MAASAI MARA UNIVERSITY

SCHOOL OF SCIENCE AND INFORMATION SCIENCES

DEPARTMENT OF MATHEMATICS AND PHYSICAL SCIENCES

MODELLING VOLATILITY OF KES/USD EXCHANGE RATES USING TIME SERIES MODELS

(A CASE STUDY OF THE KENYAN EXCHANGE RATES)

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A RESEARCH PROJECT SUBMITTED TO THE DEPARTMENT OF MATHEMATICS AND PHYSICAL SCIENCES IN THE SCHOOL OF SCIENCE AND INFORMATION SCIENCES FOR THE FULFILMENT OF THE REQUIREMENT FOR THE AWARD OF BACHELOR OF SCIENCE DEGREE IN APPLIED STATISTICS WITH COMPUTING OF MAASAI MARA UNIVERSITY

DECLARATION

This Research Project is my original work and has not been presented for a degree in any other university.

Sign:______________ Date:________________

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BS03/049/2012

This proposal has been submitted for examination with my approval as the University Supervisor.

Sign: ________________ Date:________________

Dr.Karanja

ABSTRACT

Research work examines the accuracy and forecasting performance of volatility models for the KES/USD exchange rate return in Kenya using the EGARCH and TARCH. In fitting these models to the daily and monthly exchange rate returns data collected from CBK which extended from the period January 2008 to December 2015, In this study, performance of Time series models (asymmetric EGARCH and TARCH models) in forecasting the volatility behavior of Kenya FOREX market was examined. Daily FOREX rates data, ranging from January, 2008 to December, 2015 was put to statistical manipulation to examine the FOREX volatility behavior in Kenya.

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DEFINATION OF TERMS

Exchange rate: is the currency of one country to another country

Volatility: refers to variability in prices or returns such as stock returns and exchange rate

Exchange rate volatility: refers to the tendency for foreign currencies to appreciate or depreciate in value, thus affecting the profitability of foreign exchange trades.

ACRONYMS

ARCH - Auto Regressive Conditional Heteroskedasticity

CBK -Central Bank of Kenya

EARCH-Exponential Generalized Auto Regressive Conditional Heteroskedasticity

FOREX -Foreign Exchange

GARCH -Generalized Auto Regressive Conditional Heteroskedasticity

GED - Generalized Error Distribution

GJR GARCH - Glosten-Jagannathan-Runkle Generalized Autoregressive Conditional

KES -Kenya Shillings

TARCH-Threshold Auto Regressive conditional Heteroskedasticity

CHAPTER ONE

INTRODUCTION

1.1 Background of the study

Modeling of exchange rate volatility has become a significant aspect and undertaking in financial markets and the economy. This is because the volatility of exchange rate refers to the tendency for foreign currencies to appreciate or depreciate in value, thus affecting the profitability of foreign exchange trades. The volatility is the measurement of the amount by which these rates change and the frequency of those changes. It has gained substantial interest to market participants, investors, policy makers in understanding the changes and the financial steadiness of an economy. Broad research sees it's important in the volatility of security evaluation, and risk management, trading and hedging approach, stock market and fiscal policy resolution making.

In finance, researchers continually put a lot of interests in modeling volatility of exchange rate proceeds, failing which could lead to devastation and likely fall down in the fiscal market. A critical element of risk management is measuring the possible future losses of an collection of assets, and in order to measure these possible losses, estimates ought to be prepared for future volatilities and correlations.

Each financial system uses both economic and financial policies for stabilization. In Africa economies, banks plus other financial institutions plays crucial responsibility as depositories and provides financial mechanism for household fortune, maintaining payment scheme and used as vehicles for implementing economic and financial policies for maintaining assertion in the monetary sector and hence economic progression. They mostly invest in foreign exchange rate hence the requirement for precise modeling of volatility. The fiscal policy aim at enhancing local revenue mobilization reduces the entire budget deficit as well as reduces local debt. Monetary policy focuses on maintaining price stability, consistent with great and sustainable economic growth. CBK strengthens its implementation in the aspect of monetary policy through improving its liquidity forecasting and establish a reserve obligation on foreign currency deposits to manage the growth in the growing size of total commercial banks deposits.

Exporters and importers encountered transaction losses if not managed appropriately, and as a result correct prediction models are needed to evade these losses through hedging and to lower the cost of foreign exchange transaction.

CHAPTER TWO

LITERATURE REVIEW

2.0 INTRODUCTION

2.1 Review of theoretical data

Modeling volatility has been subject of broad study among academics and practitioners for many years. There are diverse research and opinions on modeling the volatility of exchange rate in a given economy

Volatility clustering and leptokurtosis are normally observed in financial time series (Mandelbrot, 1963). Another trend often encountered is the so called "leverage effect"

(Black, 1976), which occurs when stock prices change is negatively correlated with changes in volatility. Observations of this type in financial time series have led to the use of a wide range of varying variance models to estimate and forecast volatility.

In his seminal paper(Engle ,1982) proposed to model time varying conditional variances with auto-regressive conditional heteroskedasticity (ARCH) process using lagged disturbance empirical evidence based on his work showed that a high ARCH order is needed to capture the dynamic behavior of conditional variance. The generalized ARCH (GARCH) model of Bollerstev fulfils this obligation as it is based on an infinite ARCH specification which reduces this number of estimated parameter from infinity to two.

ARCH and GARCH models capture volatility clustering and leptokurtosis, but as their distributions are symmetric, they fail to model the leverage effect. To address this problem, many nonlinear extensions of GARCH have been proposed, such as the Exponential GARCH (EGARCH) model by Nelson (1991), the so-called GJR model by Glosten et al. (1993) and the Asymmetric Power ARCH (APARCH) model by Ding et al. (1993). Alberg et al. (2006) investigated the forecasting performance of GARCH, EGARCH, GJR and APARCH models

and found that the EGARCH model, which used a skewed Student-t distribution, produced significant results than any other model. Sandoval (2006) examined the daily exchange rate data, from year 2000 to 2004, of seven Asian and emerging Latin American countries, by applying the ARMA, GARCH, EGARCH and GJR- GARCH models for modeling the exchange rates and capturing the important characteristics of data. Sandoval (2006) pointed out that, in the developing countries the absence of statistical significance between asymmetric and symmetric models was conditional to the application of in-sample and out-of-sample tests jointly.
Hussein and Jalil (2007) applied the parametric and non-parametric techniques on daily exchange rate of Pak Rupee / US Dollar exchange rate and tried to measure the success of intervention in foreign exchange market in Pakistan, which was done either in shape of alteration in the exchange rate level or smoothing the exchange rate fluctuations. The GARCH results, as reported by Hussein and Jalil (2007) proved that intervention was successfully altered, in both direction of exchange rate and smoothed the fluctuations in exchange rate while the event study confirmed that the intervention was successful for level and volatility of the exchange rate.

Olowe and Ayodeji (2009) used a number of GARCH models to investigate the volatility of Naira/US Dollar exchange rate in which the hypothesis of leverage effect was rejected by all asymmetry models, though all the coefficients of the variance equations were significant, the TS-GARCH and APARCH models proved to be the best models. On the other hand, EGARCH model showed that in Nigerian foreign exchange market, with all variances being non-stationary, the volatility is highly persistence.
Khalid (2008) analyzed the capability of existing exchange rate models by using the monthly data of 20 years of Pakistan, India and China and reported that for the developing economies, the model based on macroeconomic fundamentals perform better than the random walk model in both in and out sample.

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. They thus applied various conditional distributions to both symmetric and asymmetric GARCH type models. The conditional distributions considered were student-t and GED. Four exchange rates were selected: Naira-Euro, Naira-British pound, Naira-Japanese Yen and Naira-USD. Data used span between 10/12/2001 and 14/12/2011. An AR (1) model was estimated as the mean equation because in the log return series, autocorrelation was only significant at first lag. They selected an asymmetric GARCH model with t distribution in most cases but for Naira-USD, a GARCH-GED model was specified.

Rotich (2014) models USD/KES, EUR/KES and GBP/KES 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 favorable 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 that is 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 GBP/KES and the EUR/KES were both fitted by an EGARCH (1, 1) model while USD/KES was fitted by an AR (1)/EGARCH (1, 1).

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 and 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. Kurtosis coefficients for all currencies returns were greater than three indicating that the underlying distributions of returns are leptokurtic. The Jaque-Berra normality test indicates that the distribution of exchange rate returns for all the currencies have tails which are significantly heavier than that of the normal distribution. Results for the volatility estimation show that the estimated GARCH (1, 1) models are significant at 5 percent significance level and fit the data well. The plots of the GARCH (1, 1) models revealed decreasing volatility in the exchange rate returns implying relative stability in the exchange rate.

2.2. Statement of the Problem

Exchange rate volatility is an important factor involved in the decision making of investors and policy makers. The literature provides a number of volatility measures to develop model of volatility behavior of time series. Many developing economies have experienced high exchange rate volatility. The Kenya shilling has registered mixed performances against the United States dollar. The fluctuations ranged between 36.23 in 1993 when Kenya shilling was strongest and 106.15 in September 2015 when it was at its weakest. These fluctuations tend to increase exchange rates risk. This risk is what needs to be examined and perhaps quantified. Volatile exchange rates are associated with unpredictable movements in the relative prices in the economy. Therefore, exchange rates stability is one of the main factors that promote total investment, price stability and stable economic growth.

2.3. Objectives of the Study

2.3.1. General objectives

The main objective of this study is to estimate time series analysis for forecasting exchange rates of KES against USD using their historical exchange rates.

2.3.2. Specific objectives

i. To identify the volatility characteristics of KES/USD exchange rates.
ii. To build a volatility model that will capture better the characteristics of volatility of KES/USD exchange rate.

2.4. Significance of the study

It will be of great importance to policy makers, investors and researchers in promoting development of the capital market and foreign exchange market stability in emerging economies To come up with a model that helps to evaluate and predict exchange rates volatility that will direct the central bank in formulating future strategies on the regulation of foreign exchange markets.

It will report to several consumers of exchange rates data and lead policy makers on currency risk and how to deal with currency crisis if it occurs.

It will be of immense assistance to global investors to trade knowing that the Kenyan market has various foreign exchange rates activities.

CHAPTER THREE

METHODOLOGY

3.1. Introduction

This section outlines the research methodology of the study.

3.2. Computing the daily returns

The daily data rates of KES / USD is changed into the nominal returns by implementing the technique of continuously compounded annual rate of return. Daily returns will be measured using following method:

$r_t = \log(N_t/N_{t-1})$…………………………………. (1)

The dependent variable is the daily nominal return, where r_t is the return on the day t, N_t is the **exchange** rate at time t and N_{t-1} is the exchange rate at time t-1.

3.3. Stationarity of data

The existence of unit root shows that price movements are non- stationary, while the non-existence of unit root will indicate the stationary of the data, given non-stationary is undesirable; the data in this study is changed into daily returns to attain stationary before the use of the models. This study is focused to model and compute exchange rate volatility of time series models.

3.4. Unit Root Test

In testing the unit root test we employ the ADF test with this equation:

$$X_t = \alpha + \beta_t + \rho X_{t-1} + \sum_{j=1}^{n} \sigma_j \Delta X_{t-j} + e_t \quad \ldots\ldots\ldots\ldots.. (2)$$

Where e_t is the white error term and $\Delta X_{t-j}=X_{t-1}-X_{t-2}$, $\Delta X_{t-2}=X_{t-2}-X_{t-3}$ and $\Delta X_{t-3}=X_{t-3}-X_{t-4}$ etc.

This equation will test the null hypothesis of the unit root against the trend stationary alternative.

H_o:p=1 against

H_a:p<1

3.5. Exponential GARCH (EGARCH) process

EGARCH model by Nelson (1991) accounts for an asymmetric response to a shock. A commonly used model is the EGARCH (1, 1) given by:

$$\log(\sigma_t^2) = \alpha_0 + \alpha_1 \left| \frac{u_{t-1}}{\sigma_{t-1}} \right| + \beta_1 \log(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sigma_{t-1}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (4)$$

The term γ, accounts for the presence of the leverage effects, which makes the model asymmetric. When the asymmetric model for volatility is applied, it allows the volatility to respond, more readily, when the prices are falling due to the negative lagged residual than with corresponding increases due to a positive lagged residual.

1. $\gamma = 0$, then the model is symmetric
2. $\gamma < 0$, then negative shocks generate more volatility than positive shocks
3. $\gamma > 0$, then positive shocks generate more volatility than negative shocks

3.6. Threshold ARCH (TARCH) process

The TARCH (p, q) model by Zakoian (1994) and Glosten et al. (1993) has the following specification:

$$\sigma_t^2 = \omega + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \sum_{j=1}^{q} \square u_{t-i}^2 + \sum_{i=1}^{n} \gamma_k u_{t-k}^2 I_{t-k}^{-} \quad \ldots\ldots\ldots\ldots\ldots \quad (5)$$

$$I_{t-k}^{-} = \begin{cases} 1 \; if, \; u_t < 0 \\ 0 \;\; otherwise \end{cases}$$

In this model, a positive lagged residual $u_{t-1} > \mathbf{0}$ and a negative lagged residual $u_{t-1}<0$ have different effects on the conditional variance.The difference between the TARCH and EGARCH is that TARCH assumes leverage effect as quadratic and the EGARCH assumes leverage effect as exponential.

CHAPTER FOUR

DATA ANALYSIS AND PRESENTATION OF RESULTS

4.1 Data

Exchange rate, expressed in terms of KES, consist of daily representative exchange rates of the Kenya currency against US dollar. The data was obtained from www.centralbank.com.The time period of data comprises from January, 2008 to December, 2015, with 1928 observations. The time series plot of the daily and monthly exchange rate data is shown below in Figure 1(a),(b) respectively.

The time series plot of daily and monthly returns is given in Figure 2(a),(b) below. The return series clearly shows volatility clustering in the data.

Figure 1(a)Time series plot for daily exchange rate

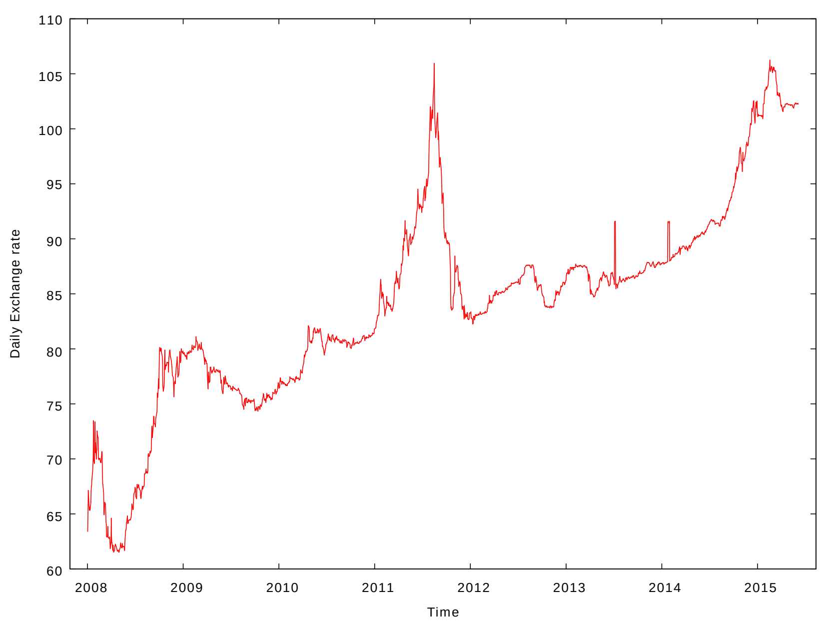


Figure 1(b)Monthly exchange rate

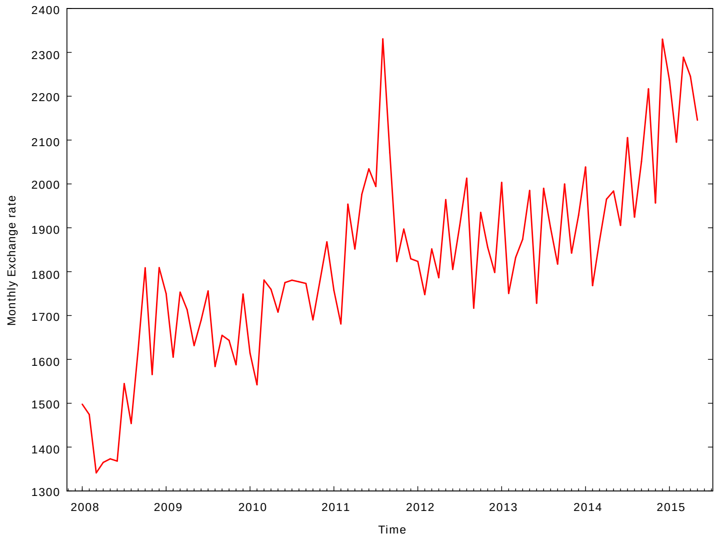


Figure 2(a):Time series plot of daily returns

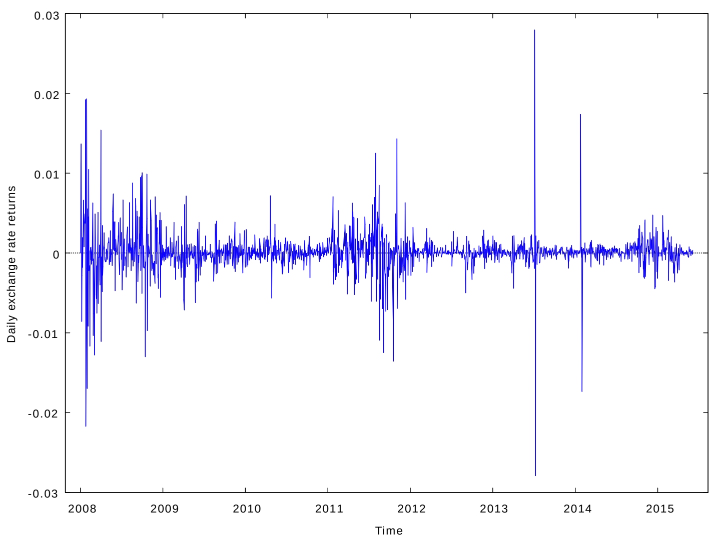
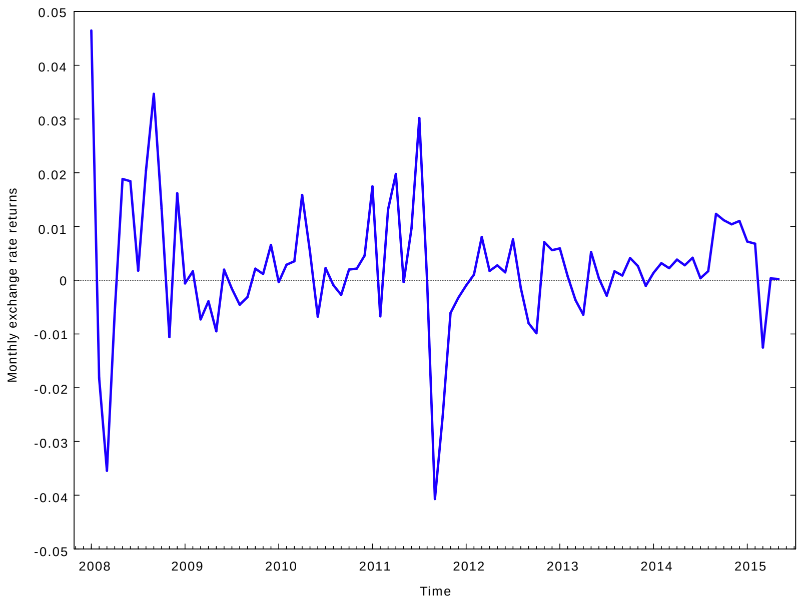


Figure 2(b): Time series plot of monthly returns



4.3 Test for stationarity

ADF tests for stationarity was carried out on the exchange rate return data and the model selection used is the Akaike Information Criterion (AIC).

H_o: p=1 against

H_a:p<1

The ADF test of the returns gives a p-value smaller than 0.01 which leads us to reject the null hypothesis and conclude that the series is stationary.

4.4: Data Analysis

4.4.1 Analysis of EGARCH Model

EGARCH parameters, shown in Table 1 and 2 below show the calculated coefficients and the p-values of the EGARCH model on daily and monthly exchange rate returns. This section interprets key results derived from estimating the EGARCH model in this study. Coefficients of the EARCH model for USD in this case are positive. The constant (ω) for daily and monthly returns are 0.003123 and 0.045190 which are significant at the 1% levels. The EGARCH term α are equally significant for both daily and monthly returns at 1% significant level. EARCH term β is also significant at 1% since its less than one therefore EGARCH is covariance stationary. The leverage effect term, γ measures asymmetric shock effect and is also significant at 1% significant level.

Table 1: Results of EGARCH Model on daily exchange rate return

	Coefficient	p-value
const	0.000356644	8.83e-07 ***
AR1	0.0892210	0.1015
Variance equation		
const	-1.20598	6.63e-07 ***
omega	0.003123	0.0004
alpha	0.612395	0.0017 ***
gamma	0.0117397	0.00944
beta	0.819258	1.33e-045 ***

Table2: Results of EGARCH model on monthly exchange rate return

	Coefficient	p-value
const	0.00131640	0.0002 ***
AR1	0.270972	0.0509 *
variance equation		
const	-10.4324	0.0065 ***
omega	0.045190	0.02101
alpha	0.534704	0.0059 ***
gamma	0.242129	0.0162 **
beta	0.832296	6.02e-031 ***

4.4.2: Analysis of TARCH model

Tables 3 and 4 below display TARCH parameters on the daily and monthly returns, where output shows calculated coefficients and the p values of the TARCH coefficients. In the mean equation, the terms C remains significant for daily and monthly return. In the variance equation, ω, α, and β terms remained significant for both the daily and monthly exchange rate returns. In a TGARCH model," good news" ($\mu_{t-1}>0$) and „bad news" ($\mu_{t-1}<0$) have differential effects on the conditional variance; good news has an impact of α, while bad news has an impact of (α+γ).in this case good news has an impact of 0.546and bad news has an impact of 0.509 in daily exchange rate returns. For monthly exchange rate return, good news has an impact of 0.386 and bad news has an impact of -3.778. Therefore since γ≠0 the news impact is asymmetric. The leverage effects for monthly returns are significant at 1% indicating the presence of asymmetric effect.

Table3: Results of TARCH model on daily exchange rate return

	coefficient	**p-value**	
const	-2.15516e-05	1.74e-088	***
AR1	0.0961639	0.0000	***
Variance equation			
Const	7.67847e-07	0.1352	
omega	8.97181e-07	0.1143	
alpha	0.546318	0.0099	***
gamma	0.0368358	0.00244	
beta	0.505588	0.009	***

Table4: Results of TARCH model on monthly exchange rate return

	coefficient	p-value
const	0.00197514	0.0033 ***
AR1	0.284286	0.0135 **
variance equation		
const	0.000123203	0.8409
0mega	0. 498094	0.00587
alpha	0.386065	0.0126 **
gamma	-0.608250	0.0060 ***
beta	0.568318	3.19e-09 ***

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.0 CONCLUSIONS

Research work has discussed the application of GARCH model variants in determining volatility of Exchange rate for KES against US dollar. Here; we have focused on two particular asymmetric models that is EGARCH and TARCH model.

The EGARCH results have indicated first order autoregressive behavior in the exchange rate return, while the variance equation showed that the asymmetric behavior was shown by the time series, that is, positive and negative news has different impact on volatility progression. Whereas, the results of TARCH model supported the asymmetric behavior in monthly exchange rate returns. From the results, it was found that the EGARCH is the best model to explain the volatility behavior of exchange rate data.

The results of these models, applied on the exchange rate of KES against the US Dollar can be very much helpful for the investor's decision and policy making. The results can also be helpful to understand the historical patterns of exchange rate behaviors, and thus being helpful to predict the future movements of exchange rate markets.

These results proved that the EGARCH model remains the best in explaining the volatility behavior of the data, since the coefficients of mean and variance equations are significant. The TARCH model supports the time series exchange rate, following the asymmetric behavior and depicts the presence of leverage effect in monthly returns.

5.1. RECOMMENDATIONS

Future researches directions could be investigated to improve the modeling KES/USA dollars exchange rate volatility which could be better estimated by selecting shorter time intervals as well as introducing long run persistence of shocks in the volatility with fractionally integrated models and symmetric models (FIAPARCH, FIGARCH, TS-GARCH and GARCH-M) that allow to better capture the dynamics of the return series

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APPENDIX E

Work plan

TIME / ACTIVITY	SEP - DEC 2015	JAN 2016	FEB 2016	MARCH 2016	APRIL 2016	APRIL-MAY 2016
Proposal development						
Piloting of data collection instruments						
Data collection						
Data analysis and presentation						
conclusions and recommendations						
Project editing and binding						
Presentation to Maasai Mara University						

APPENDIX F

Budget

Details	**Kshs**
Research Cost	1000
Printing and Binding	2000
Miscellaneous	1500
Total Kshs	**4500**