence of asymmetry suggested that the symmetry imposed by the GARCH (1, 1) model was restrictive. From the results, conditional velocity differed across kwacha exchange rates examined. It can be inferred that, "exchange rates are characterized by different conditional volatility such that imposing a uniform GARCH model specification on all exchange rates may be inappropriate". PCA deals with the variance structure of a set of observed variables through a linear combination of the variables (components). It was conducted on 39 conditional variances generated from GARCH and EGARCH models, split into real and nominal measures. The correlation coefficients indicated very close relationships among conditional volatility in exchange rates with the pattern observed with the Zimbabwe dollar being the only exception. There was evidence in support of EGARCH model as the best fitting model and emphasis was made on the importance of testing the appropriateness of the model specifications as opposed to imposing a uniform GARCH model.

Statistical performance measures were calculated to identify the best model in the case of in-sample as well as the out of sample case. The lower the values of RMSE, MAE, MAPE and theil-u, the better the forecasting accuracy of the given model. The trading performance measures such as annualized return, annualized volatility, information ratio and maximum drawdown are used to select the best model. Their findings reveal that ARMA and AR are selected as the best model as per in-sample trading performance outcomes whereas TARCH model is nominated as the best model according to out-of-sample trading performance outcomes without transaction costs. (GARCH model in the case of transaction costs).

Maana et al. (2010) applied the GARCH process in the estimation of volatility of the foreign exchange market in Kenya using daily exchange rates data from January 1993 to December 2006. Currencies used were USD, sterling pound, Euro and Japanese Yen. Data used was obtained from the CBK database and to estimate volatility in exchange rates, logarithm rates returns were used. From the descriptive statistics for exchange rate returns, skewness coefficients were greater than zero indicating that the exchange returns distributions are not normal. The positive skewness coefficients indicate that the distribution of the returns is slightly right skewed implying that depreciation in the exchange rate occur slightly more than appreciation.

Dukich et al (2010) assess the adequacy of GARCH models by considering three exchange rate sequences JPY, Euro, British pound and evaluating how well the GARCH model replicates the empirical nature ofthese sequences. Their period of observation was January 4, 1999 to January 4, 2010 with over 2700 trading days. They assessed the assumptions fitting the GARCH model before fitting the model for each of the LPR sequences. Their tests showed that the GARCH model was suitable for fitting this data. Three GARCH models were then fitted: GARCH (1, 1), GARCH (1, 2), GARCH (2, 1). Much as assumptions underlying the GARCH models were satisfied for each of the LPR sequences, none of the GARCH models considered was able to capture the empirical nature of the LPR sequences appropriately. They suggested use of other varieties of GARCH family models to better capture the properties of the LPR series.Baba Insah (2013) investigated the presence and nature of real exchange rate volatility in the Ghanaian economy. His findings show that GARCH (1, 1) was the right model for modelling exchange rate volatility in Ghana. He started by testing for the presence of ARCH (1) effects using a Breusch-Pagan test. As much as there was evidence of ARCH effects, the ARCH (1) model was not suitable. GARCH (1, 1) on the other hand performed well in modelling the exchange rate volatility.

Zhou (2009) looks at the stylized facts as well as the time varying volatility of S & P 500 stock index. A comparison is made between the ARMA (0,2)/APARCH (1,1) model with the normal, student-t and skew-t distribution. Asset returns exhibit fat tails as well as asymmetry. Zhou(2009) uses a skewed-t distribution which is able to capture leptokurtosis of asset returns and then models the asymmetry in the conditional variance equation as a non-linear GARCH model i.e. the ARMA(0,2)/APARCH (1,1) model with non-gaussian errors. He gives a brief description of the normal, student-t and skewed-t distribution density functions as well as their log-likelihood function which together with AIC and BIC criterions are used to determine the best fitting distribution. The JB test rejected the null hypothesis of normal distribution. To test for stationarity, the ADF and PP tests are used. The transformed return series is found to be stationary. The ACF of the observations and the squared observations show some relevant autocorrelation so an ARMA (p,q) model is used to t the asset returns. His conclusion is that the ARMA (0,2)-APARCH (1,1) with skew-t distribution is the best fitted model to use for the conditional heteroscedasticity and this is then used to forecast.

Adedayo et al. (2013) use the student-t and GED distribution to model the innovations of the Naira-USD exchange rate. They looked at studies carried out on the Naira exchange rate series such as those by (Olowe, 2009) and (Ezike and Amah, 2011). Some of the shortcomings they saw are that the authors considered monthly data in their investigations and based on this, the series' characteristics were not well captured. Also, the studies only considered one or two exchange rates out of many. Other than that, the studies assumed a normal distribution and did not look at different distributional forms. Lastly, they felt that due to the volatility and asymmetry in exchange rate series, daily data should have been applied to examine these properties.

III. METHODOLOGY

The behaviour of volatility of currency exchange rate has captured the interest of past researchers. In this study modelled, the volatility of the log-return on currency exchange rate using the GARCH model. The data of the study consist of official daily currency rate between Kshs against US Dollar, Euro and sterling pound from CBK for the period of twenty five years, from 1st January 1997 to 1st June 2022.

The GARCH model have been suggested for capturing special features of financial data, and most of these models have property that the conditional variance depend on the past. The GARCH modelling considers the conditional error variance of a function of the past realization of the services. Campel at all (1997) argued that “it is both logically inconstant and statistically inefficient to use and model volatility measures that are based on the assumption of constant variance over some period when the resulting series progress through time. In this chapter we are going to discuss the volatility model and how to estimate the parameters of GARCH model using MLE and discuss how to use different plots of residuals that is, ACF plot, time series plots, normal plots and Histogram in model checking. Finally we will employ the Ljung BOX-Pierce Q-test for checking the adequacy of the GARCH (1, 1) model.

Volatility

Volatility refers to the spread of all likely outcomes of an uncertain variable. Typically, in Financial Markets, we are often concerned with the spread of asset returns.

Statistically, volatility is often measured as the sample standard deviation:

$$\sigma = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(r_t - \mu)^2}$$

Where σ is the standard deviation, r_t is the return on day t and μ is the average return over the T-day period. Volatility is related to, but not exactly the same as, whereas volatility as a measure strictly for uncertainty could be due to a positive outcome Poon (2005).

Volatility Model

In financial markets, fluctuation of prices (or returns) goes under the name of volatility- how much prices (or returns) are changing over a given period. Linear models are unable to explain a number of important features common to much financial data, including leptokurtosis, volatility clustering, long memory, volatility smile and leverage effects. That is, because the assumption of heteroscedasticity (or constant variance) is not appropriate when using financial data, and in such instances it is preferable to examine patterns that allow the variance to depend upon its history. The GARCH model, as developed by Bollerslev (1986), is an extension of the ARCH model similar to the extension of an AR process to ARMA process. When modelling using ARCH model, here might be a need for a large value of the lag, hence a large number of parameters. This may result in a model with a large number of parameters, violating the principle of parsimony and this present difficulties when using the model to adequately describe the data. An ARMA process may have fewer parameters as compared to an ARCH model, and thus a GARCH model may be preferred to an ARCH model. There are variety of extensions of the ARCH family of models that include the EGARCH, the IGARCH by Amos (2009) which are not discussed in this research study. To model the non-constant volatility parameter, we consider GARCH –type models. Bellerose (1986) proposed a GARCH (p,q) model, which can represent a greater degree of inertia in its parsimonious and give significant results.

The GARCH model is used in this research project to model the volatility of log-return on currency exchange rate. The model has only three parameters that allows for infinite number of squared errors to influence the current conditional variance (volatility). The conditional variance determined through GARCH model is a weighted average past squared residuals. However, the weights decline gradually but they never reach zero. Essentially, the GARCH model allows the conditional variance to be dependent upon the previous own lags. The general framework of this model, GARCH (p, q), is expressed by allowing the current conditional variance as well as the p past conditional variances as well as the q past squared innovations. We used GARCH model of different order that is, GARCH (1,1) for modelling volatility of log-returns on the currency exchange rate with data from CBK. For the log-return series $\{r_t\}$, let $Z_t = r_t$ of the GARCH (p, q) process

$Z_t = \sqrt{\sigma_t e_t}$

$Z_t^2 = \sigma_t e_t$

But

$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i Z_{t-i}^2 + \sum_{t=j}^{p} \beta_j \alpha_{t-j}^2$

For

$$i = 1,2,3 \ldots \ldots \ldots \ldots q$$
$$j = 1,2,3 \ldots \ldots \ldots \ldots p$$

Where α is the standard deviation, σ^2 is the variance, α_0 is constant, α_i andβ_j are weight given to Z^2 and σ^2 respectively.

The following conditions; $\alpha \geq 0, \alpha_i \geq 0$ and $\beta_j \geq 0$ are given in order for the variance to be positive (for stationarity) that is, for stable GARCH model, where p is the number of lagged σ_t^2 terms and q is the number of lagged Z_t^2 terms

Error,e_t, is assumed to be normally distributed with zero mean and conditional variance,

σ_t^2. All parameters in variance equation must be positive, and ($\alpha + \beta$)<1 implies that the unconditional variance is infinite, its conditional variance evolves over time and if ($\alpha + \beta) = 1$, then the process does not have infinite variance. GARCH $(p, q$)can be reduced to a pure ARCH (q) model if $p = 0$ which can be written as

$$\sigma_t^2 = \alpha_0 + \sum_{t=j}^{p} \beta_j \sigma_{t-j}^2$$

Where α_0 is constant and β_j is weight given to σ^2 for $j = 1,2,3 \ldots \ldots \ldots .. p$

Therefore from GARCH (1,1), α_i and β_i are referred to as ARCH and GARCH parameters respectively.

The strength and weakness of GARCH model can easily be studied by focussing on the simplest GARCH (1,1) model with

$$\alpha_t^2 = \alpha_0 + \alpha_1 Z_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$
$$0 \leq \alpha_1, \beta_1 \leq 1, (\alpha_1 + \beta_1) < 1$$

A large Z_{t-1}^2 or σ_{t-1}^2 gives rise to large σ_t^2 which means that a large Z_{t-1}^2 tends to be followed by another large Z_t^2 generating again the well known behaviour of volatility clustering in financial time series. The tail distribution of GARCH (1,1) process is heavier than that of normal distribution .The model provides a simple parametric function that can be used to describe the volatility evolution.

Model Identification

When modelling volatility we first require the mean equation. The following models are used in developing the mean equation.

AR (p) Model

An Autoregressive model models exchange rate returns as a function of past returns. An AR (p) model is defined as;

$$y_t = \mu + \sum_{i=1}^{p} \theta_i \, y_{t-i} + e_t$$

Where y_t is the exchange rate return at time t, y_{t-i} is the exchange rate return at time $t-i$, μ is the mean, θ_i is the weight and e_t is the error term. The PACF of the exchange rate series can be used to determine the order of the AR model as it cuts off at lag p. The AR model is estimated and fitted as the mean equation.

MA (q) Model

The Moving average model models exchange rate returns as a function of current and past residuals. An MA (q) model is defined as;

$$y_t = \mu + \sum_{j=1}^{q} \emptyset_j \, e_{t-j} + e_t$$

Where y_t is the exchange rate return at time$t$, μ is the mean, $\emptyset_j$ is the weight,e_t is the current error term ande_{t-j} is the past error terms. To determine the order of the MA model, the ACF is used as it cuts off at lag q. The model is estimated and fitted as the mean equation.

ARMA (p,q) Model

The ARMA model describes the current exchange rate return as function of past exchange rate returns, current and past residuals. This model is a combination of the AR (p) and MA (q) models. The model is defined as;

$$y_t = \mu + \sum_{i=1}^{p} \theta_i \, y_{t-i} + e_t + \sum_{j=1}^{q} \emptyset_j \, e_{t-j}$$

wherey_t is the exchange rate return at time t, y_{t-i} is the exchange rate return at time$t-i$, μ is the mean, θ_i and $\emptyset_j$ are weights and e_t is the error term at time t, ande_{t-j} is the past error terms. The conditional variance is then modelled if there is the presence of ARCH effects in the residuals of the mean equation.

GARCH Model

During modelling the volatility of currency exchange rate using GARCH (p, q) model, the main challenge is to select a suitable model's order. Model identification provides useful tools and in this regard. The project will assess whether the fitted model offers an optional balance between goodness-of-fit and parsimony. By inspecting the ACF of the suitability difference time series, the project will identify whether the order of GARCH model gives the best model to model currency exchange data.

The task of the project will be to reduce non-stationary series into stationary series of the GARCH model. By inspecting the ACF of the suitably difference time series. The project will be able to select a tentative model. Non stationary is often indicated by ACF plot with very slow decay that is, the tendency for the ACF, the project will be able to choose the order of and of the GARCH (p, q). The order of the given models will be chosen based on ACF plots where when most of the correlation are outside the boundary ;indicates non stationary , and when all the correlation are within the required boundary, it indicates stationary hence gives room for selecting the required order.

Alternative approach to model selection will be the use Akaike information criterion (AIC) by Hirotogu Akaike (1974) on an extension of the maximum likelihood method in its estimation. Bayesian Information Criterion (BIC) or Schwarz criterion (also SBC, SBIC)is a criterion for model selection among a finite set of models. It is based, in part, on the likelihood function and it is closely related to the Akaike Information Criterion (AIC). When fitting models, it is possible to increase the likelihood by adding parameters, but doing so many results in over fitting. Both AIC and BIC resolve this problem by introducing a penalty term for the number of parameters in the model; the penalty term is larger in BIC than in AIC. The BIC is an asymptotic result derived under the assumption that the data distribution is in the exponential family. If we let:

$x =$The observed data

$n =$ The number of data points in, the number of observations, or equivalently, the sample size

$k =$ The number of free parameters to be estimated, if the model under consideration is a linear regression, is the number of regressors, including the intercept;
$p(x|M) =$ the marginal likelihood of the observed data given the model; that is, the integral of the likelihood function $p(x|\theta, M)$ times the prior probability distribution over the parameters of the model for fixed observed data; $L =$ the maximised value of the likelihood function of the model, that is, $L = p(x|\theta, M)$ where 0 are the parameter values that maximize the likelihood function.
The formula for the BIC is;

$$-2.\ln p(x|M)^{\sim} BIC = 2.\ln L + k.\ln(k)$$

Under the assumption that the model errors or disturbances are independent and identically distributed according to a normal distribution and that the boundary condition that the derivative of the log likelihood with respect to the true variance is zero, this becomes (up to an additive constant, which depends only on n and not on the model)
$BIC = n.\ln(\alpha_e^2) + K.\ln(n)$; where α_e^2 is the error variance which is defined as;

$$\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2$$

$$BIC \sim X^2 + k.\ln(k)$$

Given any two estimated models, the model with the lower value of BIC is the one to be preferred. The BIC is an increasing function of x and an increasing function of k. That is, unexplained variation in the dependent variable and the number of explanatory variables increases the value of BIC. Hence, lower BIC implies either fewer explanatory variables, better fit, or both. The BIC generally penalizes free parameters more strongly than does Akaike information criterion, though it depends on the size of n and relative magnitude of n and k. It is important to keep in mind that the BIC can be used to compare estimated models only when the numerical values of the dependent variables are identical for all estimates being compared.

Model Estimation

The estimation of GARCH model parameters in practise is not straightforward. Most of the implemented method for estimation of parameters includes;
Maximum Likelihood Estimation (MLE) but any other convenient one may be used that is, Quasi Maximum Likelihood Estimation among others. The main idea behind MLE is to find, for a given set of data and specified model estimation, data that is, the parameters that maximize the likelihood function provides efficient methods for quantifying uncertainty through confidence intervals. MLE is non-trivial in that the likelihood questions needed to be worked on specifically for the different type of distributions.

Estimation of GARCH (p,q) Model

Estimating the GARCH (p,q) model will be carried out using the MLE method. Assuming, that the returns $\left\{r_t = f(y_1, y_2, \dots, y_n|\underline{\alpha}) = \prod_{t=q+1}^{n} \frac{1}{\sqrt{2\pi\sigma_t^2}} exp\left(-\frac{y_t^2}{2\sigma_t^2}\right) \times f(y_1, \dots, y_q|\underline{\alpha})\right\}$
let$r_t = Z_t$ and is a conditionally normally distributed, then we have

$$p(Z_t|F_{t-1}) = \frac{1}{\sqrt{2\pi\sigma_t}} exp\left\{\frac{-1}{2\sigma^2} Z_t^2\right\}$$

Where F_{t-1} is the sigma algebra containing the past information of Z_t and σ_t up to time $t-1$ and for Z_t^2, mentioned in equation 3 and σ_t^2 mentioned in equation 4
By considering GARCH(1,1) referred in equation (3.2.6). The task was to look for the log likelihood function $L(\alpha_0, \alpha_1, \beta_1)$by writing as a function of parameters $\alpha_0, \alpha_1, \beta_1$ as follows,

$$L(\alpha_0, \alpha_1, \beta_1) = \sum_{t=2}^{n} \alpha_t^2(\alpha_0, \alpha_1, \beta_1) + \log P_z(Z_1)$$

$$= \sum_{t=2}^{n} \log p(Z_t/F_{t-1}) + \log P_z(Z_1)$$

$$= \frac{-(n-1)}{2}\log(2\pi) - \frac{1}{2}\sum_{t=2}^{n}\log\sigma_t^2 - \frac{1}{2}\sum_{t=2}^{n}\frac{Z_t^2}{\sigma_t^2} + \log(Z_1) \qquad (3.2.10)$$

Where P_z is the stationary marginal density of Z_t. A problem is that the analytical expression of P_z which is known in GARCH models and the above equation (3.2.10) likelihood function cannot be optimized. In conditional likelihood function

$$L^b(\alpha_0, \alpha_1, \beta_1) = \log P(Z_1, \dots \dots ., Z_n|Z_1)$$

The expression $\log P_z(Z_1)$ disappears (if it's conditional)

$$L^b(\alpha_0, \alpha_1, \beta_1) = \sum_{t=2}^{n} \sigma_t^2(\alpha_0, \alpha_1, \beta_1)$$

$$\sum_{t=2}^{n} \log(p_z)|F_{t-1} = \frac{(n-1)}{2}\log(2\pi) - \frac{1}{2}\sum_{t=2}^{n} \sigma_t^2 - \frac{1}{2}\sum_{t=2}^{n} \frac{Z_t^2}{\sigma_t^2}$$

The parameter α_0 is chosen, so the unconditional variance is constant everywhere that is, with variance

$$\alpha_0 = \frac{\alpha^2}{\left(1 - \sum_{i=1}^{q} \alpha_i - \sum_{j=1}^{p} \beta_j\right)}$$

Solving for the parameters, we look for partial derivative of equation with respect to α_0, α_1 and β_1 respectively where and get;

$$\frac{\partial L^b(\alpha_0, \alpha_1, \beta_1)}{\partial \alpha_0} = -\frac{1}{2}\sum_{t=1}^{n} \frac{1}{\alpha_t^2} + \frac{1}{2}\sum_{t=1}^{n} \frac{Z_t^2}{\sigma_t^4}$$

$$\frac{\partial L^b(\alpha_0, \alpha_1, \beta_1)}{\partial \alpha_1} = -\frac{1}{2}\sum_{t=1}^{n} \frac{Z_{t-1}^2}{\alpha_t^2} + \frac{1}{2}\sum_{t=1}^{n} \frac{Z_t^2 Z_{t-1}^2}{\sigma_t^2}$$

$$\frac{\partial L^b(\alpha_0, \alpha_1, \beta_1)}{\partial \beta_1} = -\frac{1}{2}\sum_{t=1}^{n} \frac{\alpha_{t-1}^2}{\alpha_t^2} + \frac{1}{2}\sum_{t=1}^{n} \frac{\alpha_t^2 \alpha_{t-1}^2}{\sigma_t^4}$$

Recalling equation and equating equations, and to zero, we obtain the system of the three equations with the three unknowns. But since was constant we were interested in looking for parameters and which are solved from the derivative recursively.

When estimating GARCH (p,q) model using MLE, the initial values of both the squared returns and past conditional variances are needed in estimating the parameters of the model. Assuming $Z_1, \dots \dots Z_q, \sigma_{p+1}^2 \dots \dots .. \sigma_t^2$ are known, the conditional log likelihood is given by;

$L = \log f(Z_{q+1}, \dots \dots, Z_t, \sigma_{p+1}^2, \dots \dots \dots \sigma_t^2 / Q, Z_1, \dots \dots ., Z_q, \sigma_1^2, \dots \dots .. \sigma_p^2)$

$$= -\frac{1}{2}\sum_{t=m+1}^{T} \log(2\pi\sigma_t^2) - \frac{1}{2}\sum_{t=m+1}^{T} \left\{\frac{Z_t^2}{\sigma_t^2}\right\}$$

with

$$Q = (\sigma_{0'} \sigma_1 \dots \dots .. \sigma_{p'} \beta_1 \dots \dots \dots \beta_q)$$

and

$$m = \max(p, q)$$

Model Diagnostic

After applying, the GARCH models, the project will check the goodness-of –fit based on residuals and more specific on the standardised residuals Tackle (2003). The residuals are assumed to be independently and identically distributed following either normal or standardised t-distribution Tsayi (2002) andGourrieroux (2001). The checks validate the model assumptions of the model identification, checking whether the hypothesis made on the residuals is true. Residuals must satisfy the requirement of a white noise, zero plots of residuals will include the normal plot, ACF plots, time series plots and histogram. For a well fitted model, the histograms of the residuals should be approximately symmetric. The normal probability plot should be a straight line while the time plot should exhibit random variation. For ACF plots, all the correlation should be within the boundary which indicates stationarity in data. The ACF of the standardised residuals will be used to check the adequacy of the conditional variance model. The project will employ the Ljung- Box-Pierce-Q-Test for quantitative checks, to check for the adequacy of the GARCH (p,q) model.

Data acquisition

The research was based on the daily exchange rate between the Kenyan shilling (KES) and the united states dollar. The data was obtained from the yahoo finance database, which contains data from 1st December 2003 to 1st June 2022. The data, therefore, contains a total of 28968 trading days. The reason for this dataset selection is as follows. One to study the volatility of the kes-USD exchange rate before the emergence of the Covid 19, and two to study the impact of the covid 19 on the exchange rate volatility.

To fit the model, daily returns of the exchange rate are used, as shown in the equation below.

$$R_t = \frac{p_t}{p_{\{t-1\}}}$$

Where p_t is the daily exchange rate between the Kenyan shilling and U.S. dollars observed at the time t, p_{t-1} is the daily exchange rate observed at time t-1, and R_t is the resulting daily return.

IV. RESULTS AND DISCUSSIONS

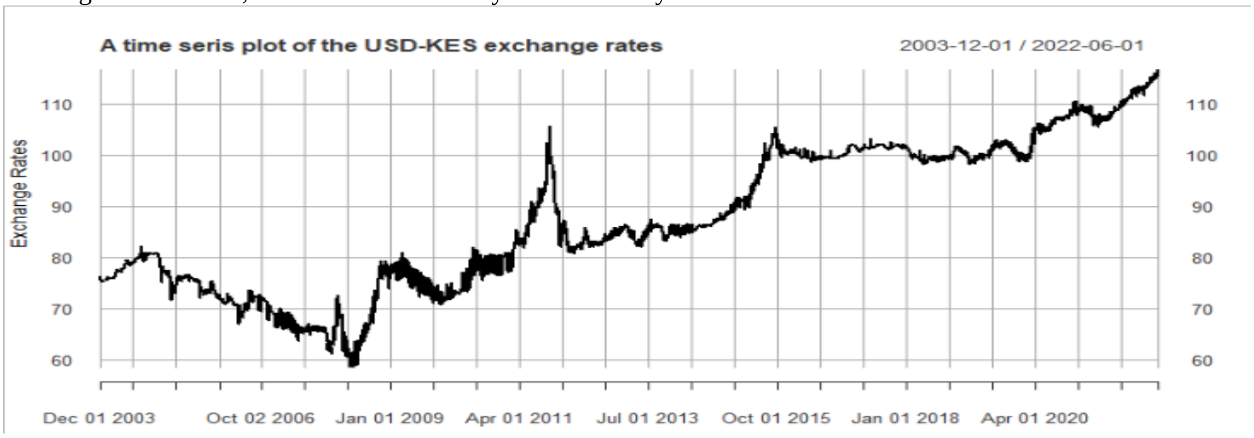
Exploration data analysis

The results in table 1 show that during the study focusing period, the average exchange rate was 87.68, while the minimum exchange rate was found to be 58.53, while the maximum was 116.70.

Table 4.1: The basic summary of the KES_USD exchange rates

Minimum	1st quantile	Mean	Median	3rd quantile	Maximum
58.6999	76.1399	87.6791	85.4089	100.3300	116.70

Besides, we would plot a time plot for the exchange rate. The result in figure 4 shows the upward trend in the exchange rate. Further, there seems to be no cyclic seasonality in the data.



A time series plot for the KES_USD exchange rate

The daily return

When estimating the volatility, it is advisable to use returns. Therefore, the current study utilizes the daily returns. The summary in Table 4.2 shows that, on average, the daily return was found to be 0.002, where the returns were found to range between -0.0021 to 0.0601.

Table 4.1 The descriptive summary for the daily returns

Minimum	1st quantile	Mean	Median	3rd quantile	Maximum
-0.0564	-0.0021	0.0002	0.0000	0.0021	0.0601

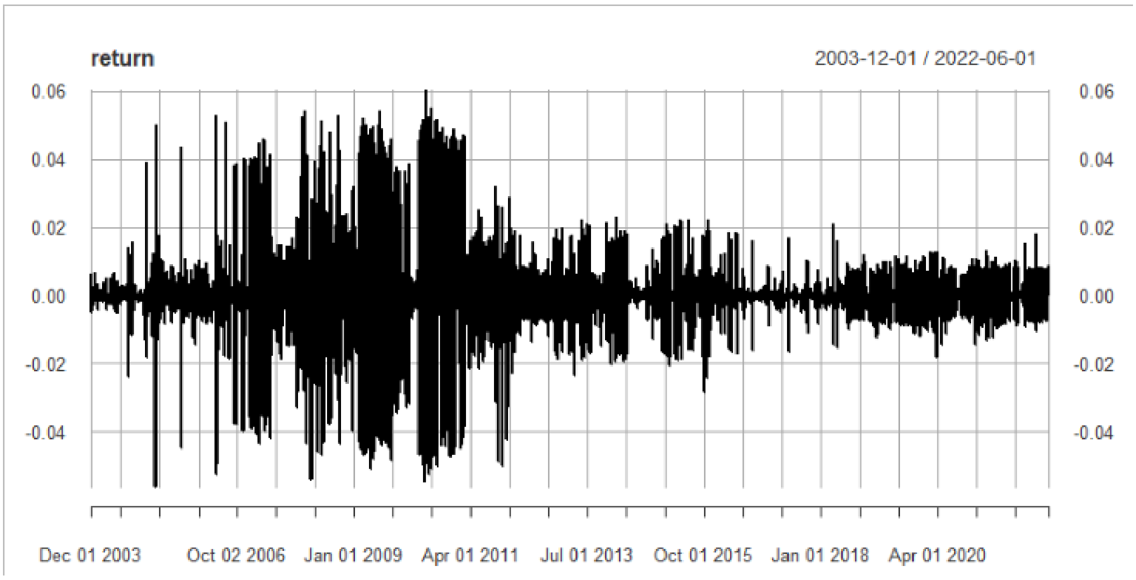


Figure 4.1 A time plot for the daily return

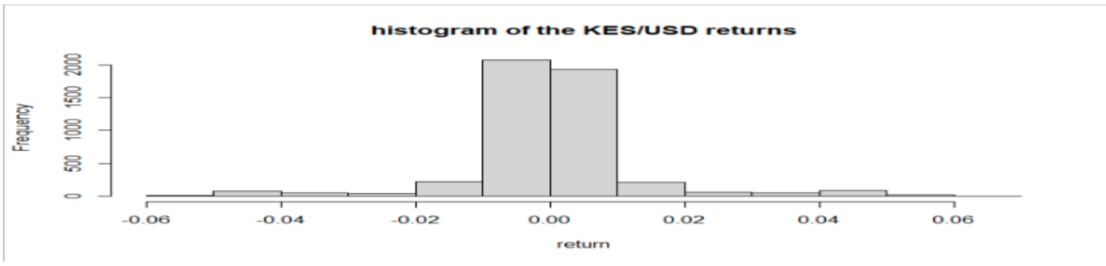


Figure 4.2 The histogram showing the distribution of the daily returns

The results in Figure 4.2 show high spikes 2005 and 2016, besides Figure 4.3 shows the return distribution.

The height of each bar represents the frequency in the number of days that a specific daily return range has happened. If the daily return behaves like a normal-distributed variable, then about 2.5% of the days the KES/USD returns would be less than its mean menu two times its standard deviation. Remember that for a normally distributed variable, in the range plus/minus two standard deviations from its mean, we will find about 95% of the values. Look at the real data and see how many days the KES/USD has offered returns less than 2 times its standard deviation (volatility) of daily returns. Then, identify how many days the KES/USD has offered extreme returns less than the mean minus two times its volatility. The mean of daily returns was given 0.0001627097 while the Standard deviation was 0.01235234

Extreme values of the return.
The sample days with the extreme values on the return

Date	Daily Returns
3/4/2005	-0.05637085
8/30/2005	-0.04496364
5/4/2006	-0.05255043
5/11/2006	-0.04918954
9/11/2006	-0.03792787
9/26/2006	-0.0377319

There are 157 extreme days with returns less than the 95% C.I. of daily returns. Then, we have had more extreme returns than expected; table 4.3 shows a sample of such days. This represents about 3.299706 % of the total number of days, greater than the expected 2.5%. Then, 3.299706% of the time, the S&P 500 has experienced a -2.454446% or MORE loss. If we believe that the KES/USD will behave similarly in the future, then we can say that there is a probability of 3.299706% that I can lose -2.454446% or MORE in only ONE DAY. We can also say that there is a probability of 96.700294% (100% - 3.299706%) that the MAXIMUM loss I can experience in ONE DAY is -2.454446%. Then, the 3.299706%VaR of the daily KES/USD returns is -2.454446%.

Expected Shortfall

Expected Shortfall with a probability prefers to the expected average loss of an investment in ONE period (in this case, in one day) once the probability p of a bad scenario happens. Then, the absolute value of p % VaR. Calculating the E.S. using the previous KES/USD daily returns example. To estimate the E.S. at the 3.299706% probability, having calculated the average of the days when the KES/USD returns have been less than -2.454446%. The Expected Shortfall at the 3.299706% probability is the average of this extreme return, at -4.021342.

Testing for the ARCH effect.

The ARCH effect assumes that the return variance is changing with time. Thus, in this case, the study seeks to test the hypothesis;

Null hypothesis: there is no ARCH effect in the squared return, against

Alternative: There is an ARCH effect in the squared return.

To test the hypothesis, the Box LJung test was conducted. The results yielded are $X^2 = 60155, df = 365, p-value < 0.001$. The results suggest evidence of the ARCH effect in the squared return. Thus, the autoregressive models can be used to analyze the volatility as follows.

Model specification and hyper parametric tuning

A total of 36 models were GARCH models were fitted. The parameters ranged from GARCH (1,1) to GARCH (6,6) inclusive. This seeks to determine the best parameters that soothe the sample data. The best model will be determined based on the Akaike information criteria AIC. The model with the least AIC was considered for the training and the prediction of the 120 ahead steps of the volatility. Table 4.4 shows the 36 fitted GARCH models and their respective AIC. Clearly, the results show that the GARCH (4, 5) results in the least AIC of -7.35124. Thus, the GARCH (4,5) is then trained using the data.

The summary of various GARCH(P,D) and their respective AIC

P\Q	[,1]	[,2]	[,3]	[,4]	[,5]	[,6]
[1,]	-7.31848	-7.32845	-7.344	-7.34595	-7.34986	-7.34912
[2,]	-7.31794	-7.32804	-7.34359	-7.34553	-7.35098	-7.35024
[3,]	-7.3174	-7.32749	-7.34317	-7.34511	-7.35057	-7.34982
[4,]	-7.32509	-7.32819	-7.3426	-7.345	-7.35124	-7.3505
[5,]	-7.32745	-7.32874	-7.34199	-7.34435	-7.35082	-7.35008
[6,]	-7.32783	-7.32837	-7.34133	-7.34369	-7.35008	-7.34967

Estimation of the GARCH model

A GARCH (4,5) is fitted for the data. The estimated GARCH parameters are shown in Table 4.5. the results show that the intercept mu is positive. This shows that the KES_USD exchange rate is likely to have a positive return. Of importance to the variance of the estimated model are the alpha and the beta values. As expected, the beta and alpha values sum is 0.9990, which is less than 1. Thus, the GARCH model has not failed. Thus, conditional probability cannot increase indefinitely, and unconditional volatility is positive. Considering the results in table 4.5, the average squared variance of the model was found to be 0.000002. Further, considering the significance of the parameters, only aplah3, beta 1,2, and 3 were found not to be significant in the estimation.

Table 4.2 The estimate of the GARCH model parameters

	Estimate	Std. Error	tvalue	Pr(>|t|)
Mu	0.000286	0.000072	3.9561	0.000076
Omega	0.000002	0.000001	2.2753	0.022888
alpha1	0.223704	0.016078	13.9133	0
alpha2	0.034958	0.014365	2.4336	0.014948

alpha3	0	0.012283	0	1
alpha4	0.030347	0.012517	2.4244	0.015333
beta1	0	0.042	0	1
beta2	0	0.038965	0	1
beta3	0	0.030203	0	1
beta4	0.101874	0.028619	3.5597	0.000371
beta5	0.608117	0.030201	20.1356	0

To compare the performance of the fitted model, a GARCH (4,5) was simulated using the estimated parameters. Figure 4.4 shows the density plot for the actual and simulated volatility. The result shows that the fitted volatility was heavily peaked compared to the simulated. Besides, the two sides were found to have long tails. The model was found to result in a MAPE of 3.096498.

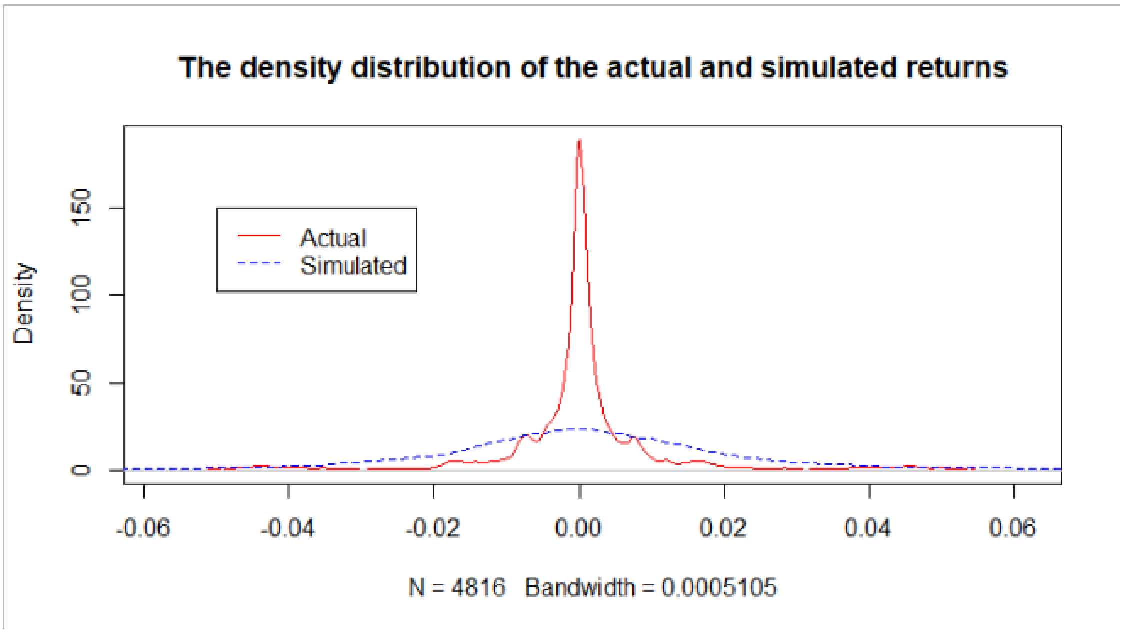


Figure 4.3 The density plot for the actual and simulated volatility

Residual analysis
Table 4.3 Q-Statistics on Standardized Residuals

	Statistic	p-value
Lag[1]	405.3	0
Lag[2*(p+q)+(p+q)-1][2]	407.4	0
Lag[4*(p+q)+(p+q)-1][5]	426.5	0

Table 4.7 Q-Statistics on Standardized Squared Residuals

	Statistic	p-value
Lag[1]	3.385	0.06578
Lag[2*(p+q)+(p+q)-1][26]	10.155	0.77292
Lag[4*(p+q)+(p+q)-1][44]	12.175	0.98576

The hypothesis to be tested is that there is no serial correlation on the model residuals. The results in table 4.6, the high p-values, lead us to accept the null hypothesis of no serial correlation. This further strengthens the observation of the ACF of squared standardized residuals in Figure 4.5.

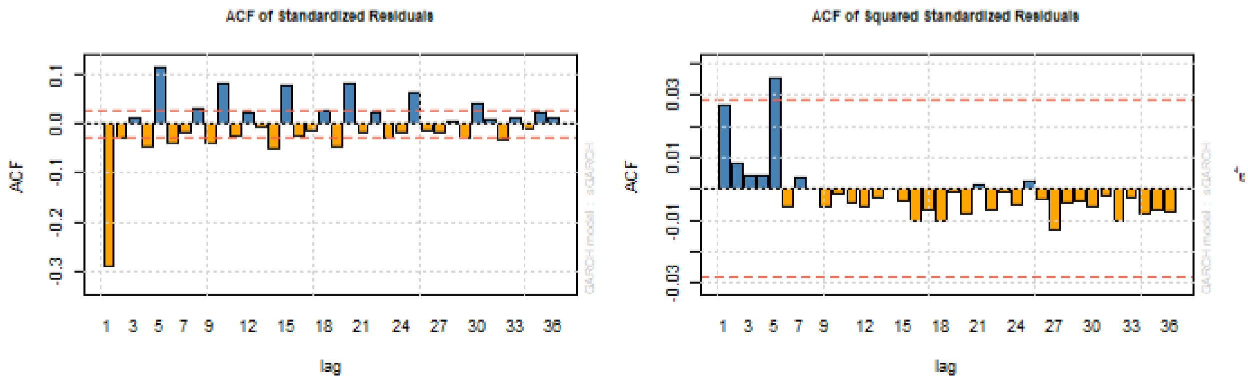


Figure 4.4 ACF of Standardized Residuals and Standardized Squared Residuals

Forecasting

Using the fitted GARCH (4,5), we forecast the 240-step volatility. Figure 4.6 shows the 240 ahead step forecasting of the volatility. It was observed that the forecast for the volatility experienced the seasonality up to July, whereas past that, the volatility is forecasted to have a constantan increase. The forecasted 95% value at risk for the next ten days is shown in Table 4.7.

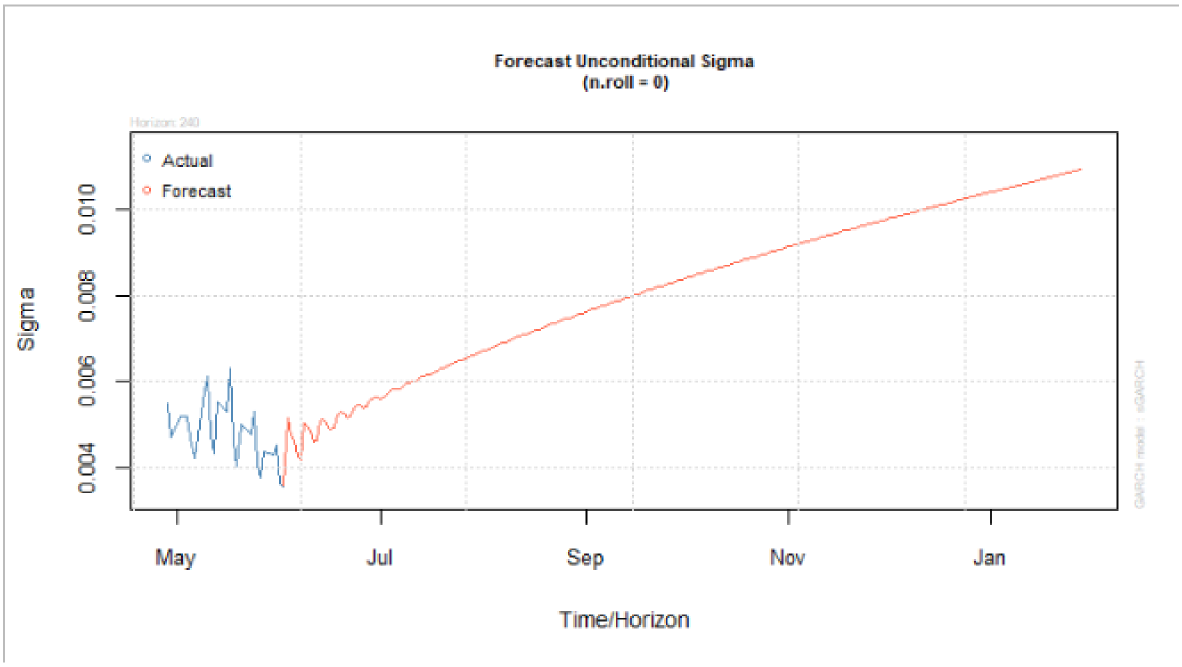


Figure4. 5 240 ahead step forecasting of the KES_USD volatility

Table 4 The forecasted ten days ahead Value at Risk (VaR).

	6/2/2022
T+1	-0.01178
T+2	-0.01088
T+3	-0.01059
T+4	-0.0097
T+5	-0.00957
T+6	-0.01152
T+7	-0.01134
T+8	-0.01109
T+9	-0.0105
T+10	-0.01054

4.4.1 Analysis of the volatility of four periods.
Further, the data was splinted into four groups; 2003-2008, 2009-2014, 2015-2019, 2019- 2022. Their respective time series and volatility plots are shown below.

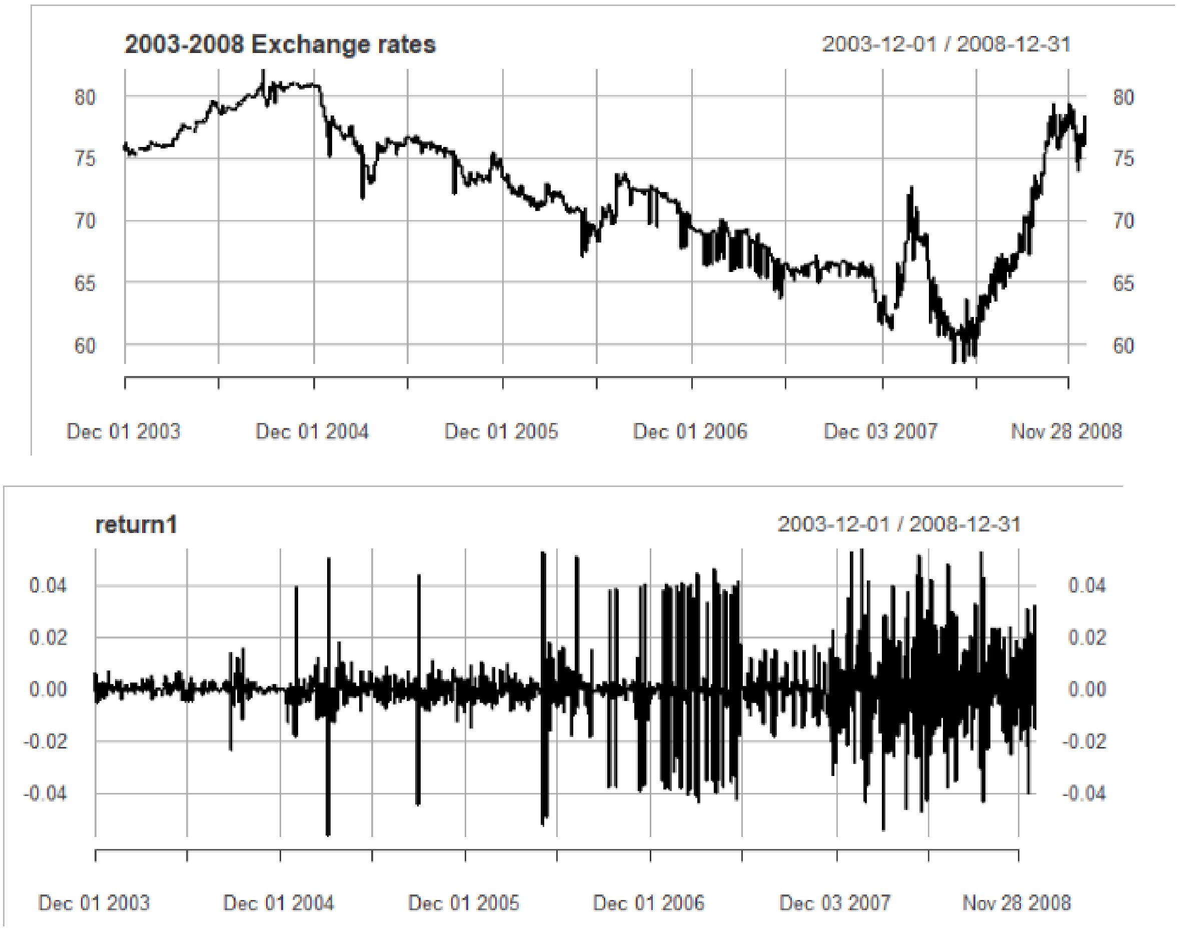
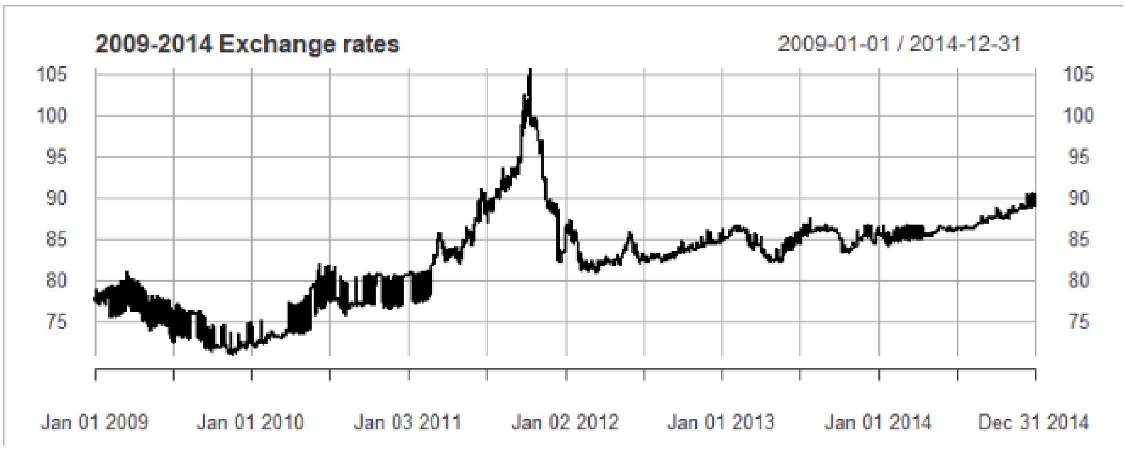


Figure 4.6 2003-2008

In the period 2003-2008, see figure 4.7, there were higher spikes in the exchange rate in mid-2007 and towards the end of 2008 compared to the other years.



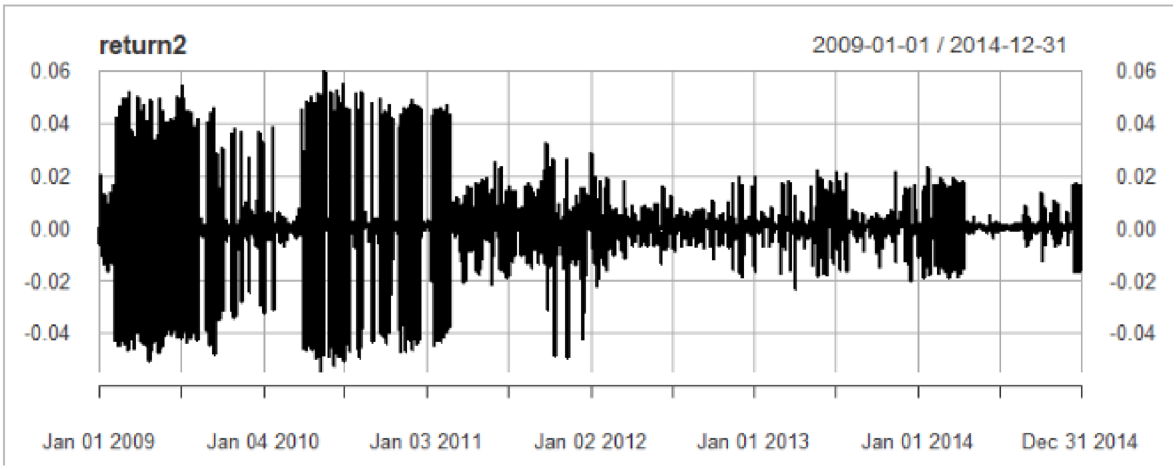


Figure 4. 7 2009-2014

There have been a high spike in 2009 and some part of 2020 and 2011 compared to the other years. See figure 4.8

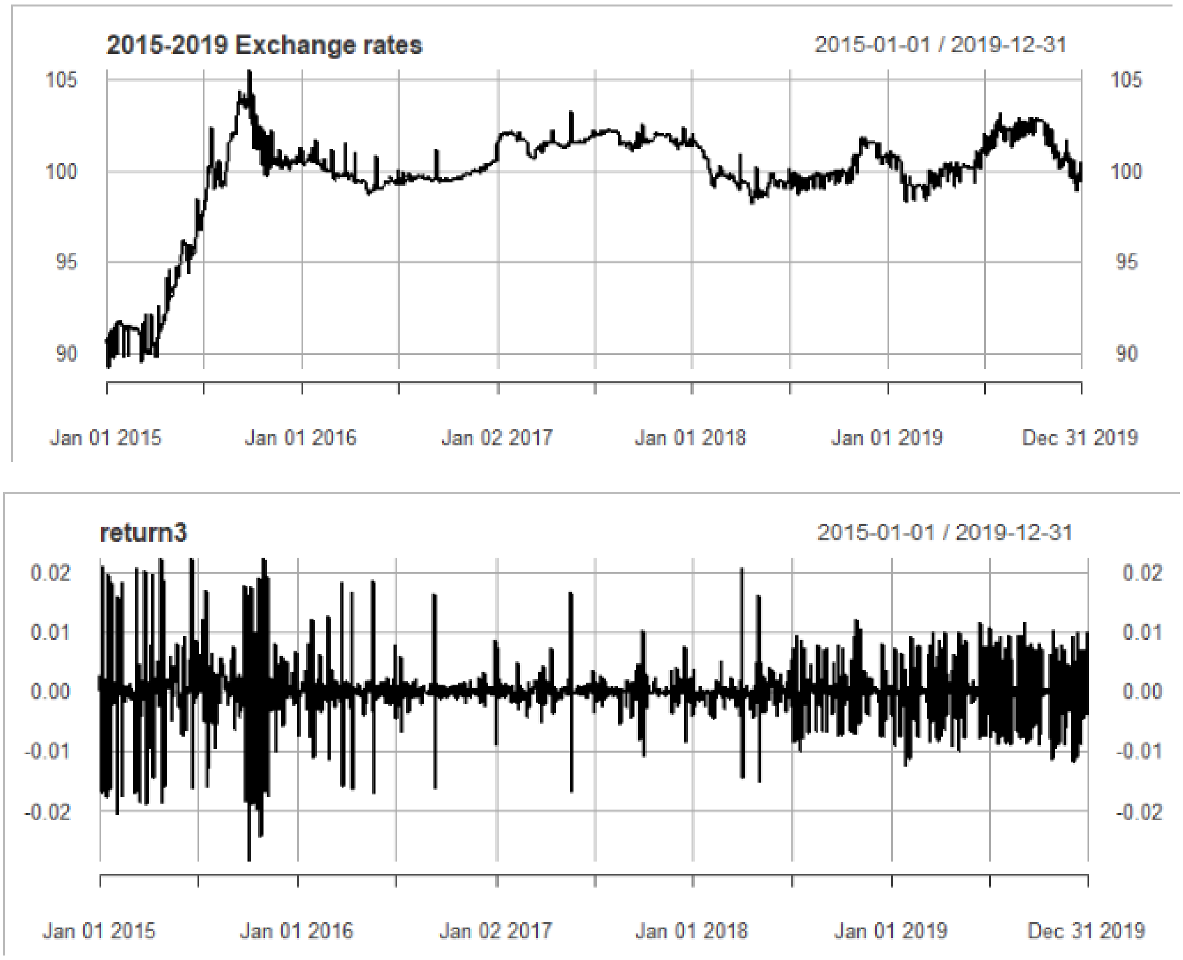


Figure 4.8 2015-2019

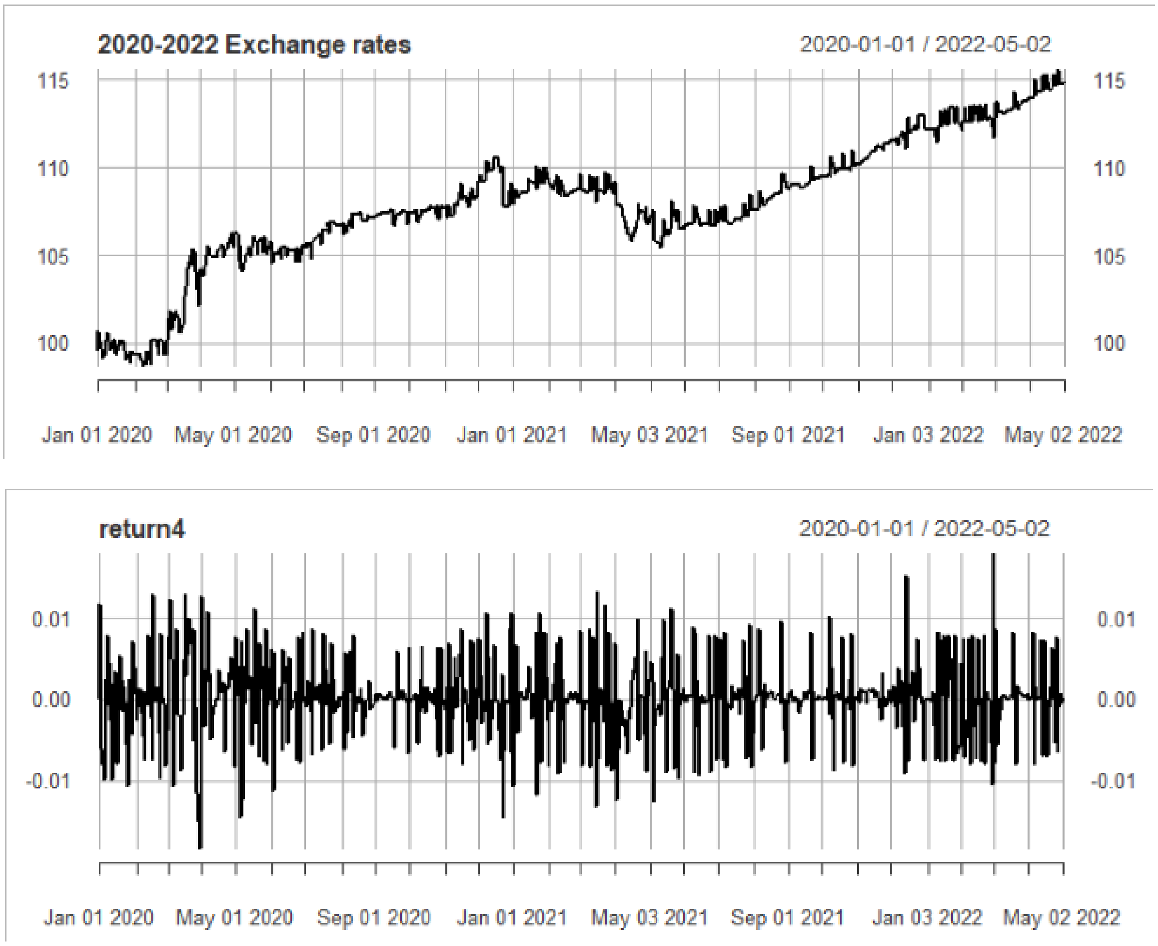


Figure 4.9 2020-2022

There have been high spikes in almost all the years from 2015-to 2019; see figure 4.9. Similarly, high spikes have been observed in all the 2020-2022 time periods see figure 4.10.

V. Discussion

The spikes and dips represent the KES/USD exchange rate return series volatility. An important observation is that the spikes in volatility are attributed to an appreciation of the KES against the USD. 1995 saw the dollar at the lowest rate ever attained. Mid 1997, when compared to the exchange rate, returns also show an appreciation of the currency.

The years 2000 and mid-2003 also show high spikes compared to the rest of the period. These also correspond to an appreciation of the KES. The year 2000 marked the crossing over into a new millennium, negatively affecting many currencies. Yet, for the KES, the beginning of that year saw a steady appreciation of the currency.

The period 2005-2009 had erratic spikes clustered towards the end of 2007 up to a few months into 2008 where it reached its highest at 73, followed by persistence in the volatility. After that, it started to appreciate a low of around 63, where we see a single outstanding volatility spike. In that period in Kenya, the significant occurrence was the elections in December of 2007, culminating in post-election violence that spilled over to the beginning of 2008. It can be observed from the exchange rate returns that the exchange rate had well appreciated before the elections and hence the onset of the volatility spikes; this persists for a while as the exchange rate begins to appreciate but then dies down. CBK attributed the KES/USD exchange rate depreciation to increased demand for the dollar-driven by expectations of increased importation of maize. (Kenya Monthly Economic Review, December 2008)

In 2010-2014 another significant occurrence in the Kenyan economy was the greatest depreciation the currency has ever faced. The KES/USD exchange rates went as high as 105 in October, which saw the Central bank of Kenya increase lending rates to curb the runaway inflation. The difference with this volatility spike is that it occurred after the depreciation of the KES, contrary to the spikes in the other periods which occurred after a currency appreciation. This could easily be explained by the fact that in 148 days, i.e., from 07/06/2011 to

27/10/2011, the exchange rate ranged from 86-to 105 and then back to 100, which brought about the high fluctuation.

Towards the end of 2011, another notable spike is associated with a currency appreciation. When the KES/USD exchange rate hit the all-time high of 105, no significant volatility spikes were observed, but when the exchange rate started coming down, a significant spike was observed just at the beginning of 2012. In 2011 remarkable event in the Kenyan economy was the shilling crash. The CBK attributed the exchange rate appreciation to "tightening of Monetary Policy stance in November 2011 through June 2012 to reduce inflationary expectations and exchange rate volatility".(Kenya Monthly Economic Review, December 2012).In conclusion, the KES_USD exchange rate volatility has been shown to rates occur before and just before the currency's appreciation.

VI. Conclusions And Recommendations

Conclusions

Information on volatility of exchange rates is crucial to various groups such as importers, exporters, investors, policy makers, Governments etc. There is thus need to build models that can then be used for simulation and possibly forecasting. Stylized facts about financial time series such as volatility clustering and persistence were observed. Normality assumption was rejected in the original exchange rates data as well as in the residuals of the fitted model. This was inferred from the QQ-plots, histogram, JB statistic as well as the skewness and kurtosis coefficients. The chosen model with the skewed student-t distribution was better suited to accommodate the skewness and kurtosis in the exchange rates return series.This study opted for lower specifications of the GARCH models in spite of existence of higher orders because empirical evidence shows that the lower specifications are able to sufficiently capture the characteristics of exchange rates while at the same time upholding the principle of parsimony (Kocenda and Valachy, 2016)

The test for existence of asymmetry in the KES/USD was compelled by recent empirical evidence of strong support for its existence in foreign exchange markets (Firdmuc & Horvath, 2017). The EGARCH model provides a better t than the GARCH model and its advantages over the GARCH model are that first, it can capture leverage effects and secondly, that there is no restriction that the parameters $\alpha_1$and β_1 must be positive. (Hansen and Lunde, 2015; Andersen, Bollerslev, Chou and Kroner, 1992) are of a different opinion; that foreign exchange returns usually exhibit symmetric volatility unlike equity markets. They say that past positive and negative shocks have the same effects on future volatility. Bollerslev, Chou and Kroner (1992) argue that, "Whereas stock returns have been found to exhibit some degree of asymmetry, the two sided nature of foreign exchange markets makes such asymmetries less likely."

The fact that $\gamma \neq 0$ leads us to conclude that the exchange rates return series exhibits some leverage effect. For the KES/USD, this value is positive meaning that a positive shock has more impact on exchange rate volatility than a negative shock. This is in contrast to the leverage effects results in the developed countries. The EGARCH model was able to capture this.

The data was further split into four sub periods and volatility in each period is examined separately. The periods are as follows:2003-2008, , 2015-2019, with 2261 observations, 2009-2014with 1827 observations, 2015-2019with 1826 observations and 2019- 2022with 1541 observations. Each of the four periods has an election year included. Spikes in volatility are observed at times when there is an appreciation of the KES/USD currency further confirming leverage effects.

Recommendation

1. In the future research a wider sample of exchange rates should be used to compare the performance of the most commonly used foreign currencies in the market and the inclusion of other asymmetric GARCH-type models, testing and comparing their predictive performance.
2. Use of Bayesian statistics in modelling exchange rate volatility.
3. A study with other asymmetric GARCH models.

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