Strathmore UNIVERSITY

MODELLING VOLATILITY IN THE CURRENCY USING STOCHASTIC MODELS (GARCH AND EGARCH)

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DECLARATION

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the Research Project contains no material previously published or written by another person except where due reference is made in the Research Project itself.

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Signature..

Date....10/02/2021..

This Research Project has been submitted for examination with my approval as the Supervisor.

Meleah Oleche

Signature..

Date....10/02/2021..

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Abbreviations

ACF	Autocorrelation Function
ADF	Augmented Dickey Fuller
AIC	Information Criterion
ARCH	Autoregressive Conditional Heteroskedastic
ARIMA	Autoregressive Integrated Moving Average
GARCH	Generalized Autoregressive Conditional Heteroskedastic
Ksh	Kenyan Shilling
USD	United States Dollar
US	United States
EGARCH	Exponential Generalized Autoregressive Conditional Heteroscedastic
USD/KSH	United States Dollar to Kenya shilling exchange rate
EGP	Egyptian pound
ZAR	South African rand
USD/ZAR	United States dollar to South African rand
USD/EGP	United States dollar to Egyptian pound exchange rate

Abstract

This study looks into modelling variations in the rate of exchange by utilizing stochastic models. To do this, there are two models we focused on. The two models that are utilized in this study are the GARCH model and the EGARCH model. First, we test for the presence of arch effects in order to know whether these models would be applicable in modelling the volatility of the exchange rates. In addition, for us to know which order of GARCH and EGARCH model to use, we compared the information criteria for the different order GARCH and EGARCH models and chose the one which had the smallest information criteria.

From the results we obtained by modelling volatility using both the GARCH and EGARCH models, we notice that the EGARCH model gives us superior results when compared to GARCH. This is because there is presence of asymmetric effects when modelling volatility of the exchange rates which is evident by the gamma coefficient being statistically significant. Hence, EGARCH is preferred when modelling volatility in the exchange rates of the currencies.

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CHAPTER ONE: INTRODUCTION

1.1 Background of the study

Issues that deal with exchange rate are of importance to researchers in modern economic theory. Exchange rate is of vital significance in the volume of trade and investment and its volatility decreases the volume of international trade as well as foreign investment. It is also viewed as a fundamental economic variable which is considered by investors of foreign currency, exporters and governments for policy making. The foreign rate of exchange is normally under the control of central banks as well as under other financial institutions.

Modelling coupled with forecasting of exchange rate has been widely discussed due to the failure of the agreement for fixed currencies between countries in the mid of 20th century (Bretton Woods agreement, 1944). Most frequently and commonly applied models in trying to measure variation in the rate of exchange are namely the GARCH and ARCH models created by Bollerslev and Taylor (1986) and Engle (1982) respectively.

The matter of modelling volatility in the rate of exchange became important when most countries opted out of the fixed rate of exchange system and moved towards the floating rate of exchange system. Several researchers have demonstrated evidence of some connection between volatility in the rate of exchange and other macroeconomic fundamentals. Arize et al in the year 2000 did research on the effect variations in the rate of exchange has on foreign business.

Other researchers have used time series analysis of financial returns to examine the features or characteristics of volatility in the rate of exchange such as volatility persistence and volatility clustering. Researchers such as Bollerslev (1990) and Tse and Tsui (1997) revealed proof of volatility clustering and persistence which implied that great values and minor values in the logarithmic returns are observed in groups, and also found proof of asymmetric effects which implies that GARCH model together with its many extensions have the capability to model and forecast variations in the rate of exchange.

A country's currency is managed by the Central Bank of that country which allows the rate of exchange to freely float against other currencies. It also has an obligation to maintain price stability, foster liquidity when it comes to the financial system and showing support to the youth by providing employment opportunities, who are the largest population in a country, and growth of the economy.

The rate of exchange of the Kenya shilling between 2003 and 2010 averaged between seventy-four Kenya shillings to seventy-eight Kenyan shillings, Ksh 74 - Ksh 78, to 1 United States dollar. From 2010, we have seen the Kenyan shilling weakening against the United States dollar over the years until 2020. By the end of 2019 December, the Kenyan shilling was trading between Ksh 100 and Ksh 101 against 1 United States Dollar. As at end of March 2020, the Kenyan shilling was trading between Ksh 106 and Ksh 107 against 1 United States dollar. This is the highest that the Kenyan shilling has ever traded at since Kenya achieved independence. This can be largely attributed to the corona virus epidemic which could cause a recess in developing countries if the matter is not handled with caution, speed, and efficiency. This matter has seen the national debt level reach the highest it has ever been due to the weakening of the Kenyan shilling.

We modelled the volatility in the currency of the United States dollar to the South African rand and the United States dollar to the Egyptian pound. From 2010, the United States dollar to South African rand exchange rate has also been weakening. By end of 2019, the South African rand was trading between ZAR 14 and ZAR 15 to 1 United States Dollar. As at end of March, the South African rand was trading between ZAR 17 and ZAR 18 to 1 United States Dollar.

From 2010, the United States dollar to Egyptian pound exchange rate has also been weakening. By the end of 2019, the Egyptian pound was trading between EGP 16 and EGP 17 against 1 United States dollar. As at end of March 2020, the Egyptian pound was trading between EGP 15 and EGP 16 against 1 United States dollar. The Egyptian pound was the only currency which did not weaken against the United States dollar from the end of last year to March 2020.

1.2 Problem Statement

The goal of this research is modelling the volatility in the rate of exchange of the United States Dollar to Kenyan shilling (USD/KSH), United States dollar to South African rand (USD/ZAR) and United States dollar to Egyptian pound (USD/EGP). There are various researchers who have handled the subject of modelling volatility in the rate of exchange around the world.

Maana et al (2010) applied the GARCH model in the estimations of the volatility of the foreign exchange market in Kenya using daily exchange rate. Manamba Ephra (2017) applied the GARCH and EGARCH models to model volatility in the exchange rate of the Tanzanian Shilling to the United States dollar. Frank B K Twenefour (2015) applied ARCH models to model variations in the Ghana currency to United States dollar rate of exchange in Ghana.

In Kenya, many of the researchers utilized the GARCH model to model the foreign exchange volatility. Our interest is to find out if an EGARCH model can be used in modelling volatility of the United States dollar to Kenya shilling rate of exchange, United States dollar to South African rand rate of exchange and United States dollar to Egyptian pound rate of exchange, as was done in Tanzania by Manamba Epaphra (2017).

Many researchers illustrate the importance of modelling variations in the rate of exchange to the economy. Dimitrios Serenis (2014) shows the impact volatility in the rate of exchange has on exports. Robert C. Feenstra and Jon D. Kendall (1991) show the connection between volatility in the exchange rate and international prices. Those are just few examples of researchers who illustrate the importance of modelling volatility in the rate of exchange.

We did not find any comprehensive research paper in Kenya that uses the GARCH and EGARCH models to model exchange rate volatility of the United States Dollar to the Kenyan shilling (USD/KSH), United States dollar to South African rand (USD/ZAR) and United States dollar to Egyptian pound (USD/EGP). Hence, we identified this topic as one we would like to take up. We will use both GARCH and EGARCH models to model the volatility of the three rates of exchange.

1.3 Research Objectives

1.3.1 General Objective

To model the volatility in the exchange rate of the United States dollar and the Kenyan Shilling, the United States dollar and the South African rand and the United States dollar and Egyptian pound using two different models.

1.3.2 Specific Objectives

- Determine stylized facts of the rate of exchange.
- Utilization of a GARCH model to try and model variations in the rate of exchange.
- Utilization of an EGARCH model to try and model volatility in the rate of exchange.
- Compare and contrast the results from those two models mentioned above.

1.4 Significance of the research

Foreign exchange markets assist any country in transactions or dealings with another country. The management of a forex market is controlled by the central bank of that specific nation. Hence, this research can be useful to some commercial banks, but it is mostly useful to The Central Bank of Kenya.

The Central bank of a country frequently intervenes to maintain the exchange rate of the country's currency within a desired range and to smooth fluctuations within that range. There are other researchers who have dealt with the topic of modelling volatility in the rate of exchange of the United States dollar and the Kenyan shilling, the United States dollar and the South African rand and the United States dollar and Egyptian pound. My research is just to add to the findings done by other researchers who handled this topic.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

There has been a wide study on modelling volatility in the rate of exchange using GARCH models. Christie (1982) and Nelson (1991) provided proof of the presence of asymmetric effects in stock returns. They suggested that the leverage effect relies on the direction of the price changes. Nelson (1991) decided to address the issue of asymmetric effects. He came up with the EGARCH model that was able to capture asymmetric effects.

Peter Mwita and Cyprian Omari (2017) handled the topic of modelling volatility in the USD/Ksh exchange rate by utilizing the GARCH models. They compared the performance of the GARCH and its extensions in their capability to determine Value at Risk (VaR) in the USD/KSH exchange rate. They concluded that the most efficient models during estimation and forecasting of VaR in the USD/KSH exchange rate are the APARCH model, GJR-GARCH model and EGARCH model with student's t-distribution.

Suliman Zakaria (2012) used the GARCH methodology in modelling volatility in the rate of exchange of 19 Arabian nations. From the results, he deduced that the volatility in the exchange rate is sufficiently modelled by the GARCH (1,1) and EGARCH (1,1).

Robert Akumbobe (2015) modelled the exchange rate volatility of Ghana Cedi-United States Dollar. He used symmetric model (GARCH) and asymmetric model (EGARCH). This asymmetric model was highly capable of identifying commonly observed stylized facts about returns such as leverage effects and volatility persistence. He argued that EGARCH (2, 2) was the overall best fitted model. The above researchers further motivated my interest in using the EGARCH model to model volatility in the exchange rate of the USD/KSH in Kenya.

2.2 Theoretical Framework

Robert Engle (2001) showed that in the occurrence of heteroskedasticity and volatility clustering in situations where procedures for estimating standard errors and confidence intervals are not clearly established, these situations are best handled by the application of ARCH or GARCH models.

We will briefly look at several models that have been used overtime for volatility modelling. This section highlights the basic model properties that have been put forward before to model volatility.

2.2.1 Autoregressive Conditional Heteroskedastic (ARCH) MODEL

The ARCH model was invented in the 1980s by Robert Engle. This model was able to analyze effects which are not explained by the econometric models. The error term can be termed as the residual result not accounted for by the ARCH model. Models in econometrics assumed that the variations in the error term will be the same. In some instances, the variance may not be identical or homoscedastic. Hence, the variance may be non-uniform or heteroskedastic. The error term has a variance which can be said to be not only non-uniform but also dependent, meaning it is affected by the variances which occurred before. This condition where variance is influenced by those variances that occurred in the past is called conditional variance. ARCH models attempt to model the variance of the error terms and rectify the challenges resulting from the variance being non-uniform.

The ARCH model aims to give a gauge of volatility which can be utilized in making of finance choices. (Omwukwe et al, 2011) concluded that ARCH models formulate conditional variance of returns as a function of previous information by use of the sample standard deviations via maximum likelihood procedure.

The ARCH model has some disadvantages. Firstly, it has restrictions when it comes to parameters. Secondly, positive and negative returns are afforded similar treatment by considering the square of these past returns. Finally, due to its slow response to large shocks, volatility is often over predicted. These issues led to the development of the GARCH model.

2.2.2 Generalized Autoregressive Conditional Heteroskedastic (GARCH) MODEL

Bollerslev (1986) formulated the GARCH model to address the issue of forecasting volatility in asset prices. This model was an advancement of the ARCH model invented by Robert Engle in 1982. We use GARCH models when the variation in the error term is changing over time or in other words, it is heteroskedastic. Heteroskedasticity means that the variation of the error term has an irregular pattern. The GARCH model assumed that the variations of financial returns were not constant over time and that these variations were autocorrelated or dependent on each other. Since the introduction of this model by Bollerslev, other modifications of the GARCH model have been invented. An example is the IGARCH which restricts the volatility parameter.

GARCH models were observed to provide better measurement of risk than can be obtained through the standard deviation alone. When it comes to comparing the two models, the GARCH model was able to capture volatility clustering. Something that was not considered in the ARCH model.

The main disadvantage of the GARCH model was that it was unable to capture asymmetric effects. Hence, in a situation where we have asymmetric effects and we use the GARCH model which only captures symmetric effects, the GARCH model may not give us the correct results. The above issues led to the development of the EGARCH model.

2.2.3 (EGARCH) Exponential Generalized Autoregressive Conditional Heteroscedastic model

This model was invented by Nelson in 1991 because of the limitation of the GARCH model. The GARCH model did not have the capability to capture the asymmetric effects in modelling volatility. The EGARCH model proved to be very good in capturing asymmetrical effects.

The distinctions between the EGARCH and the GARCH models are that the EGARCH model utilizes the logged conditional variance to ease the positiveness restriction of coefficients of the model and it can respond asymmetrically to both positive and negative values of the returns.

2.3 Empirical Framework

Chong et al (2002) employed the GARCH model to capture volatility in the rate of exchange of the Malaysian Ringgit to Sterling Pound which resulted in choosing to reject the hypothesis of a model which has a constant variance, they argued that the GARCH models gave superior results when compared to the native random walk models. Since he rejected the fact of constant variance, the GARCH model was put into use because it can deal with data which has no constant volatility.

Rituparna Kar and Nityananda Sarkar (2006) handled the topic of mean and volatility dynamics of Indian rupee to United States dollar exchange rate. They utilized the GARCH model and they also employed the EGARCH model in order to obtain the volatility. The results from these models implied that return on Indian rupee encounters instabilities and that the most suitable model to be used in capturing volatility is EGARCH.

Danson et al. (2012) looked into economic growth in Kenya and how it may be influenced by volatility in the foreign rate of exchange. His findings gave an implication of existence of periods of volatility in many macroeconomic factors in Kenya and therefore, he approved the use of GARCH model in capturing the volatility of these macroeconomic factors, he never investigated if there was presence of asymmetric effect. He concluded that the correlation between real exchange rate volatility and the growth of the economy in Kenya is negative. Hence, we see the significance of modelling volatility in the rate of exchange to the economy.

Md. Zahangir Alam (2012) looked into the utilization of GARCH model and its other various extensions in modelling the volatility of the Bangladesh currency to the United States dollar exchange rate using the daily foreign exchange rate series fixed up by Bangladesh Bank. The conclusion was that the EGARCH and TARCH models gave the best results when it came to in-sample and out-of-sample trading performances, respectively. This further encouraged me to apply the EGARCH model which is effective when dealing with asymmetric effects.

Muhammad Amin and Milton Abdul (2017) investigated how accurate the volatility models are and the how the volatility models perform when it comes to forecasting the exchange rate of Sierra Leone's currency to United States dollar. They employed the GARCH and asymmetric GARCH models and ARMA with normal distribution and non-normal distribution. From their findings, they deduced that the GARCH and the asymmetric GARCH models were better fitted when they used a non-normal distribution when determining the conditional variance. During modelling of the exchange rate of the USD/Ksh we will use a student's t distribution.

S. M. Abdullah and Salina Siddiqua (2017) handled the research topic of modelling and forecasting volatility in the rate of exchange in Bangladesh by utilizing GARCH models. They were comparing results when one uses a normal error distribution versus when one uses a student's t error distribution. They concluded that the latter helped the models meet the requirements of the tests carried out and showed that the forecasting accuracy was much better. They emphasized the importance of using student's t error distribution as it gives better forecasting results.

Tony Caporale and K. Doroodian (2001) handled the topic of Central bank involvement and volatility in the rate of exchange. They used daily observations of exchange rate intervention in the Japanese yen to United States dollar and German mark to United States dollar exchange markets, this paper finds evidence of the effect of the intervention on the spot rates. A GARCH model is used to determine the result of involvement on uncertainty in the rate of exchange. This reinforced the opinions given by the following researchers, Friedman and Schwartz. These two researchers claimed that intervening in the exchange rate will lead to destabilization of the forex market as it introduces additional uncertainty. In a situation like Kenya, the Central Bank of Kenya should not intervene daily. But should only intervene when there are signs of the Kenyan shilling weakening.

CHAPTER 3: METHODOLOGY

3.1 Data Source

We used daily data of the United States dollar to Kenyan shilling exchange rate from 1st of January 2016 to 31st of December 2019 which was got from yahoo finance. After getting the data, we will transform it to a logarithmic return series as the data we downloaded is a price series. And this logarithmic return series will be obtained in the following way:

$$r_t = \log(X_t) - \log(X_{t-1})$$

Where r_t denotes the return on the series and X_t denotes the exchange rate at time t.

3.2 Methods

3.2.1 Testing for Stationarity

We utilize the Augmented Dickey Fuller (ADF) test which was invented by Dickey and Fuller in 1979 to test whether our data is stationary. The null hypothesis, H_0, of the ADF test asserts that data being used is indeed non-stationary while on the other hand we have the alternative hypothesis, H_a, which asserts that data is stationary.

This means that when we use the ADF test, we compare the p value to the level of significance. If the p-value is greater than the significance level, we do not reject the null hypothesis of non-stationarity and if the p-value is smaller when compared to the significance level, the null hypothesis which asserts that the data is non-stationary is rejected in favour of the alternative hypothesis which asserts that data is stationary. If our data is not stationary, we will have to difference it.

3.2.2 Volatility Clustering

We use the ts.plot() command so as to establish whether the USD/KSH, USD/ZAR and USD/EGP exchange rates appear in clusters.

By volatility clustering we imply that periods which have high volatility are followed by other periods of high volatility and periods which have low volatility are followed by other periods of low volatility.

3.2.3 Testing for Arch Effects

We test for evidence of Arch effects in the residuals before fitting any GARCH model to the exchange rate data by using the langrage multiplier test where our test statistic is represented by

$\lambda = nR^2$

Where:

n is the sample size

R^2 is the coefficient of determination for the regression

The null hypothesis states that there is no presence ARCH effects up to order p in the residuals of the test statistic while the alternative hypothesis states that there is presence of ARCH effects.

3.2.4 GARCH Model

We use this model which was invented by Bollerslev in 1986. It serves as an expansion to the theory of the basic ARCH model.

We consider the equation:

$a_t = r_t - \mu$

Where:

a_t is the error term with mean o and variance σ^2 $(0, \sigma^2)$

r_t is return on exchange rate.

μ is the mean

a_t from the above equation follows a GARCH (m, s) process if and only if:

$a_t = \sigma_t \varepsilon_t$

$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i \, a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \, \sigma_{t-j}^2$

ε_t can be described as an independent identically distributed random variable which has a mean of o and a variance of 1. ε_t is most of the time assumed to follow either a student t distribution, Generalized Error distribution (GED) or a standard normal distribution

$\alpha > 0$ and $\beta > 0$

α_i are the error coefficients or ARCH parameters

β_i denote the lag coefficients of the conditional variance or GARCH parameters.

For stationarity to hold in the GARCH model:

$(\alpha_i + \beta_i) < 1$ where $i = 1, 2, \ldots, p$

GARCH (1, 1) it is outlined as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

3.2.5 EGARCH model

In order to beat some shortcomings of the GARCH model, Nelson (1991) developed the EGARCH model.

In order to allow the model to capture asymmetric effects, Nelson considers the weighted innovation:

$$g(\varepsilon_t) = \Theta\varepsilon_t + \gamma[\,|\varepsilon_t| - E(|\varepsilon_t|)]$$

Where Θ and ε are real constants and both ε_t and $[\,|\varepsilon_t| - E(|\varepsilon_t|)]$ can be said to zero mean independent identically distributed series with continuous distributions.

$E(|\varepsilon_t|) = (2/\pi)^{1/2}$ for a Gaussian random variable.

An EGARCH (q, s) model can be written as:

$a_t = \sigma_t \varepsilon_t$

$\log(\sigma_t^2) = \omega + \beta log(\sigma_{t-1}^2) + \gamma\varepsilon_{t-1} + \alpha[\varepsilon_t - \mathrm{E}(|\varepsilon_t|)]$

CHAPTER FOUR: DATA ANALYSIS

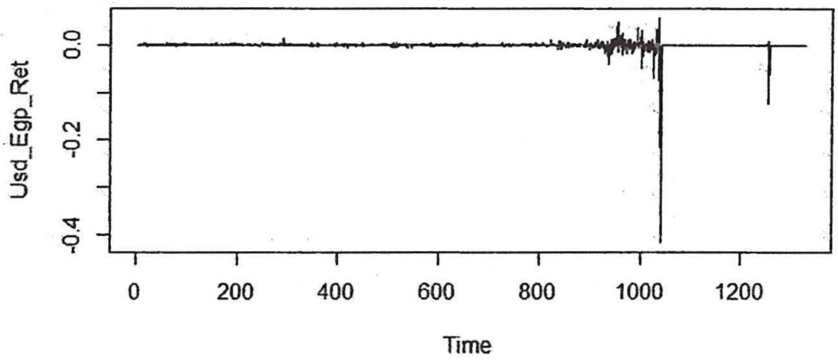
4.1 Test for Stationarity

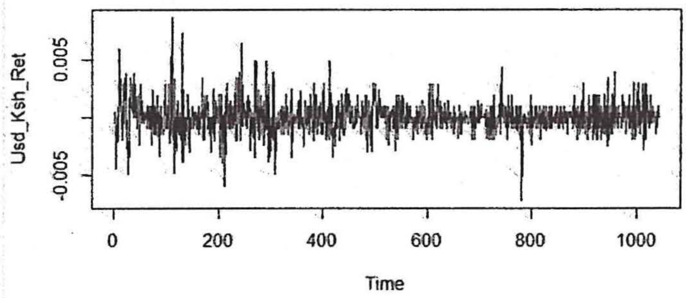
We utilized the Augmented Dickey Fuller test in order to observe whether the returns of the three exchange rates (USD/ZAR, USD/EGP, USD/KSH) are stationary or non-stationary. After running the test and getting the results, we compared the p value to the significance level of 0.05. The p value for the returns of the three currencies was 0.01, which is less than the significance level of 0.05. Hence, the returns of the three currencies are said to be stationary because their p values are less than the significance level which makes us reject the null hypothesis of non-stationarity.

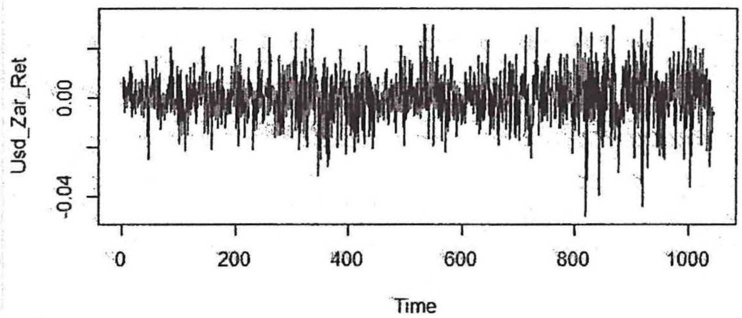
4.2 Volatility Clustering

We utilized the ts.plot () command in order to observe whether the three exchange rates (USD/KSH, USD/ZAR, USD/EGP) appear in clusters.

The above command gives us a plot of the exchange rates against time and from that, the plots for the different returns of exchange rates were observed to behave in such a way that major changes are accompanied by other major changes and minor changes tend to be accompanied by minor changes of either sign. By sign we mean either positive or negative.







4.3 Test for Arch Effects

We were able to test for Arch effects in the three exchange rates using the Lagrange Multiplier test. The null hypothesis of the Lagrange Multiplier test states that there is no presence of Arch effects while the alternative hypothesis states that there is presence of Arch effects.

The Arch test for the USD/KSH exchange rate gave us a p value which was less than the significance level of 0.05. Hence, the null hypothesis of no arch effects was rejected in favour of the alternative hypothesis of presence of arch effects. The Arch test for the USD/EGP exchange rate gave us a p value which was higher than the significance level of 0.05. Therefore, the null hypothesis of no arch effects was not rejected for the USD/EGP exchange rate.

The Arch test for the USD/ZAR exchange rate gave us a p value which was less than the significance level of 0.05. Hence, the null hypothesis of no arch effects was rejected in favour of the alternative hypothesis of presence of arch effects.

4.4 GARCH Model

Since we saw that the United States dollar to Egyptian currency has no presence of Arch effects. The GARCH model will not be suitable to model its volatility so we will be modelling volatility for the United States dollar to the Kenyan Shilling (USD/KSH) exchange rate and the United States dollar to South African Rand (USD/ZAR) exchange rate.

In order to identify the GARCH order model we would use we compared the Akaike information criteria and Bayes information criteria for GARCH (1,1), GARCH (2,1) and GARCH (2,2) for the USD/ZAR exchange rate and the USD/KSH exchange rate. We normally pick the model with the smallest information criteria and for USD/ZAR and USD/KSH exchange rates, GARCH (1,1) had the lowest information criteria. From this we determined that GARCH (1,1) would be appropriate for modelling volatility in both situations.

USD/KSH GARCH(1,1)

	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**
Mu	-0.000017	0.000031	-0.537512	0.590914
Ar1	0.367281	0.434816	0.844681	0.398289
Ma1	-0.404446	0.424351	-0.953093	0.340543
Omega	0.000000	0.000002	0.049403	0.960598
Alpha1	0.162361	0.221372	0.733431	0.463296
Beta1	0.798562	0.165971	4.811448	0.000001

From the results obtained using RStudio, ar1, ma1, omega and alpha1 are not statistically significant. We get to this conclusion by looking at the p values and for p values which are greater than the significance level of 0.05, we do not reject the null hypothesis of not significant. Beta1 on the other hand is said to be significant as it has a p value which is less than 0.05. Hence, we reject the null hypothesis of not significant.

USD/ZAR GARCH (1,1)

	Estimate	Std. Error	t value	Pr(>|t|)
Mu	0.000159	0.000303	0.52482	0.599710
Ar1	-0.965860	0.006130	-157.55490	0.000000
Ma1	0.982842	0.000635	1547.54183	0.000000
Omega	0.000001	0.000001	1.24544	0.212969
Alpha1	0.038346	0.009525	4.02594	0.000057
Beta1	0.950434	0.011761	80.81387	0.000000

From the results obtained, ar1, ma1, alpha1 and beta1 are all statistically significant. By observing the p value and comparing it to the 0.05 significance level, we arrive at this conclusion. Omega is the only value which is not significant.

4.5 EGARCH Model

Since the USD/EGP exchange rate has no presence of ARCH effects. We will use the EGARCH model only on USD/ZAR exchange rate and USD/KSH exchange rate. It is very useful where we have presence of asymmetric effects.

USD/KSH EGARCH (1,1)

	Estimate	Std. Error	t value	Pr(>|t|)
Mu	-0.000025	0.000017	-1.4176	0.156315
Ar1	-0.110391	0.035352	-3.1226	0.001793
Ma1	0.074838	0.032843	2.2786	0.022688
Omega	-1.253517	0.186672	-6.7151	0.000000
Alpha1	-0.043481	0.039254	-1.1077	0.268004
Beta1	0.904459	0.014103	64.1306	0.000000
Gamma1	0.338574	0.056233	6.0209	0.000000

From the above results, all values are significant except the alpha1 and Mu coefficient. We also see that the gamma1 coefficient is statistically significant and it is positive. This means that there is presence of asymmetric effects in the USD/KSH exchange rate.

USD/ZAR EGARCH (1,1)

	Estimate	Std. Error	t value	Pr(>|t|)
Mu	0.000322	0.000296	1.0898	0.275793
Ar1	-0.966458	0.007450	-129.7247	0.000000
Ma1	0.984167	0.000384	2562.2681	0.000000
Omega	-0.088154	0.002235	-39.4430	0.000000
Alpha1	0.048766	0.014924	3.2677	0.001084
Beta1	0.990238	0.000052	18943.8161	0.000000
Gamma1	0.062958	0.004981	12.6391	0.000000

From the results, all the values are significant except Mu at the 0.05 significance level. The gamma1 coefficient is statistically significant and it has a positive. This means that there is presence of asymmetric effects in the USD/ZAR exchange rate.

CHAPTER FIVE: CONCLUSION

Modelling and forecasting the volatility in the returns of rates of exchange has grown to be an important and crucial subject in finance. The main aim of this paper is to model volatility in the exchange rate for the USD/KSH, USD/ZAR and USD/EGP. In trying to model volatility using the GARCH and EGARCH model, we determined the volatility of the USD/EGP exchange rate cannot be modelled using the GARCH and EGARCH models as there was no presence of arch effects. On the other hand, USD/KSH and USD/ZAR exchange rates returns exhibited presence of arch effects. In order to know which order of GARCH or EGARCH we would use, we compared the information criteria for the different GARCH and EGARCH models and from this we picked the one with the least information criteria.

The empirical results show that the conditional variance is quite persistent for USD/KSH and USD/ZAR returns. They also show presence of volatility clustering. Since we run a test to know which order of GARCH or EGARCH model to use, we can conclude that the volatility of the rates of exchange can be modelled by the GARCH (1,1) model.

However, from the results we have seen that there is the presence of gamma which is statistically significant. This means that there is presence of asymmetric effects and therefore, an EGARCH (1,1) model can also be used to model the volatility in the rates of exchange. The EGARCH model is superior to the GARCH model when it comes to modelling the volatility of the rates of exchange, which is proven by the presence of asymmetric effects evident by the gamma term being statistically significant. Hence, the EGARCH model is preferred.

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