CHAOS AND NONLINEAR DYNAMICAL APPROACHES TO PREDICTING EXCHANGE RATES IN KENYA

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A Thesis Submitted in Partial Fulfillment of the Requirements for the Award of the Degree of Doctor of Philosophy in Finance.

University of Nairobi

October 2011

DECLARATION

This thesis is my original work and it has not been presented for any degree in another University.

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DEDICATION

I dedicate this thesis to my dear parents who sacrificed much to bring me up.

ACKNOWLEDGEMENTS

Work of this magnitude is rarely the result of a single hand or head. Perhaps the only things that the author can legitimately lay claim on are the mistakes that may still remain in this thesis. Consequently, the author owes many people debts of one kind or another by the time the study comes to the end. So I wish, therefore, to thank most heartily all those who contributed toward the successful completion of this study without implicating them in the errors of commission or omission in this thesis. Without implying that those not mentioned here had a lesser than substantial contribution, I wish to single out the following individuals for special mention. First and foremost, I wish to thank Prof. Ganesh P. Pokhariyal and Prof. Moses M. Manene, both of the School of Mathematics, Dr. Rose W. Ngugi of the School of Economics and Dr. Gituru Wainaina of the School of Business, for their unswerving support, guidance and constant advice. Without their commitment, this study would never have seen the light of day. I wish also to thank Prof. Erasmus Shubi Kaijage and Dr. Josiah Omollo Aduda for their comments that helped improve the form of this thesis.

My gratitude also goes to Dr. Martin Ogutu of the School of Business and Mr. Bethwel Kinyanjui of the School of Economics whose frantic efforts finally managed to get me going at long last after so many frustrating and false starts. I would like also to appreciate the good company of my classmate Dr. Chris Kiptoo of the Central Bank of Kenya without whose admonition the urge to sit back and languish in self-pity would have overwhelmed me. I also thank Prof. Jairus M. Khalaghai for his advice and encouragement, and Sarah W. Kimani for assisting me with data collection.

Lastly, I wish to thank the Vice Chancellor Prof. George A.O. Magoha who quickly granted me a fee waiver upon request at the time when my studies would have come to a premature end. His action ensured that I successfully reached the end of my doctoral studies. In the same vein, I also thank the Deputy Vice Chancellor Administration and Finance Prof. Peter M.F. Mbithi for his prompt action when my request for a fee waiver reached his desk.

May God bless you all!

LIST OF ABBREVIATIONS

ARCH	Autoregressive Conditional Heteroskedasticity
ASD	Australian Dollar
BDS	Brock, Dechert, Scheinkman
BP	British Pound
BLM	Bartlett-Lewis Model
CAD	Canadian Dollar
CAPM	Capital Asset Pricing Model
CD	Correlation Dimension
CIP	Covered Interest Parity
CKR	Czech Kroner
DM	German Deutschmark
ECU	European Community Union
E-GARCH	Exponential Generalized Autoregressive Conditional Heteroscedasticity
EMH	Efficient Market Hypothesis
EMT	Efficient Market Theory
EUR	Euro
FFr	French Franc
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
HKD	Hong Kong Dollar
IBM	International Business Machines
ICTs	Information Communication Technologies
IID	Independent and identically distributed
IMF	International Monetary Fund
LE	Lyapunov Exponent
LM	Lagrange Multiplier
NGOs	Non-Governmental Organizations
NSM	Neyman-Scott Model
NZD	New Zealand Dollar
PST	Peseta

Rbl	Russian Ruble
SFr	Swiss Franc
SMEs	Small and Medium Enterprises
TAR	Threshold Autoregressive Model
TJY	Japanese Yen
UIP	Uncovered Interest Parity
USD	United States Dollar
VECM	Vector Error Correction Model
ZL	Italian Lira

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ABSTRACT

The liberalization of the foreign exchange rate market in Kenya was meant to increase market efficiency. However, this does not seem to be the case as evidence by high and persistent volatility in the market. Excess volatility increases the cost of doing business and the prices of essential goods and services to consumers. This reduces allocation efficiency of economic resources and consequently affects economic growth and development in Kenya. Thus it becomes necessary for the Central Bank of Kenya (CBK) to intervene in the foreign exchange market. Attempts by the Central Bank of Kenya (CBK) to intervene in the market to reduce excessive volatility have either been too little or too late. Often such interventions have even contributed to increased market volatility. For effective intervention the CBK must understand the data generating process (d.g.p.) for the observed exchange rates and volatility clusters. However, no such model is currently available and CBK interventions more often than not fail to meet expectations of market participants and citizens in general. This study contributed to the filling of this gap by examining the data generating process for exchange rates and volatility in the KSH/US$ market. The study used data for daily, weekly and monthly closing prices of the KSH/US$ exchange rates; the 1-month, 3-, 6- and 12- months forward and risk premia; the daily, weekly and monthly Government of Kenya (GoK) and the USA government Treasury Bills rate. The study covered the period starting January 1995 to June 2007.

Therefore, the objectives of this study were to analyze market efficiency, volatility, and chaos in the foreign exchange market in Kenya for the period starting January 1995 to June 2007. As a matter of procedure, firstly, the study employed the normality test, the serial correlation test, the unit root test, the information content of the term structure of the risk premiums and analysis of seasonality to examine market efficiency. Secondly, the study analyzed volatility clustering in the market. Lastly, the study analyzed the presence, occurrence, distribution and duration of chaos in the market. The objective was to determine the data generating process for the observed returns and volatility clusters in the market.

There are five major findings from this study. Firstly, the results from the data analysis strongly suggest that the foreign exchange market is not efficient in the weak form. The spot

market is characterized by returns that are not normally distributed. The returns are positively serially correlated implying that the exchange rate has been depreciating most of the time. Returns are also mean- reverting. The results also showed the existence of a time varying risk premium. The term structure of the risk premia contains significant information that can be used to predict the future spot exchange rate.

Secondly, the results strongly suggest that the foreign exchange market is highly volatile. Both extremely low and extremely high volatility are clustered and are well described by the GARCH model. Thus, volatility in the foreign exchange market is predictable, at least in the short run. Also, the distribution of extreme returns and extreme volatility over thresholds at particular time intervals strongly suggests that they are well described by the same distribution - the Generalized Extreme Value (GEV) distribution. Further, the results strongly suggest that the distribution of volatility cluster members follows the inverse power law, irrespective of the scale at which these are examined.

Thirdly, there are seasonal patterns in returns and volatility in the foreign exchange market. Foreign exchange returns display seasonal patterns around holidays, in April, May, June, July and August. Volatility also revealed significant seasonal patterns in March to June, and September to December. Seasonality may reflect the economy-wide events such as reading of the government budget and the tourism season, as well as the institutional arrangements within the market.

Fourthly, the results show that the term structure of the risk premiums rises with the investment horizon. Thus, as the investment horizon rises from one month to twelve month, the risk premiums demanded also increases to reflect the increasing exposure to risk at longer maturities. This suggests that the yield curve is upward sloping. Short-term (1- and 3-months) and long-term (6- and 12-months) risk premiums also appear to move pro-cyclically, rising during economic expansions and falling during economic recessions. However, short-term risk premiums displayed greater amplitude than longer-term premiums over time. Also when short-term risk premiums are falling, the 6-months and 12-months risk premiums are also declining. When short-term risk premiums are rising, longer-term risk premiums are also rising. Therefore, the yield curve typically shifts upward or downward each week or month instead of twisting or rotating about some point along the yield curve.

Fifthly, the evidence strongly indicates that the foreign exchange rate market is nonlinear and chaotic. The results of the BDS test and the Lyapunov exponent test strongly suggests the presence of nonlinearity and chaos in the returns; the forward premia and the risk premia. The maximum duration of volatility and chaos in the market is six months. Chaos is ascribed to either risk-aversion or speculation in the foreign exchange market.

The results of this study have a number of implications for the theory, practice and policy of Finance. For the theory of Finance, the results show that using the Theory of Point Processes enriches the repertoire of models available for the study of market volatility. This model captures well the time dependency in the distribution of volatility magnitudes. For the practice of Finance, the findings indicate that investors cannot earn abnormal profits in the market only in the long run. Market fundamentals influence the behavior of exchange rates in the long run. Two key policy implications are worthy noting. First, to be effective, CBK intervention in the market should be no later than five days after the start of excessive volatility in the market. Second, the CBK should among other things focus on reducing speculation in the foreign exchange market since this is what increases volatility.

CHAPTER ONE
INTRODUCTION

1.1 Background to the Study

Modern financial theory assumes a smooth, linear, rational, stochastic or random and homogeneous world. The implication is that financial markets are stable and extreme prices, extreme returns and extreme volatility are rare. However, these assumptions are not consistent with the existence of persistence in asset returns nor can they rationalize the prevalence of currency crises or asset market crashes that indicate market instability. These strong assumptions are buttressed by two ideas; first, they are based on the idea that markets are always at equilibrium. That means markets are stable and can fairly price assets. The reason is that asset prices are influenced by so many market participants. Second, these assumptions arise from the idea that asset prices are random. This means that market participants have no memory of the past. Consequently, asset markets are assumed to be efficient. Thus, asset prices cannot be predicted since they are independent and random variables. Using the law of large numbers, as the number of observations of these asset prices becomes extremely large the probability distribution (or the data generating process) becomes the normal distribution with a unique mean, a constant variance, zero skewness and a kurtosis equal to 3. The assumptions of a unique mean and a constant variance are the defining characteristics of the Efficient Market Hypothesis (EMH).

Contrary to these assumptions, the real economic world is seldom at equilibrium. Economic evolution rarely emanates from a state of economic equilibrium. Empirical evidence shows that attempts to enforce equilibrium have caused economic, social and political degeneration and anarchy. Moreover, market participants have memory and their decisions and actions are strongly influenced by their nature and nurture. Consequently, asset prices, returns and volatility show persistence or trends in time. Hence the arguments and contribution of this study that financial markets are nonlinear, often disorderly, complex and chaotic (Peters, 1991).

Since the liberalization of the foreign exchange markets in Kenya there has been increased and extreme market volatility. This means that economic and financial liberalization ushered in a period of foreign exchange markets volatility and instability. Thus, the KSH/USD foreign exchange market is unstable since it is characterized by extreme and persistent volatility. This has raised concern among ordinary citizens, the private sector, and some politicians that the Central Bank of Kenya (CBK) should intervene in the foreign exchange market to reduce volatility. Often, CBK interventions in the market have failed to reduce market volatility and instability which has negatively impacted on information, pricing and economic efficiencies. Also for effective intervention the CBK must understand the data generating process for the observed extreme market volatility. Therefore, information on the presence, magnitude, distribution and duration of persistent extreme volatility (chaos) in the KSH/USD market is very important in this endeavor but nonetheless lacking.

However, it is still debatable whether the observed extreme volatility and instability in the market can be attributed to stochastic processes or deterministic processes. Hence, the arguments in this study that chaos theory might explain the behavior of extreme foreign exchange rates and extreme volatility in Kenya. The rationale is that chaos theory captures well the behavior of both stochastic and deterministic processes. Chaos is attributed to a deterministic or stochastic, nonlinear dynamic and complex process that generates random looking effects such as changes in foreign exchange rates. A chaotic system has three unique characteristics. First, the system displays sensitive dependence on initial conditions. This means that two points initially separated by an infinitesimally small distance will exponential diverge from one another as time goes into the infinite future. Second, the system has a fractal dimension or scale, that is, it has a non-integer scale like 1.5. This means that the system is complex and has a trend. A pure random system or white noise has a fractal dimension equal to 2. Time series that are mean reverting have a fractal dimension greater than 2. Thirdly, the system has at least one positive Lyapunov exponent. A Lyapunov exponent measures the degree of instability of a dynamical system. This means that a chaotic system is inherently unstable or far from equilibrium. Consequently, chaotic systems are predictable only in the very short run.

1.1.1 Market Efficiency

Efficient foreign exchange markets play at least two important roles in the economy. First, these markets are essential for risk-sharing. They enable portfolio managers to improve their ability to hedge the risk of unpredictable changes in the exchange rates. They also enable speculators to take positions consistent with their views on future foreign exchange rate movements. Second, efficient foreign exchange markets represent the best tool for aggregating market participants' opinions concerning the future volatility of market returns. Therefore, an efficient foreign exchange rate market should foster the implementation of hedging and speculative activities at affordable costs (risk sharing and pricing efficiency), and accurately aggregate market beliefs concerning asset returns volatility (information efficiency).

Three forms of market efficiency can be distinguished based on the information used to form expectations of future prices. First, the weak-form of efficiency in which security prices reflects all historical information. Second, the semi-strong form of efficiency in which security prices reflect all publicly available information. Third, the strong-form of market efficiency in which, security prices incorporate all private and public information. Thus, the absence of the weak-form of market efficiency precludes the existence of the other forms of market efficiency. Hence, this study examined the weak-form of efficiency in the KSh/US dollar spot and forward currency markets in Kenya since the US dollar is the leading world currency.

One implication of market efficiency is that asset returns are random. Therefore, returns on an efficient asset market are normally distributed or Gaussian. However, there is no consensus about the data generating process producing the observed returns on the securities markets. At least two major competing explanations can be identified in the literature. The first group argues that returns are generated by a stationary, non-Gaussian distribution that belongs to the Stable Paretian family of distributions. For example, Mandelbrot (1963, 1967) and Fama (1965, 1970) adduced evidence in favor of the Stable Paretian distribution. The second group argues that returns are generated by the Gaussian distribution with time-varying parameters. However, comparing the performance of the candidate data generating processes has been hampered by the fact that they are not nested. This study contributes toward this debate by applying extreme value theory to the distribution of extreme returns and extreme volatility in the foreign exchange market. This approach has an advantage over previous methods used in the literature since the various data generating processes need not be nested for comparison purposes.

The analysis of foreign exchange market efficiency provides an opportunity to contribute to two different lines of research. First, the analysis of risk sharing efficiency of the foreign exchange market raises issues of the existence of arbitrage opportunities, the strongest contradiction of market efficiency. Second, starting from Hodrick and Srivastava (1984), many studies have measured informational efficiency of foreign exchange markets by testing the unbiasedness of the forward rate as a predictor of the future spot rate. The common finding has been that the forward rate is a biased predictor of the future spot rate. This has been attributed to either the presence of the risk premium or to irrationality of market participants. Thus, there is no consensus about which of these two competing explanations is superior to the other.

However, there is an emerging consensus that developing economies deserve a different approach to testing the UIP condition compared to developed economies (Aliper, et al., 2009). In particular, emerging economies are characterized by: relatively volatile economic conditions and ongoing structural changes; the peso problem; the fear of floating by monetary authorities that drive them to over-stabilize their currencies causing a stronger simultaneity bias; and incomplete institutional reforms (Alper, et al., 2009). These factors introduce other risks like currency risk, default risk and political risks that may cause failure of the UIP condition. Therefore, applying the same tools for testing UIP in developed countries to developing economies may invariably lead to rejection of the UIP hypothesis.

1.1.2 Nonlinearity and Chaos

It is now a fact in finance that daily asset returns are skewed more peaked and fatter tailed than a normal distribution. Hence asset returns are nonlinear and could be chaotic. This behavior has been attributed to irrational expectations, herding behavior among investors and inefficiency in information processing. The returns also display seasonal patterns. Volatility in the asset markets show that periods of quiescence and turbulence tend to cluster together. The fact that volatility in asset markets is clustered was first noted by Mandelbrot (1963) but it was more or less neglected until recently. Asset return data were usually tested for autocorrelation in the mean using the popular autoregressive moving average (ARMA) models (Box and Jenkins, 1970). However, such models could not detect the dependence in the variance of the time series data.

There are two divergences from randomness in exchange rates: seasonality (regular occurrence or under-dispersion) and volatility clustering (over-dispersion). Volatility clustering arises from dependence in the variance or scale parameter of the data generating process. This fact is well captured by the generalized conditional heteroscedasticity (GARCH) models of Engle (1982) and Bollerslev (1986). The main handicap of the GARCH specification is the assumption that innovations are exponentially distributed. Therefore, information on the distribution of magnitudes and durations of volatility cannot be directly derived from the GARCH model. This study therefore, extended this literature by using the statistical theory of point processes to examine the occurrence, magnitude and duration of chaos in the foreign exchange market.

In summary, the EMH assumes rational and homogeneous expectations in the market while chaos theory assumes rational and heterogeneous expectations in the market. The EMH can be tested with respect to a particular information set and the profit derived from trading on such information. Chaos and nonlinearity can be tested using the Brock, Dechert and Scheinkman (BDS) and Lyapunov exponent tests. The empirical evidence available on the efficiency of the foreign exchange market is mixed (Fama, 1991; Froot and Thaler, 1990). Empirical evidence on chaos in the foreign exchange market is also mixed. LeBaron (1994: 398), in an extensive review of literature on nonlinear dynamics and chaos in economics and finance, concluded that "chaos is still a very open question in economic research".

1.1.3 The Foreign Exchange Markets in Kenya

The foreign exchange markets in Kenya, like elsewhere, are international markets. Unlike the stock market, the foreign exchange market is geographically dispersed. Trade on the foreign exchange market takes place throughout the day (24 hours). Therefore, international foreign exchange markets influence the activities on the local foreign exchange markets. The main participants in the foreign exchange markets are commercial banks, the Central Bank of Kenya (CBK), Forex bureaus, insurance companies and pension funds, corporations, Non-Governmental Organizations (NGOs), Small and Medium Enterprises (SMEs) and individuals. By bringing together many buyers and sellers, the foreign currency exchange market increases liquidity and fosters an efficient price discovery process. This is important because foreign exchange rates have a significant impact on the exports and imports in the economy.

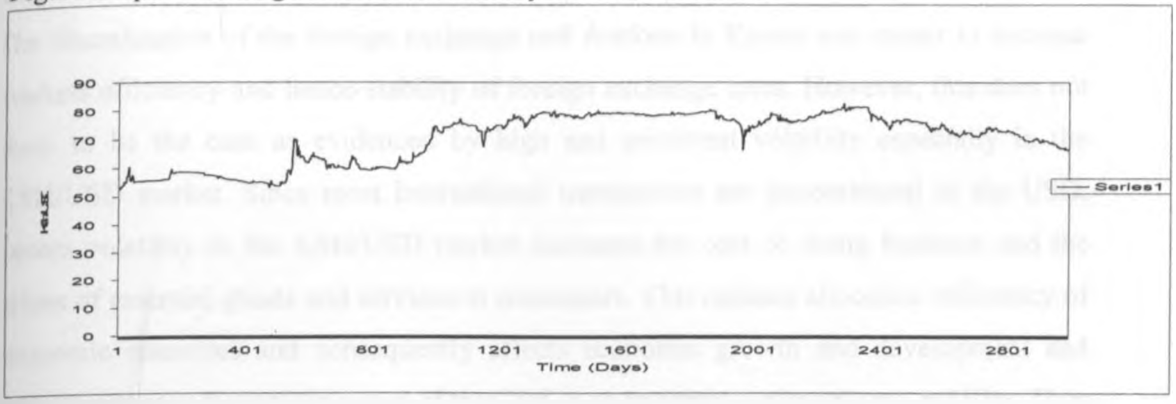
Before 1993, the foreign exchange markets in Kenya were heavily controlled by the government. Trade in foreign currency was highly restricted to a few individuals and corporations. The CBK was the only institution that bought and sold foreign currency. Acquiring foreign currency involved significant paper work, waiting time and other transaction costs. Consequently, participants in the foreign exchange markets were exposed to more risk that they could not diversify away or get compensated. This repression of the foreign currency markets led to the development of the black market for foreign currency. Nevertheless, the foreign exchange markets remained thin and therefore illiquid. However, in 1995 the Exchange Control Act was repealed and more commercial banks and foreign exchange bureaus were licensed to deal in foreign currency. Individuals and businesses were free to buy and sell foreign currency but a few restrictions still remained on how much could be transacted. The rise in the number of participants in the foreign exchange markets was aimed at increasing the liquidity of the foreign exchange market thereby improving market efficiency.

The foreign exchange market mechanism in Kenya has also evolved through time. Prior to 1993, the exchange mechanism in Kenya was the crawling peg. In this exchange mechanism, the value of the Kenya shilling was allowed to fluctuate against foreign currencies but as determined by the CBK. This system replaced the fixed exchange rate mechanism earlier where the value of the Kenya shilling was fixed against that of foreign currencies and could be adjusted only infrequently.

Financial liberalization programs initiated in the 1990s saw the value of the Kenya shilling freely fluctuate against foreign currencies. Beginning in 1993, the exchange rate was subject to the market forces of demand and supply. However, CBK intervention is only allowed in the event that movements in the exchange rates do not reflect market fundamentals. For instance, between January and May 1993, the Kenya shilling was devalued by more than 70% against the US dollar. The Kenya shilling was devaluated again by about 6% between June and September 1993. Thereafter, CBK intervention in the foreign exchange market has been sporadic.

The behavior of the Ksh/USD exchange rates, returns and volatility are displayed in Figures 1, 2 and 3, respectively, below. The volatility in the exchange rate at the beginning of the sample period is attributed to the CBK intervention in the market as mentioned above. There is also an evident upward trend in the exchange rate over the sample period.

Figure 1 Spot Exchange Rates from January 1995 to June 2007



One implication of the EMH is that exchange returns are normally distributed. Figures 1 - 3 suggest that the behavior of foreign exchange returns in Kenya from January 1995 to June 2007 is not normally distributed. It is characterized by both high and low volatility clustering

Figure 2 Foreign Exchange Returns on the Spot market January 1995 to June 2007

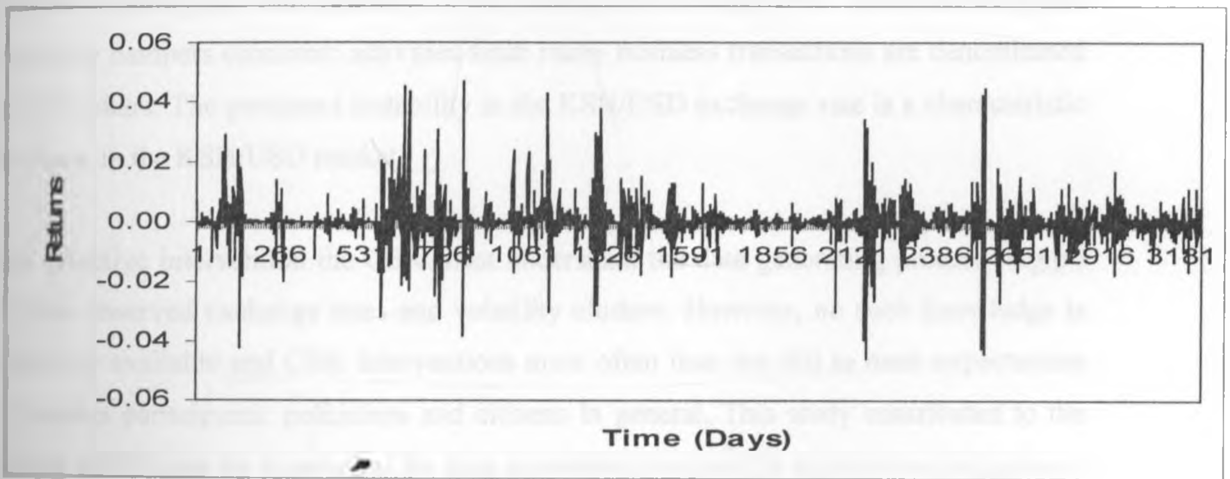
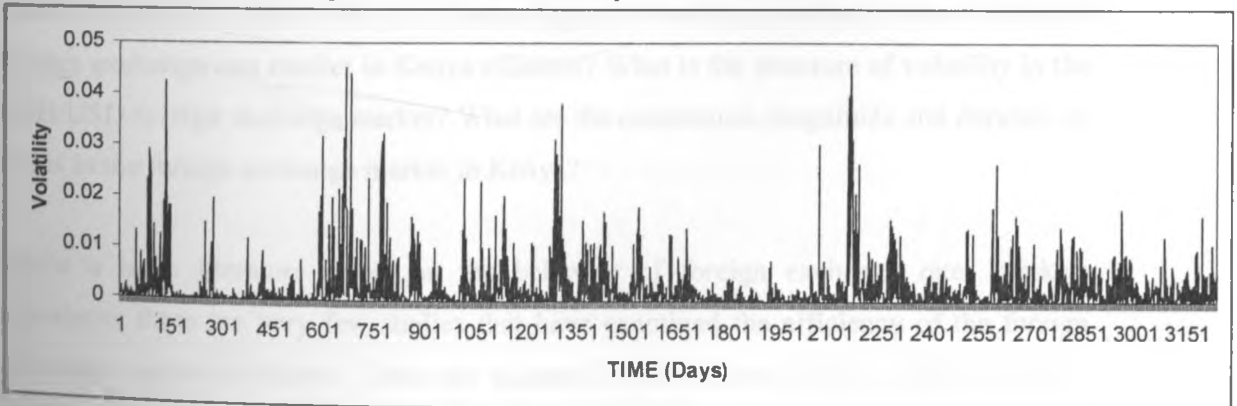


Figure 3 Volatility on the Spot Market from January 1995 to June 2007



1.2 Statement of the Problem

The liberalization of the foreign exchange rate markets in Kenya was meant to increase markets efficiency and hence stability of foreign exchange rates. However, this does not seem to be the case as evidenced by high and persistent volatility especially in the KSH/USD market. Since most international transactions are denominated in the USD, excess volatility in the KSH/USD market increases the cost of doing business and the prices of essential goods and services to consumers. This reduces allocation efficiency of economic resources and consequently affects economic growth and development and social welfare in Kenya. One goal of the CBK is to maintain exchange rate stability. Thus it becomes necessary for the Central Bank of Kenya (CBK) to intervene in the foreign exchange market whenever the market becomes excessively volatile in order to stabilize the KSH/USD exchange rate. However, attempts by the Central Bank of Kenya (CBK) to intervene in the KSH/USD market to reduce excessive volatility have either been too little or too late. Also often such interventions have even contributed to increased extreme market volatility and the instability of the KSH/USD exchange rate. This instability and volatility hampers economic activities since many business transactions are denominated in US dollars. The persistent instability in the KSH/USD exchange rate is a characteristic of chaos in the KSH/USD market.

For effective intervention the CBK must understand the data generating process (d.g.p.) for the observed exchange rates and volatility clusters. However, no such knowledge is currently available and CBK interventions more often than not fail to meet expectations of market participants, politicians and citizens in general. This study contributed to the filling of this gap by examining the data generating process for extreme exchange rates and extreme volatility clustering in the KSH/USD market. Therefore, the study sought to extend the frontiers of knowledge by answering the following questions: Is the KSH/USD foreign exchange rate market in Kenya efficient? What is the structure of volatility in the KSH/USD foreign exchange market? What are the occurrence, magnitude and duration of chaos in the foreign exchange market in Kenya?

While a large literature exists on the behavior of foreign exchange rates markets elsewhere, there are very few studies that have examined the efficiency of the foreign exchange markets in Kenya. These are Kurgat (1998), Ndunda (2002), Muhoro (2005), and Kimani (2007). Kurgat (1998) examined the spot markets efficiency using data from the foreign exchange bureaus. He found out that significant arbitrage profits existed in this market and therefore, he concluded that it is not efficient. However, it is still debatable whether such arbitrage opportunities could have been spotted ex ante.

In another study, Ndunda (2002) analyzed the efficiency of the forward exchange market in Kenya. She examined whether the forward discount rate was an unbiased predictor of the future spot rate. Her conclusion was that the forward rate is, indeed, a biased predictor of the future spot rate. Citing econometric flaws in previous empirical studies, Kimani (2007) re-examined the efficiency of the forward market focusing on the irrational behavior of market participants. She concluded that the forward exchange market is inefficient due to irrational expectations of market participants. Though Muhoro (2005) like Kurgat (1998) analyzed the presence of arbitrage opportunities in the spot foreign exchange markets, she focused on the issue of triangular arbitrage using two currencies – the US dollar and the Euro and a large sample (57 bureaus). She found that the foreign exchange market is inefficient due to the existence of significant arbitrage profits. Again, such a conclusion is subject to the critique above. While Kiptoo (2007) examined the impact of real exchange rate misalignment on imports and exports in Kenya, he did not address the issues of market efficiency, volatility clustering and chaos in the market.

Several hypotheses were formulated to analyze the above issues. First, it was hypothesized that the foreign exchange market is inefficient. Second, it was hypothesized that foreign exchange returns are nonlinear. Third, it was hypothesized that the foreign exchange market is chaotic.

1.3 Objectives of the Study

The general objective of this study is to examine the chaos and nonlinear approach to predicting foreign exchange rates in Kenya. The specific objectives were to:

1. Test the efficiency of the foreign exchange rate market in Kenya.
2. Examine the volatility structure in the foreign exchange rate market in Kenya.
3. Determine the presence, occurrence, distribution and duration of chaos in the foreign exchange rate market in Kenya.

1.4 Motivation of the Study

The interest in the efficiency of asset markets and chaos should be important to academics, practitioners, investors and the Government of Kenya. This emanates from at least the following reasons. The first reason is that quantitative measurement of the risk attached to a currency or a portfolio of currencies depends significantly on the shape of the tails of the distribution of returns. The skewness and kurtosis are determined by the shapes of the tails of a distribution, and therefore, influence risk measurement for returns in the foreign exchange rate market. Skewness is a measure of asymmetry and risk-averse investors generally seek to avoid negative skeweness, where there is a non-zero probability that some large negative returns might arise (Kahneman and Tversky, 1982). Kurtosis is a measure of whether or not the data are peaked or flat relative to the normal distribution. It indicates how thin or fat the tails of the distribution actually are. A risk-averse investor usually prefers a distribution with a low kurtosis, that is, a risk-averse investor prefers a situation where the probability of large positive or negative returns outcomes is no higher than in the normal distribution. Therefore, estimates of risk in the market based on the assumption that returns are normally distributed are most likely to underestimate the investors' exposure to risk.

The second reason is that models of portfolio analysis make several important assumptions about the shape of the distribution, which may not be proper in practice. For instance, the traditional measures of risk, such as the variance or standard deviation, assume that the distribution of returns is symmetrical, thus has a skewness of zero, and that only a normal proportion of extreme returns of either sign may occur, that is, it has an excess of kurtosis of zero. However, in the analysis of major currencies against the US dollar, Calderon-Rossell and Ben-Horim (1982) found that the distribution of returns was negatively skewed and exhibited a large excess kurtosis. Such findings are not consistent with a normal distribution, and strongly suggest that academic views of risk need to be re-examined and standard finance models such as the capital asset pricing model (CAPM) be further extended to account for non-normal distributions. Attempts at this exercise have a long history but not much has been achieved in finance. A pioneering and successful study on this issue is by Kraus and Lichtenberger (1976); a more current study in this area is Wolfe and Fuss (2010).

The third reason is that analyses of managerial views of risk, which have been confirmed in psychology and behavioral finance (Helliar et al, 2001) strongly, suggest that the skewness and the kurtosis of the distribution are important parameters in decision-making. The evidence adduced from empirical studies in these disciplines suggest that business individual's are keen on the downside of the distribution and are focused on the magnitude of negative values when evaluating risky outcomes. Therefore, the analysis of the returns distribution would be crucial in this process, more so if it yielded important information on the size and the probability of the extreme tail of negative foreign exchange rate returns. The Gamma distribution is a good example of such a distribution.

The fourth reason, as correctly argued by Kearns and Pagan (1997), is that both academics and practitioners should attempt to characterize the exact nature of the distribution of returns rather than assume a particular distribution that may be inappropriate. They suggested that current techniques such as Value at Risk (VaR) analysis needed inputs about the actual distribution of returns.

The fifth reason is that the hedging procedures used in portfolio insurance will break down if the affected securities' prices move by more than 4 percent on any given day (Leland, 1985). Thus, those responsible for implementing the hedging procedures implied by portfolio insurance should be curious about how frequent returns are likely to lie beyond this benchmark.

The sixth reason emanates from the fact that finance literature on the stock market in the US and the UK indicates that the generalized extreme value (GEV) distribution may provide a more appropriate model of the distribution of US and UK stock returns than the Generalized Pareto Distribution (GPD). Currently, no empirical study has been done in Kenya especially on the foreign exchange market applying these models and the present study addresses this.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter presents a brief literature review on the foreign exchange rate market efficiency, volatility clustering and chaos. This chapter is organized as follows. Section 2.2 examines the theory and evidence on foreign exchange market efficiency. Section 2.3 presents the evidence on volatility in the foreign exchange markets. Section 2.4 analyzes the theoretical and empirical distributions of extreme returns in the foreign exchange market. Section 2.5 discusses empirical evidence on the efficiency of the foreign exchange rate market in Kenya and summarizes the chapter.

2.2 Efficiency of the Foreign Exchange Rate Markets

In an efficient market asset prices fully reflect all information available to market participants. Therefore, it is impossible for a trader to earn excess returns to speculation. Scholars' interest in foreign exchange market efficiency goes back to arguments concerning the information content of financial market prices and how this impacts economic efficiency (Fama, 1970). In its simplest form, the efficient markets hypothesis can be reduced to a joint hypothesis that foreign exchange market participants are, in an aggregate sense, endowed with rational expectations and are risk neutral. The hypothesis can be changed to adjust for risk, so that it then becomes a joint hypothesis of a model of equilibrium returns and rational expectations (Campbell, Lo and MacKinlay, 2006). The analysis of market efficiency focuses on the assumptions of independent and identically distributed (IID) increments, the independent increments, the uncorrelated returns and a constant risk premium in the foreign exchange market.

2.2.1 Uncovered Interest Parity and Market Efficiency

Assuming market participants are risk neutral, the expected foreign exchange rate change must be equal to the interest rate differential. This condition is known as the uncovered interest rate parity (UIP) condition. In many empirical studies, however, discussions of foreign exchange market efficiency have taken place in the context of the relationship between spot and forward exchange rates (Levich, 1975; 1977). Therefore, researchers have implicitly used a link between spot and forward rates and interest rates known as covered interest rate parity (CIP).

Assuming rational expectations, the expected change in the exchange rate only differs from the actual change by a rational expectations forecast error. Thus, under the assumption of covered interest rate parity the uncovered interest rate parity condition can be tested by estimating a regression of the form (Bekaert and Hodrick, 1993):

$$\Delta_k s_{t+k} = \mu + \beta\left(f_t^{(k)} - s_t\right) + e_{t+k}. \tag{2.1}$$

The variables $\Delta_k s_{t+k}$, f_t, s_t and e_{t+k} are the change in the foreign exchange rate between periods t and $t+k$, the logarithm of the k-period forward rate, the natural logarithm of the spot rate and the regression error, respectively. If agents are risk neutral and have rational expectations the slope parameter β is expected to be equal to unity and the disturbance term e_{t+k}, the rational expectations forecast error under the null hypothesis, is expected to be uncorrelated with the information available at time t.

The empirical studies based on the estimation of (2.1), of a large variety of currencies and time periods, generally report results which reject the efficient markets hypothesis under risk neutrality (Frankel, 1980; Fama 1984; Bekaert and Hodrick, 1993). It is a stylized fact that estimates of β, using other exchange rates against the dollar, are generally closer to minus unity than plus unity (Froot and Thaler, 1990).

If the exchange rate did literally follow a random walk, then the estimated value of β in (2.1) will be close to zero, the state of efficiency of the market notwithstanding. Therefore, regressions of the form (2.1) as tests of simple efficiency are seriously confounded by the near random walk behavior of spot exchange rates. In the light of these problems, a better method for testing the simple efficiency hypothesis is to test the orthogonality of the forward rate forecast with respect to a given information set by imposing the restriction $\beta = 1$ in (2.1) and testing the null hypothesis that $\alpha = 0$ in regression of the form.

$$s_{t+k} - f_t^{(k)} = \alpha\Theta + e_{t+k}, \tag{2.2}$$

where, Θ is a vector of variables selected from the information set available at time t, Θ_t. Orthogonality tests of this kind, using lagged forecast errors of the exchange rate in question in Θ, (a test of weak form efficiency), have generally rejected the simple risk neutral efficient markets hypothesis. Moreover, even stronger rejections are usually obtained when additional information is included in Θ_t (tests of semi-strong form efficiency, e.g., Hansen and Hodrick, 1980).

Using daily data for five UK sterling exchange rates (Germany mark, Belgium Franc, French franc, Italian lira and US dollar), McFarland, McMahon and Ngama (1994) rejected the forward unbiasedness hypothesis for three (Belgian franc, French franc and German mark) of the five exchange rates and argued that this result may be due to the presence of a risk premium for the Belgian and French francs and to rational expectations failure in the case of the German mark. The results also indicated that, with the exception of the German mark, the forward rates and future spot exchange rates are co-integrated.

Clarida and Taylor (1997) re-examined the question of whether the forward exchange rate contains relevant information about the future of the spot exchange rate. They developed an empirical framework that is able to accommodate rejection of the pure efficiency hypothesis while still allowing forward premium to contain information about future spot rate changes. Clarida and Taylor (1997) provided evidence suggesting that the information content of the term structure of forward premium is in fact considerable.

Chinn and Meredith (2004) tested for the uncovered interest parity using interest rates on longer maturity bonds for the group of seven countries. In the short run, the failure of UIP resulted from the interaction of stochastic exchange market shocks with endogenous monetary policy reactions. In the long run, in contrast, exchange rate movements were driven by the "fundamental" leading to a relationship between interest rates and exchange rates that were more consistent with UIP.

The empirical researches on UIP above have generally relied on a linear framework. However, there are several studies that have demonstrated that the relationship between expected exchange rates and interest rates differentials (and hence forward premium) may be nonlinear due to the presence of transfer costs (Baldwin, 1990; Dumas, 1992; Hollified and Uppal 1997), central bank intervention (Mark and Moh, 2004) and presence of limits to speculation (Lyons, 2001). Baillie and Kilic (2005) provided evidence that the relationship between spot exchange rate change and the lagged forward premium displays significant nonlinearities and asymmetry. However, the nonlinear dynamic is inconsistent with general implications of the theories based on transaction costs, and/or limits to speculations in the foreign exchange market.

In summary, the increasing sophistication in the econometric techniques employed has generated increasingly strong evidence against the UIP hypothesis. Several explanations of the forward premium anomaly have been presented in the literature. For instance, this anomaly has been attributed to a time varying risk premium (Hodrick, 1987; 1992); the peso problem (Lewis, 1995); nonlinearity (Mehl and Cappiello, 2007) and irrationality and heterogeneity of market participants (Frankel and Froot, 1987). An excellent survey of the forward premium puzzle, and suggested explanations is provided by Hodrick (1987), Engle (1996) and Isard (2006). Therefore, even though more than 20 years have passed since Fama (1984) called this inconsistency the "forward discount puzzle" the failure of UIP is still one of the most prominent puzzles in international finance. In fact, there is no consensus on how to explain the puzzle yet, and researchers still continue to tackle the problem (Ichiue and Koyama, 2007).

2.2.2 Time-Varying Risk Premium and Market Efficiency

There are at least two schools of thought in the debate about the efficiency of the foreign exchange markets. One school of thought argues that the rejection of foreign exchange markets efficiency hypothesis may be attributed to the irrationality of market participants (Bilson 1981; Longworth 1981; Cumby and Obsfeld, 1984). Yet another school of thought contends that the rejection of the EMH in the foreign exchange market is due to the existence of time varying risk-premium (Fama, 1984; Hodrick and Srivastava, 1984; Hsieh, 1984; and Wolff, 1987). Moreover, the issue of the relative size and variability of the exchange risk premium is still controversial even among those who argue for the presence of time varying risk premium as the principal cause of failure of the EMH (Fama, 1984; Frankel, 1988).

The failure of the simple, risk neutral efficient markets hypothesis may be a result of risk-averse behavior of market participants or due to the deviation from the pure rational expectations hypothesis, or due to both of these phenomena. If foreign exchange markets participants are risk averse, the uncovered interest parity condition may be distorted by a risk premium, ζ_t, because agents demand a higher rate of return than the interest differential as compensation for bearing the foreign currency risk. Therefore, arbitrage will ensure that the interest rate differential is just equal to expected rate of depreciation of the domestic currency plus a risk premium.

Similarly, using the covered interest rate parity condition, the forward premium can be expressed as consisting of two components – the expected depreciation and the risk premium. The presence of a risk premium has significant implications for regressions of the rate of depreciation onto the forward premium, as expressed in equation (2.1). These were first noted by Fama (1984) who also considered a similar regression of the excess return from taking an open forward position, $f_t^{(k)} - s_{t+k}$ onto the forward premium,

$$f_t^{(k)} - s_{t+k} = \mu + \delta\left(f_t^{(k)} - s_t\right) + e_{t+k}, \tag{2.3}$$

where e_{t+k} is the regression error.

Froot and Frankel (Frankel and Froot, 1987a; 1987b; Froot and Frankel, 1989) examined further whether irrationality of market participants or the existence of risk premium is the economically important reason for the rejection of the EMH. Using data covering five years (1981-1985), they concluded that variation in the forward dollar discount of the four most actively traded currencies (DM, SFr, Yen, BP) is due to changes in expected depreciation rather than risk premium and that the forward discount bias is mainly caused by irrationality. In a later study, Frankel and Chinn (1993) extended the analysis by Froot and Frankel (1989) by considering a new data set which covered 17 currencies over a different time period (1989 - 1991). They found evidence supporting the existence of the time varying risk premium for a number of currencies.

Cavaglia et al, (1994) also extended the analysis of Frankel and Froot (1987b) and Froot and Frankel (1989) and corroborated some of the results of Frankel and Chin (1993). They used a new data set of market participants' expectations that covered bilateral exchange rates relative to the US dollar and relative to the German mark over a period of five years (1986-1990). They concluded that the bias in the forward discount is attributable to both the failure of rational expectations and the existence of a time varying risk premium. However, they noted that some of their results are sensitive to the exchange rate regime.

In summary, the adduced evidence using the UIP approach suggests both that significant excess returns exist in the foreign exchange market, which can be predicted using current information, and that the variance of these predicted returns is larger than that of expected changes in the exchange rate. Thus, it is apparent that a time varying risk premium confounds the simple efficiency tests discussed above. Therefore, it must be isolated and included in the regression model of the form (2.1). There is also no consensus about the explanation of the forward discount. Some scholars have attributed it to irrational expectations while others to the time varying risk premium.

2.2.3 Calendar Effects and Market Efficiency

The calendar effect refers to the phenomenon that exchange returns show consistent and significantly different behavior at different time intervals like days of the week, and months of the year. Therefore calendar effects provide evidence of seasonality in the foreign exchange market which contradicts the EMH. A type of calendar effect often recognized in high frequency returns is day-of-the-week dependency. Mondays appear to be the least volatile, while Thursdays and Fridays are the most volatile (Andersen and Bollerslev, 1998). Finally, motivated by the apparent importance of market openings and closures, there is a possibility that volatility behaves differently in periods leading into or out of such markets closures.

Calendar anomalies in equity markets are well documented (Ogden, 1990; Ziemba, 1991). Many studies have found that asset returns are different on days of the week, month-of-the year, turn-of-the-month and before holidays. However, there are very few studies of calendar anomalies in foreign exchange rate markets. The limited research done by McFarland, Petit and Sung (MPS) (1982), So (1987), Hilliard and Tucker (1992) and Cornett, Schwartz and Szakmary (1995) indicated the presence of a day-of-the-week effect in spot rates of major currencies as well as traded futures and options of these currencies.

MPS (1982) argued that the rate of information flow that makes an impact on foreign exchange prices varies with the time of the day and the day of the week. Therefore, it is possible that the distribution of price changes on Monday, reflecting the events of the weekend, is different from price changes for other days of the week. The distribution may also be different because of the length of the non-trading interval between Friday and Monday. Moreover, Thursdays may be different if that is the day on which regular announcements are made, e.g., central bank publication of money supply figures (Taylor, 1986; Baillie and McMahon, 1989).

McFarland, et al (1982) found that the clearing system for foreign exchange transactions involving the dollar gave rise to an opportunity loss of interest for

Wednesday transactions. Transactions on Wednesday clear for "good" value on Friday in the foreign currency, but not until Monday for the U.S. dollar. The loss of two days dollar interest resulted in a lower demand for (or higher supply of) dollars relative to other currencies so that the value of other currencies relative to the dollar was higher on Wednesday. Consequently, the Tuesday to Wednesday price change tended to be positive, and the Wednesday to Thursday price change tended to be negative. Levi (1978) earlier also observed a similar effect involving the Canadian/U.S. exchange rate. Ogden (1990) and Ziemba (1991) showed that standardization of payments may cause them to be concentrated towards the end of the month. They considered three major types of monthly cash payments. These included payment of salaries, pensions by employers and other monthly obligations of the government.

Aydogan and Booth (1999) investigated calendar anomalies in the Turkish foreign exchange markets during 1986 to 1994 period. Changes in the free market and official daily exchange rates between the Turkish Lira (TL) and US Dollar (USD) and the German Mark (DM) were examined for empirical regularities on different days of the week, around the turn of the month and before holidays. Their findings revealed that free market rates exhibited day-of-the-week and week-of-month effects. In addition free market DM returns displayed a holiday effect. These calendar anomalies were explained by cash disbursement patterns, together with currency substitution in the economy. The impact of treasury auctions and banks' management of liquidity on the day-of-the-week effect were also discussed.

In summary, empirical evidence demonstrates the presence of calendar effects in the foreign exchange market. These are the day-of-the-week effect, weekend effect, the turn-of-the month effect, the January effect and the holiday effect among others. The existence of calendar effects has been attributed to several factors: information flow in the market, market clearing systems, payment systems, cash disbursement systems, and central bank interventions in the market. However, most of the research has been done in developed countries. Empirical evidence from developing countries is scanty.

2.3 Volatility in the Foreign Exchange Markets

One of the stylized facts in finance literature is that financial markets display volatility clustering. This is characterized by periods of low or high volatility following one another in the market. Literature on volatility is discussed in two parts. The first part examines the nonlinear structure of volatility in the financial markets. The second part discusses volatility clustering in the foreign exchange market.

2.3.1 Nonlinear Behavior in Asset Returns

Asset return data are usually tested for serial correlation in the mean using the popular ARIMA models. But, ARIMA models cannot detect nonlinearity in the time series data. Volatility clustering arises from dependence in the variance or scale parameter of the data generating process. This fact was well captured by the GARCH models of Engle (1982) and Bollerslev (1986). By allowing the conditional variance to depend on the past squared error terms, it directly mimics the effect that, once the market is highly volatile, it is more likely to remain so than to calm down, and the converse is also true.

The aim of most non-linear time series studies in finance has been to either fit a nonlinear model for exchange rate return behavior, or suggest a new test to identify nonlinear behavior, or both. Many of the empirical studies reviewed follow the same approaches. The studies compare two or three different models to fit the return–generating process of exchange rate returns, generally an ARIMA model, an ARCH/GARCH model, and a non-linear model. These studies share some characteristics. First, much of the early 1990's evidence on non-linearity was adduced by studies that attempted to differentiate between deterministic and stochastic systems. In these studies non-linear behavior is often noted only briefly, as it was not the main focus of the researchers. Second, many of the different non-linear models have all been successfully used to fit the same databases for the same time period. Third, all of the studies reviewed do find evidence of non-linearity in the data.

One of the stylized facts in the finance is that foreign exchange rates return volatility is time-varying. The fact that volatility changes with time and is predictable has implications for investors, since they need to be compensated for changing levels of exposure to risk. The models used to explain this heteroskedastic and correlated behavior are the ubiquitous ARCH/GARCH types introduced by Engle (1982) and Bollerslev (1986). In the ARCH model the conditional variance is modeled as a function of past squared innovations. The GARCH (1, 1) model is the dominant model in finance and is the work horse of scholars interested in modeling the volatility of asset returns.

Bollerslev, Chou and Kroner (1990) reviewed the research that has been done with all types of ARCH/GARCH models. These models have been modified to capture other stylized facts of foreign exchange returns. As pointed out earlier, investors are interested not only in the volatility of a return series, but also the mean return, because they are trading off risk and/return. The model that incorporates information about both moments of the series is the GARCH-M, or GARCH – in mean, of Engle, Lilien, and Robin (1987)

Another significant innovation to these models is Nelson's (1991) exponential GARCH. This model allows for asymmetric variance behavior due to different types of news. Volatility is at a minimum for no news, changes more quickly in response to bad news exemplified by falling prices, Black's (1976) "leverage effect", and changes slowly in response to good news.

Vlaar and Palm (1993) extended the GARCH model by including mean reversion and the jump processes in the weekly exchange rate data in European monetary system. Their model has four components: linear mean-reverting drift, generalized ARCH (GARCH), the jump factor and the LEVELS factor. Vlaar and Palm (1993) found that this model captures the dynamics of the exchange rate data better than either the mean-reverting or the GARCH models.

Ghysels and Jasiak (1998) have introduced the ACD-GARCH, which is an autoregressive conditional duration GARCH model. The improvement in this model is that it does not require equally spaced time periods. It is better characterized as a bivariate model, and the time interval between each foreign exchange transaction is one of the variables modeled. Ghysels and Jasiak (1998) used it to examine the tic-by-tic transactions of IBM during November of 1993, and suggested that volatility and trading durations are interdependent.

Andersen and Bollerslev (1998) found that GARCH models provided good volatility forecasts, in particular when a good proxy for the latent volatility, such as the realized volatility, is adopted. Conversely, when a lousy measure for the ex-post volatility, such as the squared returns, is used, GARCH models tended to give a good in-sample fit, but very poor forecasting performances.

Foreign exchange rate returns also exhibit sudden jumps not only due to structural breaks in the real economy, but also due to changes in the operators' expectations about the future, stemming from different information or dissimilar preferences. The real volatility is affected by millions of shocks that never persist for a long time, rendering its behavior mean-reverting. It follows that, to give better forecasts, a good volatility model should entail a different way of treating shocks. For instance, in the Markov Regime-Switching GARCH (MRS-GARCH) models the GARCH model is incorporated into a regime-switching framework that allows rather parsimoniously accounts for the existence of low and high volatility regimes. In both regimes, volatility follows a GARCH-like pattern, in such a way to avoid path-dependence as in Klaassen (2002). One limitation of the ARCH-type models, as pointed out above, is that one cannot easily obtain information about the occurrence and interval distribution of volatility clusters from the model. Also these models assume that the error terms are exponentially distributed which may not be the case.

A majority of the studies that investigated non-linear behavior tested the time series in its entirety, and arrived at a basic yes or no response for whether or not nonlinearity was present in the data as shown in Table 2.1 in Appendix A. Only rarely did they test a longer period to determine if there is a structural break in the mean of the series. Apart from Hinich and Patterson (1995), Ammermann (1999), Ammermann and Patterson (2001), and Brooks and Hinich (1999), no other study examined the episodic nature of non-linear behavior. Most studies only considered calendar dummy variables in the models of daily returns, but in a rather perfunctory manner, no effort was made to analyze the seasonal character of nonlinear behavior.

Hsieh (1989a, b) examined the daily closing bid prices of five foreign currencies (in terms of U.S dollars): the British pound, the Canadian dollar, the German mark, the Japanese yen and the Swiss franc, from 1974-1983. He used the BDS and the McLeod-Li tests, and found evidence of non-linearity from ARCH effects. Cao and Soofi (1999) repeated this study ten years later, and tested the daily returns of the US dollar exchange rate with the Canadian dollar, the British pound, the German mark, the Japanese yen, and the French franc. They used the Grassberg and Procaccia (1983a, b) correlation dimension and discovered that the series have a very high embedding dimension, perhaps due to the fact that exchange rates are determined by a large number of variables.

Gilmore (2001) adapted a topological method from the natural sciences that uses a qualitative test for chaos and that can be adapted to financial data. She applied it to exchange rate data, and found no evidence of chaos, but did find nonlinear dependence. Lobato (2003) used a bootstrap method, and applied the Crameer-von-Mises and Kolmogorov-Smirnov test to five U.S monthly economic time series. He found evidence of non-linearity for the personal income and unemployment rate, but none for the US dollar/Japanese yen exchange rate, the three-month T-bill rate, or the M2 money stock.

2.3.2 Empirical Evidence on Volatility Clustering in Currency Markets

There is very little research on volatility clustering in the foreign exchange rate market and other markets. Goodhart and Curcio (1991) examined price clustering in the bid-ask prices and spreads of the Deutsche mark/USD spot rate, which was the most active foreign exchange market. They showed that clustering in the final digit of the quotes for bids and asks depended on the desired degree of price resolution by traders. Grossman et al (1997) discovered further that the Japanese yen-Deutsche mark quotes exhibited the lowest degree of clustering, which was expected given that these quotes were less volatile, compared to the USD-DM and JPY-USD quotes.

Mitchell (1998) further examined clustering in Australian dollar exchange rates quoted between 1978 and 1992. Psychological barriers may have partly explained the clustering that he found. Osler (2000) notes that published support and resistance levels used for technical analysis of the major currencies are frequently numbers that end in zero or five.

Fischer (2004) extended the price clustering analysis in the exchange market by controlling for central bank interventions. He answered the question: Does central Bank intervention suffer from clustering behavior? If so, then price clustered interventions may amplify uncertainty. This generates the opposite effect intended by central bank. Such activity is consistent with the empirical evidence in Dominguez (1998) who found that central bank interventions heighten exchange rate volatility. Fisher (2004) found high market dependency in the Swiss National Bank transactions data. In particular price clustering in the broker market is considerably smaller than in the dealer market. The most important determinants of price clustering were bank size and transaction volume (Fischer, 2004).

In conclusion, the evidence suggests that number preference and discreteness as evidenced by clustering, pervades all financial asset markets. The literature also indicates that the two prime reasons for the clustering are the attraction and price resolution/negotiation arguments. Clustering could also stem from any superstitious beliefs of people about numbers, beliefs that are largely influenced by culture (Brown, et al., 2002). Nevertheless, much empirical evidence on the price clustering phenomenon is largely from developed economies. There is very little or no evidence from developing countries especially in Africa (Basterfield, et al., 2003). Further, the evidence adduced is focused on price clustering in the market around particular numbers. Ordinarily, one would also wish to examine the occurrence, magnitudes and durations of volatility clusters. These variables are important inputs in the investment planning process. However, the available evidence on these issues is very limited.

2.4 Chaos in the Foreign Exchange Markets

Investment planners and regulators are interested in knowing the probability of occurrence, the magnitude and the duration of extreme returns and extreme volatility in the market. The previous section has demonstrated that volatility occurs in clusters. This information can be obtained from the GARCH model popularly employed in the finance literature. However, information on the occurrence, magnitude and duration of extreme returns and extreme volatility cannot be directly obtained from the GARCH models. In order to model these features of the foreign exchange market, this section reviews the relevant theory and models that have been proposed in the literature.

2.4.1 Theory of Stochastic Point Processes

This section discusses the theory underlying the models used to study volatility clustering in the foreign exchange rate market in Kenya. The discussion follows that of Vere-Jones (1970).

2.4.1.1 Poisson and Compound Poisson Models

The basic model for the arrival sequence of volatility clusters in the market is the stationary Poisson process. This model is usually adopted as the null hypothesis in any first analysis of a point process. It implies that the underlying process is IID, and hence random. The general (non-stationary) Poisson process on the real line is defined by at least two properties. First, there exists a non-decreasing right-continuous function $\lambda(t)$, which may be normalized so that $\lambda(0) = 0$, such that the number of events in an interval $(a, b]$ has a Poisson distribution with parameter $\lambda(b) - \lambda(a)$.

Second, if I_1, and I_2, are disjoint intervals, the numbers of events in I_1, and I_2, are independent random variables. The first property implies that a Poisson random variable lacks memory or is independently distributed (*ID*). This is an indicator of the weak form of market efficiency since past prices cannot be used to predict future prices.

The stationary compound Poisson process may be characterized as the most general stationary point process, which exhibits the lack of memory property (Ross, 1993). It is a non-orderly process in which groups of events occurs at the instants of a simple Poisson process, with constant parameter λ, and the sizes of successive groups are mutually independent and governed by a common probability distribution. A more detailed analysis of volatility clustering in a given foreign exchange rate market is likely to show up divergences from the Poisson model. Deviations from the Poisson model have been observed both in the direction of over-dispersion (clustering) and under-dispersion (regular occurrence or seasonality). From an economic perspective, the former effect is generally the more important, at least with small and large volatility shocks, while the latter effect might be important only with large volatility shocks.

The two most readily applicable clustering models are due to Neyman and Scott (1958) and by Lewis (1964a). Both models are of interest in the description of volatility clustering in the foreign exchange market. Recent models focus on spatial and temporal distribution of volatility clusters (Daley and Vere-Jones, 2003).

2.4.1.2 Neyman-Scott Model (NSM)

In the Neyman-Scott model, the clustering process is assumed to be stationary and Poisson, with parameter μ. While conditional on a given cluster size, the cluster members are assumed independently and identically distributed about the cluster center with common distribution function $\psi(x)$, where x is the distance from the cluster center. The probability density function of a cluster generating process is the superposition of cluster centers and cluster members generating processes.

The two features which in practice seem to yield most information about the structure of the cluster process are the second-order properties of the counting process, as indicated by the variance-time curve or the Bartlett spectrum, and the distribution of intervals, presented in the form of its hazard function.

The second-order properties of the counting process can be expressed in terms of the first two-moment densities, the intensity (m) and covariance density (c (u)). For the Neyman-Scott model these have the following respective forms:

$$m = \mu a \tag{2.4}$$

$$c(u) = \mu b \int_0^\infty \lambda(x)\lambda(x+u)dx \tag{2.5}$$

where $a = E\ (N)$ and $b = E\ (N\ (N-\ 1))$ are the first and second factorial moments of the distribution of the cluster size and E represents the mathematical expectation variable. The asymptotic variance/mean ratio, RV, is given, as in any Poisson cluster process, by

$$RV = 1 + (2/m)\int_0^\infty c(u)du = 1 + b/a = E(N^2)/E(N) \tag{2.6}$$

The recurrence time $j(\tau)$ for the distribution of the times between successive volatility cluster centres can be derived as,

$$j(\tau) = \frac{1 - e^{-\lambda\tau} II(e^{-\lambda\tau})}{1 - e^{-\lambda\tau}}, \tag{2.7}$$

where $e^{-\lambda\tau}$ is the probability of occurrence of a cluster member, $II(e^{-\lambda\tau})$ is the empirical distribution of cluster members. The above equation can also be applied to derive a sufficient condition for the hazard function of a Neyman-Scott model to be monotonic decreasing. This property is significant in this study because it implies that the coefficient of variation (the ratio of the standard deviation to the mean) of the interval distribution is greater than unity an indication of volatility clustering.

2.4.1.3 Bartlett-Lewis (BL) Model

Bartlett (1963) and Lewis (1964a) introduced the renewal process. In this model the cluster member process is assumed to be a segment of a renewal process, initiated by the cluster center, and terminating after some finite number of renewals. The latter study contains a detailed analysis, so that it will be sufficient here to summarize a few salient points.

To specify the process of cluster members, the distribution for the cluster *size* is used (excluding the cluster center) and a distribution function F(x) for the lengths of the intervals between successive members of the same cluster. It is assumed that these cluster members are independently and identically distributed. The most interesting aspect of this model insofar as this study is concerned is the simple but flexible expression that is obtained for the interval distribution. This is given by the following expression:

$$\log_e P(0;\tau) = -\lambda\tau + \lambda a \int_0^{\tau} \{1 - F(y)\} dy. \tag{2.8}$$

Differentiating this expression yields the forward recurrence time,

$$j(\tau) = \lambda + \lambda a(1 - F(\tau)). \tag{2.9}$$

Hence the hazard function of the interval distribution takes the form,

$$h(\tau) = \lambda + \lambda a\left(1 - F(\tau) + \frac{af(\tau)}{1 + a(1 - F(\tau))}\right). \tag{2.10}$$

Lewis (1964) showed that the coefficient of variation of the interval distribution is greater than unity therefore this model also captures volatility clustering well.

2.4.2 Gamma Distribution

The probability density function of the Gamma distribution in terms of the return or volatility amount R is defined by:

$$f(\Re) = \begin{cases} \dfrac{\Re^{\vartheta-1} e^{-\Re/\kappa}}{\beta^{\tau}\Gamma(\vartheta)}, \vartheta, \kappa > 0; 0 \le \Re < \infty \\ 0, -elsewhere \end{cases} \tag{2.11}$$

where κ and ϑ, *are* respectively a shape parameter and a scale parameter, and

$$\Gamma(\vartheta) = \int_0^{\infty} R^{\vartheta-1} e^{-\Re} d\Re \tag{2.12}$$

is the Gamma function. As usual, ϑ and κ were estimated by the method of maximum likelihood estimation. The Gamma distribution has been applied in the natural sciences to model the occurrence and amount of rainfall. The models reviewed above deal with the occurrence and magnitudes of volatility separately. The Gamma distribution is an improvement upon such models since both the occurrence and magnitude of volatility can be jointly modeled (Williams, 1998).

In summary, the models reviewed above provide the investment planner and the regulator with tools necessary to analyze the occurrence, magnitudes and duration of chaos in the foreign exchange market. Specifically, the models enable the planner or the regulator to estimate the magnitude, occurrence and the duration of a given level of volatility in the market. Thus this study represents a significant departure from previous studies in the existing literature where volatility occurrence, magnitudes and their duration are not considered either separately or jointly.

2.4.3 Extreme Value Theory

All the studies reviewed above on the distribution of extreme exchange rate volatility have exclusively focused on the probability density function generating the observed foreign exchange returns. The focus on the extreme foreign exchange returns uses the limiting law instead of the density function of the returns. This section discusses the asymptotic statistical results according to the theory of extremes. Current developments in extreme value theory are also presented. The discussion follows the exposition in Gumbel's (1958) book, which provides an excellent discussion of the extreme value theory. Hence only salient issues are presented below.

Let X_1, X_2, ..., X_n be the returns observed on days, 1, 2, ..., n. Extremes are defined as maxima and minima of the n random variables X_1, X_2..... X_n. Let Y_n denote the highest daily return (the maximum) observed over n trading days. In empirical analysis the first n observations of daily returns contained in the database, X_1, X_2... X_n are used to select the largest observation denoted by $Y_{n,1}$. From the next n observations, X_{n+1}, X_{n+2}, ..., X_{2n}, another maximum called $Y_{n,2}$ is taken. From $n.N$ observations of daily returns, one thus obtains N observed maxima $Y_{n,1}$, $Y_{n,2}$, ..., $Y_{n,N}$. To determine a limiting distribution of interest, the maximum variable Y_n is reduced with a location parameter β_n and a scale parameter α_n>0 such that the distribution of standardized extremes $(Y_n - \beta_n)/\alpha_n$ is non-degenerate. Gnedenko (1943) proved the so called extreme value theorem, which specifies the form of the limiting distribution, F_y, as the length of the period over which extremes are selected tends to infinity. Three possible types of limiting extreme value distributions can be reached: The Gumbel distribution (type 1), the Frechet distribution (type 2) and the Weibull distribution (type 3).

Gnedenko (1943) gave the necessary and sufficient conditions for a particular distribution to belong to one of the three types. The shape parameter κ indicates the weight of the tail of the distribution of the parent variable X. The shape parameter κ and the normalizing coefficients α_n and β_n may be different for minima and maxima. The tail of the distribution F_x is either declining exponentially (type 1) or by a power (type 2) or is finite (type 3). For the Gumbel and Weibull distributions, all moments of the distribution of X

are well defined. For the Frechet distribution the shape parameter κ corresponds to the maximal order moment: the moments of order r greater than κ are infinite, and the moments of order r less than κ are finite (Gumbel 1958, p. 266); the distribution of X is fat tailed. The lower the value of κ, the fatter is the tail of the distribution of X. For instance, if k is greater than 1, then the mean of the distribution exists; if κ is greater than 2, then the variance is finite; if κ is greater than 3, then the skewness is well defined, and so forth. The shape parameter is an intrinsic parameter of the data generating process of daily returns and is independent of the number of daily returns n from which the maximal return is derived.

Jenkinson (1955) suggested a generalized formula that has come to be known as the Generalized Extreme Value (GEV) distribution. The tail index of this distribution determines the type of distribution: $\tau<0$ corresponds to a Frechet distribution (type 2), $\tau>0$ to a Weibull distribution (type 3), and the intermediate case ($\tau=0$) corresponds to a Gumbel distribution (type 1). The Gumbel distribution can be considered as a transitional limiting form between the Frechet and the Weibull distributions. For small value of τ (or large value of κ), the Frechet and Weibull distributions are almost indistinguishable from Gumbel distribution.

Currently, economic theory does not offer any guide about the specific form of the probability density function that best describes the returns. Therefore, selecting between the competing candidate limiting laws is derived from the qualitative characteristics of the relevant economic process. Therefore, granted that foreign exchange rate returns are significantly fat tailed and their variance is not bounded, their behavior is most likely to be well described by the Frechet distribution.

The three parameters of the asymptotic distribution of extremes: τ, α_n and β_n can be estimated empirically. There are three approaches to this task. The first approach, called parametric, consists of estimating these parameters by assuming that realized extremes are drawn exactly from this distribution. There are two commonly used parametric methods: the maximum likelihood method and the regression method. The maximum likelihood method provides efficient estimates, while the regression method provides a graphical method for determining the type of asymptotic distribution. The second approach known as nonparametric is based on the direct tail index estimation of the parent variable X and does not assume that extremes are drawn exactly from the asymptotic distribution.

The method of L-moments is applied to estimate mean or location, λ_1, the scale λ_2, the L-skewness, τ_3; and the L-kurtosis, τ_4. These L-statistics are similar to the ordinary moments, however, they are more efficient and tractable compared to the ordinary moments. The first four L-moments for a given distribution are defined as follows:

$$\lambda_1 = E[X], \tag{2.13}$$

$$\lambda_2 = \frac{1}{2}E[X_{22} - X_{1:2}], \tag{2.14}$$

$$\lambda_3 = \frac{1}{3}E[X_{3:3} - 2X_{2:3} + X_{1:3}], \tag{2.15}$$

$$\lambda_4 = \frac{1}{4}E[X_{4.4} - 3X_{3:4} + 3X_{2:4} - X_{1:4}], \tag{2.16}$$

where $X_{r:n}$ is the rth order statistic of a random sample of size n. There is a direct linear relationship between L-moments and probability weighted moments (PWM). Therefore, sample values of the L-moments can be obtained by exploiting these relationships via plotting position estimates of the probability weighted moments.

Any distribution can be summarized by values of L-moments, λ_1 and λ_2 and L-ratios τ_3 and τ_4. L-ratios are similar to the ordinary moment ratios:

$$\text{L-skewness } (\tau_3) = \lambda_3 / \lambda_2, \tag{2.17}$$

$$\text{L-kurtosis } (\tau_4) = \lambda_4 / \lambda_3. \tag{2.18}$$

2.4.4 Empirical Evidence on Extreme Movements in Financial Markets

A large empirical and theoretical literature reviewed above focused on average properties like expected returns, volatility, and correlation. Conspicuous by its absence is the focus on extreme movements in financial markets. The extreme values were treated as outliers and often deleted from the data before analysis commenced. Mandelbrot (1963) noted that empirical distributions of price changes had extraordinarily long tails and were peaked relative to samples from normal populations and suggested the non-normal stable Paretian distribution to account for the outliers.

Fama (1965) also examined two extreme cases. First, in the discontinuous stable Paretian market, a large price change over a long interval is, most of the time, the result of one or a few very large price changes that took place during smaller sub-intervals and the price path is not continuous. Second, in a Gaussian market, a large price change is more likely to be a result of many very small price changes, and the price trajectory is continuous. McCulloch (1978) analyzed the large falls and rises in the continuous price process. Jansen and de Vries (1991) applied the weight of the tails of two random variables as a better measure of increasing risk compared the standard variance. They used extremes to calculate the tail indices in the foreign exchange markets and found that extremes contain useful information for efficient determination of the variance.

Longin (1996) examined indices of the most traded stocks in the US using Extreme Value Theory and reported evidence that extreme returns obey the Fretchet distribution. Furthermore, Harry and Kucukozmen (2001) and Gettinsby et al., (2004) have produced evidence from the stock markets in the UK and US that the distributions of extreme risks and returns follow the Frechet distribution. In summary, there is emerging consensus in the financial literature that financial markets are subject to extreme movements in returns and risks. These large movements conform to the Frechet distribution.

2.4.5 Empirical Evidence on Deterministic Chaos in the Foreign Exchange Market

There is increasing evidence on the presence of chaos in economic phenomena. The existence of nonlinear behavior in several economic time series data suggests that it is possible to discover chaotic behavior in economic and financial variables. Bask (1996) considered Swedish Kroner Vs Deutch Mark, Euro, BP, US $ and Yen. This study used daily data from January 1986 to August 1995 (2409 points). By measuring the largest Lyapunov exponent, he found an indication of deterministic chaos in all exchange rate series. Another study by Bask (2002) for the same exchange rate series using 1100 daily observation (from 17 May 1991 to 31 August 1995) and employing bootstrap method, found positive Lyapunov exponents in the data. Richards (2000) also demonstrated that fractal properties are characteristic of foreign exchange markets across a broad range of countries (e.g. Australia, Canada, UK, and Japan).

Cecen and Erkal (1996) investigated the possibility of a low dimensional chaotic attractor in hourly returns of spot exchange rate recorded by Money Market Services for the British pound, Deutschmark, the Swiss Franc and the Japanese Yen. They found that the correlation dimensions estimated do not converge to a stable value and hence there was no evidence in favour of low dimensional chaotic dynamics. Schwartz and Yousefi (2003) investigated low correlation dimensions in a number of exchange rates. They used data starting 13 February 1973 to 1998 (around 6500 daily observations) focusing on returns obtained by the first order differencing of data in log form. They found low fractal dimension in DEM/USD, BP/JPY, BP/USD and JPY/USD exchange rate series.

In summary, the studies reviewed above indicate the presence of non-linearity in foreign exchange rate returns. However, evidence on mathematical chaos is mixed. Also conspicuous by their absence are empirical studies on the non-linear and complex behavior of exchange rate returns in Kenya. Table 2 in the appendix provides a summary of these studies.

2.5 Empirical Evidence on Foreign Exchange Rate Markets Efficiency in Kenya

There is little evidence available on the efficiency of the foreign exchange rate market in Kenya (Kurgat, 1998; Ndunda, 2002, Muhoro, 2005). While these three studies found significant evidence against the EMH, they are confounded by serious methodological and conceptual problems as to render their findings of questionable validity. Kurgat (1998) examined the efficiency of the forex bureaus market by investigating the presence of arbitrage opportunities in currency trade. He concluded that the forex bureaus market is not efficient. However, a second look at the results presented in Kurgat (1998) suggests that such a conclusion is counterfactual. The rejection of the null hypothesis is mainly due to arbitrage in the last two markets for the Tanzanian shilling and the Ugandan shilling, but not in the US dollar.

Ndunda (2002) tested the efficiency of the foreign exchange rate by studying the uncovered interest parity in the forward market. She rejected the null hypothesis that the foreign exchange market is not efficient. Nonetheless, there are fundamental conceptual and methodological flaws that render her findings questionable. First, the classical regression model assumes that data applied to it are stationary and integrated of the same order. Secondly, the classical regression analysis assumes that the variables used in the model are normally distributed. No test of normality or integration was reported in this study. Yet, it is a fact that asset returns are non-normally distributed and non-stationary. Consequently, the statistics computed from such a model are biased and cannot be relied upon. Lastly, the conclusion out-rightly contradicts the reported results. Specifically, the coefficient is significantly different from zero.

In yet another study on the efficiency of the foreign exchange market in Kenya, Muhoro (2005) examined the presence of location and triangular arbitrage in the currency market. Using data from both the forex bureaus and the commercial banks, she applied the same methodology like Kurgat (1998). On basis of her analysis, she rejects the null hypothesis that the foreign exchange market is efficient. However, a random check of the computed location and triangular arbitrage profits reveals serious logical and computational errors. Therefore, the results of this study are flawed and the issue of the efficiency of the foreign exchange market in Kenya needs to be re-examined. Kimani (2007) further examined the efficiency of the foreign exchange markets in Kenya. She tested the rationality of market participants' expectations. She found that forward rates are biased predictors of the future spot rates of the Euro, BP, USD, TSh and the USh. Also market participants were not rational. Therefore, empirical researches on the efficiency of the foreign exchange markets in Kenya are unanimous that the markets are inefficient. Evidently, there is no study that has examined the issue of seasonality and the presence of time varying risk premium in the foreign exchange markets. Also no study has examined the mechanisms and the processes causing the observed prices, returns and volatility in the foreign exchange market.

Conspicuous by its absence in the literature is the documentation and explanation of calendar anomalies in the foreign exchange markets of developing countries especially in Africa. There is also no study on the behavior of the risk premium in the foreign exchange market in Kenya. But the foreign exchange market plays a very important role in the economy. It is not only at the centre of international trade but also plays a major role in portfolio diversification. It is therefore, important to examine the existence and possible explanations of calendar anomalies and the behavior of the risk premium in the foreign exchange rate market in Kenya. Furthermore, though research evidence elsewhere indicates that foreign exchange rates are non-linear and chaotic; little research has focused on the nonlinear and chaotic behavior of returns and volatility in foreign exchange rate market in Kenya. There is also no research on the occurrence, magnitude and duration of chaos in the foreign exchange rate market in Kenya. This information is very important to all participants in the foreign exchange market. Therefore, this study sought to extend the frontiers of knowledge by filling in these existing gaps in knowledge. The following hypotheses were formulated and tested.

In order to address the first objective the following hypotheses were tested:

H_1: Foreign exchange rates are stationary.

H_{a1}: Foreign exchange rates are non-stationary.

H_2: Foreign exchange returns are normally distributed.

H_{a2}: Foreign exchange returns are not normally distributed.

H_3: Foreign exchange rates are serially correlated.

H_{a3}: Foreign exchange rates are not serially correlated.

H_4: Foreign exchange risk premiums are constant.

H_{a4}: Foreign exchange risk premiums are time varying.

In order to achieve the second objective the following hypotheses were tested:

H_5: Foreign exchange rate changes do not display an ARCH effect.

H_{a5}: Foreign exchange rate changes display an ARCH effect.

H_6: Foreign exchange rate changes do not have a GARCH effect.

H_{a6}: Foreign exchange rate changes have a GARCH effect.

H_7: Foreign exchange rate changes are symmetrical.

H_{a7}: Foreign exchange rate changes are asymmetrical.

H_8: Foreign exchange market does not efficiently price risk.

H_{a8}: Foreign exchange market efficiently price risk.

In order to address the third objective the following hypotheses were tested:

H_{09}: Volatility occurrence in the market is random.

H_{a9}: Volatility occurrence in the market is not random.

H_{10}: The foreign exchange market is not chaotic.

H_{a10}: The foreign exchange market is chaotic.

H_{11}: Occurrence of chaos in the market is random.

H_{a11}: Occurrence of chaos in the market is not random.

H_{12}: The distribution of chaos in the market is random.

H_{a12}: The distribution of chaos in the market is not random.

2.6 Conceptual Framework

The EMH is a statement about: (1) the theory that foreign exchange rates reflect the true value of one currency against another; (2) the absence of arbitrage in a market populated by rational, profit-maximizing agents; (3) the hypothesis that market prices always fully reflect all available information. Market efficiency is also defined with respect to the information set Θ_t if it is impossible to earn economic profits by trading on the basis of Θ_t. The EMH states that market participants cannot earn abnormal profits using the available information set Θ_t other than by chance. The expected exchange rate return k-periods ahead is given as:

$$R_{t+k} = E(R_{t+k} / \Theta_{t+k-1}) + e_{t+k}, \tag{2.19}$$

where R_{t+k} is the extent to which the actual logarithm of the exchange rate deviates from the logarithm of the expected price given the information available Θ_{t+k-1}. The expected error $E(e_{t+k} / \Theta_{t+k-1})$ is zero. This relationship is known as a fair game with respect to the information set Θ_{t+k-1}. This implies that the information Θ_{t+k-1} is fully and instantaneously impounded in foreign exchange rates. The form of market efficiency depends on the information set, Θ_{t+k-1}, used to form expectations of future returns. If the information set consists of historical information or past prices, the focus is on the weak-form of market efficiency. When the information set consists of all public information, the focus is on the semi-strong form of market efficiency or event studies. If the information set contains both public and private information, the focus is on the strong-form of market efficiency.

There are two variants of the fair game model, which are commonly used, in empirical tests of market efficiency. These are the sub-martingale and the random walk models. In the sub-martingale model the predicted price of an asset using information set Θ_{t+k-1} is greater than or equal to the current asset price. This implies that a technical trading rule utilizing all the available information Θ_{t+k-1} cannot yield more profits than a buy-and-hold strategy over the relevant investment horizon. It also means that it should be impossible to consistently earn excess returns on the market by timing the transactions so that they occur at particular calendar periods. This issue is especially important in empirical studies on market anomalies. If the predicted asset price using the information Θ_{t+k-1} is equal to the current asset price then the model is known as a martingale.

The EMH assumes that successive price changes are independent and identically distributed (IID). These two assumptions form the basis of the random walk model of asset prices. The random walk model takes the form:

$$R_t = e_t \tag{2.20}$$

where the error term e_t is independent and identically distributed with zero mean and constant variance σ^2. The random walk model can also be expressed as $R_t = \mu + e_t$, where μ is the drift in the random walk. The independence property means that both the increments and their nonlinear functions are uncorrelated. Therefore, the conditional mean and variance at time t take the forms $E[S_t / S_0] = S_0 + \mu t$ and $Var[S_t / S_0] = \sigma^2 t$, respectively. Where the spot is rate s_0 at time *0* and S_t is the spot rate at time *t*. This clearly shows that the random walk is nonstationary and that both its conditional mean and variance are linear in time.

In its basic form, the EMH can be simplified to a joint hypothesis that participants in the foreign exchange market are (1) rational and (2) risk neutral. If market participants are risk neutral, then the expected foreign exchange rate return from holding one currency rather than another is equal to the opportunity cost of holding this currency rather than the other. The opportunity cost in this case is equal to the interest rate differential between the home and foreign country. This condition is called the uncovered interest rate parity (UIP) condition and is expressed as:

$$E(R_{t+k}) = i_{t+k-1} - i^*_{t+k-1}, \tag{2.21}$$

where i_{t+k-1} and i^*_{t+k-1} are the domestic interest rate and the foreign interest rate on identical assets, respectively. If the foreign exchange market participants are risk-averse, the UIP is distorted by a risk premium because market participants demand higher compensation than the interest differential for exposure to foreign exchange risk. This is expressed as

$$E(R_{t+k}) = i_{t+k-1} - i^*_{t+k-1} - \zeta_{t+k-1}, \tag{2.22}$$

where ζ_{t+k-1} is the risk premium. When equation 2.22 is substituted into equation 2.19, the foreign exchange rate return becomes,

$$R_{t+k} = i_{t+k-1} - i^*_{t+k-1} - \zeta_{t+k-1} + e_{t+k}. \tag{2.23}$$

Thus, the forward rate can be computed as follows:

$$f_t^k = E(s_{t+k} / \Theta_{t+k-1}) + \zeta_{t+k-1}, \tag{2.24}$$

where the deviation from the risk-neutral market efficiency is ζ_{t+k-1}, f_t^k is the logarithm of the k-period forward rate and s_{t+k} is the logarithm of the k-period spot rate. Assuming that market participants are rational, the future spot rate can be expressed as follows:

$$s_{t+k} = E(s_{t+k} / \Theta_{t+k-1}) + e_{t+k}, \tag{2.25}$$

where the expectation error e_{t+k} is assumed to be IID. Subtracting equation (2.25) from (2.24) the following expression for the k-period forward rate on the foreign exchange market is obtained:

$$f_t^k = s_{t+k} + \zeta_{t+k-1} - e_{t+k}. \tag{2.26}$$

The forward premium k-periods ahead on the foreign exchange market at time t is therefore the difference between equation (2.26) and s_t and it takes the form:

$$f_t^k - s_t = \zeta_{t+k-1} + s_{t+k} - s_t - e_{t+k}. \tag{2.27}$$

The foreign exchange return $R_{t+k} = s_{t+k} - s_t$ can be expressed as follows,

$$R_{t+k} = f_t^k - s_t - \zeta_{t+k-1} + e_{t+k}. \tag{2.28}$$

By subtracting equation 2.23 from equation 2.28 it is demonstrated that if the market participants are rational and risk averse, the forward premium ($\varphi_{t+k} = f_t^k - s_t$) should be equal to the interest rate differential ($\nabla_{t+k-1} = i_{t+k-1} - i^*_{t+k-1}$) on similar assets other than the currency of denomination.

$$\varphi_{t+k} = \nabla_{t+k-1}. \tag{2.29}$$

Therefore, the deviation from condition (2.29) indicates market inefficiency in information processing or in the pricing of risk. Any remaining structure in the error term of equation 2.28 is attributed to seasonality, nonlinearity and chaos whose form cannot be determined apriori.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the research methodology employed in this study. Section 3.2 discusses the research design. Section 3.3 presents the population and sampling techniques. Section 3.4 discusses data sources and measurements. Section 3.5 discusses the data analysis techniques applied in the study.

3.2 Research Design

The empirical research design is applied in this study. This research design is the most relevant whenever time series analysis is applied to examine the behavior of data elements that are sampled at regular intervals. It also allows the behavior of the time series data (exchange rates, return, risk premia, forward premia and interest differentials) to be studied before a particular empirical model can be applied to analyze the data.

Therefore, the empirical methodology helps to eliminate the possibility of obtaining erroneous results and drawing spurious conclusions. Hence, the nature of the data analysis is determined by the actual behavior of the time series.

3.3 Population, Sample and Data Sampling Techniques

The population of this study consisted of thirty two foreign exchange markets based on the currencies traded in Kenya at the time as shown in Appendix B.

This study purposefully sampled the KSH/USD foreign exchange market. The focus on the KSH/USD market was based on the fact that the USD dollar is the most commonly used currency for international trade and asset valuations. It was also the most volatile market compared to others. Moreover, it is also the market in which conflicting results were found.

Different data were sampled at different intervals. The main sampling intervals were daily, weekly, monthly, quarterly, semi-annually and annually. The KSH/USD exchange rate data were sampled at the daily, weekly and monthly intervals. While data on the Kenya government Treasury bills rates and the US government Treasury bill rates were sampled at the 1-month, 3-months, 6-months and 12-months intervals.

3.4 Data Sources and Measurement

Foreign exchange rates data were collected from the Central Bank of Kenya covering the period from January 1995 up to June 2007. This is the period for floating exchange rates. Though, the foreign exchange market was liberalized in 1993, the first two years were excluded to obtain data that reflected the truly floating exchange rate regime. The choice of the currency was influenced by the fact that the US dollar is the major trading currency across the world and it is commonly used in asset valuation. The Ksh/USD spot market is also the one in which previous empirical studies produced spurious and contradictory results. This study mainly used the daily closing prices of the Ksh/USD exchange rates. The daily foreign exchange rate returns (R) were computed as the difference between the logarithm of the current exchange rate and the logarithm of the previous exchange rate when business closed on the market.

Data for the 1-month, 3-months, 6-months and 12-months end of period interest rates for the Kenya Government 91-day Treasury Bill Rates were annualized data obtained from the Central Bank of Kenya Website (www.centralbank.go.ke/treasurybills). Data for the 1-month, 3-months, 6-months and 12-months end of period interest rates for the US 91-day Treasury Bills rates was obtained from Treasury Department Website. These interest rates were used as proxies for the local and foreign interest rate. The expected forward rates were computed from the uncovered interest rate parity (UIP) condition using the above interest rates. The interest rate differential, the risk premium and the forward premium were measured as $\nabla_{t+k-1} = i_{t+k-1} - i^{*}_{t+k-1}$, $\phi_{t+k} = f_t^k - s_t^e$ and $\varphi_{t+k} = f_t^k - s_t$, respectively.

The calendar effects were captured using dummies (D_i). The dummy variable took the value 1 when the seasonal effect was present and the value 0, otherwise. The study examined the day-of-the-week effect, the holiday effect, and the January effect.

3.5 Data Analysis

Data analysis focused on three main issues: the analysis of market efficiency, the analysis of volatility clustering and the analysis of chaos. The specific tests are presented below.

3.5.1 Analysis of Efficiency in the Foreign Exchange Market

Market efficiency was analyzed using the parametric tests. The use of parametric tests is tied to the assumption that the specified model is correct. Therefore, these tests are used to estimate parameters and for testing hypotheses about these parameters on the assumption that the model is correct. This leads to the joint hypotheses test of market efficiency and correct model specification for equilibrium currency returns. If the EMH is rejected, it could be the case that the market is truly inefficient or due to a misspecified equilibrium model. Therefore, failure of the null hypothesis of market efficiency cannot be unambiguously interpreted.

3.5.1.1 Test for Normality

The EMH implies that returns are normally distributed. For the normal distribution, the skewness is zero and the kurtosis is 3. In this study the Jarque – Bera (JB) test of goodness-of-fit to the normal distribution is used. This test is based on the sample skewness and the kurtosis of the error terms (e_t) of equation (3.2.1).

$$R_t = \mu + e_t. \tag{3.2.1}$$

For the normal distribution the sample skewness should be close to zero and the sample kurtosis close to 3. The JB test determines whether the sample skewness and kurtosis are significantly different from their expected values, as measured by the chi-square statistic. The JB test is an asymptotic test that is applicable in large samples only. Since the sample size in this study is large (over 3000 data elements) the JB test is appropriate. The null hypothesis tested is, H_0: The error terms are normally distributed. The alternate hypothesis is, H_1: The error terms are not normally distributed. If the null hypothesis is rejected then we conclude that the foreign exchange market is not efficient in its weak form.

3.5.1.2 Serial Correlation Test

In order to test for serial correlation and avoid the joint-hypothesis problem, the model for the equilibrium returns in 2.2.23 is applied:

$$R_t = \mu_t + \sum_{t=1}^{p} \rho_t R_{t-1} + \phi(i_{t-1} - i^*_{t-1}) + e_t,$$
$$e_t = \rho e_{t-1} + \varepsilon_t. \tag{3.2.2}$$

The variable μ_t is a constant, ρ and ϕ are the coefficients of R_{t-1} and the interest rate differential, respectively, p is the optimal lag structure and e_t is an AR (1) process. The serial correlation test is used to test the null hypothesis that error terms from the AR (1) process of returns are not autocorrelated. The focus here is on the first order serial correlation of the error term of the AR (1) process. Also, if $\rho = 1$ then R_t is non-stationary (i.e. $\phi = 1$). However, due to the possibility of high serial correlation between e_t and e_{t-1} one of the assumptions of classical regression analysis is violated and OLS technique is an inappropriate estimation technique.

The problem of serial correlation was solved by fitting an autoregressive model using Cochrane-Orcutt Iterative Least Squares. The null hypothesis tested is, H_0: The error terms are serially correlated. The alternate hypothesis is, H_1: The error terms are not serially correlated. The *t*-statistics and the Durbin-Watson statistic (DW) were used to determine the significance of the correlation coefficients of the lagged error terms in the regression model (3.2.2). If the null hypothesis is rejected then the market is efficient.

There are at least two causes of serial correlation in the error terms in equation (3.2.2). First, autocorrelation can arise due to omitted variables. Second, autocorrelation can result from a misspecified model. An attempt was made to address the first problem by including seasonal dummies in equation (3.2.2). One calendar effect is tested – the January effect. The January effect is the tendency for asset returns to be high and positive in January compared to other months of the years. Thus a strategy of buying currency (USD) in December and selling them in January could be profitable thus contradicting the EMH.

The model used to test for calendar effects takes the form:

$$R_t = \mu_t + \sum_{t=1}^{p} \rho_t R_{t-1} + \phi(i_{t-1} - i^*_{t-1}) + \varphi_i \sum_{i=1}^{q} D_i + e_t. \tag{3.2.3}$$

The variables D_i are the dummies for the day of the week or the month of January. For instance, D_1 takes on the value *1* in January and *0* otherwise.

To test for the weekend effect, the null hypothesis is, H_0: $\varphi_1 < 0$. The alternate hypothesis is, H_1: $\varphi_1 > 0$. The sign and significance of φ_1 were compared to those of other days of the week. If φ_1 is positive with a high *t*-statistic than the rest of the coefficients then the results show that Monday mean returns are not only positive but significantly different from other days of the week. The null hypothesis is therefore rejected and the results show that there is no weekend effect.

In the test for the day-of-the-week effect, the null hypothesis is, H_0: $\varphi_6 > \varphi_7$. The alternate hypothesis is, H_1: $\varphi_6 < \varphi_7$. Where $\varphi_6 = \varphi_2 + \varphi_3$ and $\varphi_7 = \varphi_4 + \varphi_5$. If the null hypothesis is rejected then there is no day-of-the-week effect. To gauge the impact of seasonality on the error term, the regression error in equation (3.2.2) is also tested for serial correlation. Rejection of the hypotheses of serial correlation and calendar effects implies the foreign exchange market is efficient.

3.5.1.3 Unit Root Test

The rejection of the normality test and the presence of serial correlation in foreign exchange returns suggest the presence of trends in the data. The two common detrending procedures are first differencing and time-trend regression. First differencing is appropriate for *I (1)* time series and time trend regression is applicable to *I (0)* time series. Unit root tests can be used to check whether trending data should be first differenced or regressed on deterministic functions of time to achieve stationarity in the data. The unit root test was used to test for the permanent/temporary nature of shocks to foreign exchange returns. Again the assumption is that foreign exchange returns are constant. To examine the issue surrounding non-stationarity and unit roots associated with spot rates, the Augmented Dickey-Fuller (ADF) test, which allows for serial correlation in the error term e_t, was applied The ADF test was based on the model in equation (3.2.4). If $\rho < 0$ then R_t is stationary around the deterministic trend α_0. This is taken as evidence of market efficiency. However, if $\rho_t > 0$, $t = 1,...,p$, then R_t is non-stationary and hence shows no tendency to return to the equilibrium value after a random shock in the market. This is interpreted as evidence against market efficiency.

Empirical literature shows that while foreign exchange rates are nonstationary, their first differences are stationary (Issam and Murinde, 1997). Thus, the equation used for conducting ADF test has the general structure of equation (3.2.4).

$$R_t = \alpha_0 + \sum_{t=1}^{p} \rho_t R_{t-1} + \sum_{k=2}^{l} \delta_k \Delta R_{t-k} + \varepsilon_t, \qquad (3.2.4)$$

where ρ_t the coefficient of the lagged return, t is time, ε_t is a white noise error term. The value of l is computed as $l = \left[12\left(\frac{T}{100}\right)^{1/4} \right]$ (Schwert, 1989). T is the sample size. The test statistics are computed from the above regression. The null hypotheses is H_0: $\rho_t = 0$, $t = 1,...,p$. If the null hypothesis is rejected then it shows that the foreign exchange market is inefficient.

3.5.1.4 Testing for the Time Varying Risk Premium

In this test the assumption that foreign exchange returns are constant is relaxed. The objective is to assign some structure on the returns and reduce the size of the error term in the constant returns model. Assuming that market participants are rational and risk averse, the UIP condition will be distorted by the presence of a risk premium as in equation (2.2.23). In order to test for the presence of a time varying risk premium equation 2.2.23 was estimated assuming the error term contains the risk premium. Then the error term is tested for whiteness. If the error term is not white noise, the risk premium is removed from the error term by incorporating the term ζ_{t+k-1}. As shown in equation 2.2.23 equilibrium will exist when the expected return on holding a US dollar is equal to the interest differential between Kenya and USA minus the risk premium for holding the US dollar.

$$R_t = \mu_t + \sum_{t=1}^{p} \rho_t R_{t-1} + \phi(i_{t-1} - i_{t-1}^*) - \zeta_{t-1} + \sum_{i=1}^{q} \varphi_i D_i + e_t. \qquad (3.2.5)$$

The risk premium is computed at the 1-, 3-, 6-, and 12-months horizons. This is substituted into equation 3.2.5 and the equation re-estimated. If the coefficient of the risk premium varies over time and the error term e_t is serially correlated then the market is deemed inefficient.

Again, in equation (3.2.9) the forward premium is decomposed into three parts – the risk premium, the spot return, and the rational expectations error term. From the fact that spot exchange rates follow a martingale process, the spot return series is a martingale difference or stationary process. The rational expectations error term is stationary by definition. Therefore, the order of integration of the risk premium depends on the on the order of integration of the forward premium. Thus the stochastic structures of the risk premium and the forward premium in equation (2.2.27) have an important implication for the EMH in the weak-form in the foreign exchange market. Specifically, if the term structure of forward premium is nonstationary then the foreign exchange market is deemed as inefficient. The tests for unit roots in the term structure of forward premia are achieved by applying the Johansen Likelihood Ratio (JLR) test to the 1-, 3-, 6-, and 12-month forward premiums, sequentially.

3.5.2 Analysis of Volatility in the Foreign Exchange Market

There are three tests used to analyze the presence of linearity and nonlinearity in foreign exchange rate returns. These are the ARIMA analysis, autoregressive conditionally heteroscedasticity (ARCH) test and the Generalized ARCH (GARCH) test. The first test examines linear stochastic behavior while the next two tests focus on detecting nonlinear stochastic behavior.

3.5.2.1 Autoregressive Integrated Moving Average (ARIMA) Analysis

ARIMA (Box-Jenkins, 1970) modeling was the first step in nonlinear modeling. The ARIMA model was applied to the time series data to remove any linear structure in the data before nonlinear analysis commenced. The purpose of ARIMA analysis was to find a model that accurately represents the past and future patterns of a time series. The pattern in the time series can be random, seasonal, trending, cyclical, or a combination of these patterns.

Many time series may be represented as a linear function of past observations and a randomly distributed error term, e_t.

$$R_t = \mu + \sum_{t=1}^{p} \phi_t R_{t-1} + e_t, \tag{3.2.6}$$

where μ and ϕ_t are fixed parameters and e_t is a random variable with mean zero and is statistically independent of all e_{t-k}, $k>0$. When $\phi_t = 0$ for $t>p$, the process is designated an autoregressive process of order p, or AR (p). Through successive substitution in (3.2.6) of R_{t-1}, R_{t-2} and so on, this linear process may be expressed as a weighted sum of the current and all past error terms

$$R_t = \delta + e_t + \sum_{t=1}^{q} \phi_t e_{t-1} + \varepsilon_t, \tag{3.2.7}$$

Where δ and ϕ_t are fixed parameters. When $\phi_t = 0$ for $t > q$, the process is referred to as a moving average process of order q, or MA (q).

The third possible process is a mixed autoregressive moving average process, ARMA (p, q). It has two parts, the AR (p) process and the MA (q) process. The general mixed process ARMA (p, q) is expressed as:

$$R_t = \delta + \sum_{t=1}^{p} \rho_t R_{t-1} + \sum_{t=1}^{q} \phi_t e_{t-1} + \varepsilon_t. \tag{3.2.8}$$

When differencing in the series is used, the model is called the integrated process and referred to as an ARIMA (p, d, q) model. The variable d shows that the time series has been differenced d times to achieve stationarity.

Given a model for a particular series, predictions may be obtained by computing expected values of future observations, conditional on the history of the time series. The best fitting model for each of the five processes – the random walk, AR (p), MA (q), ARMA (p, q), and ARIMA (p, d, q) was selected using the Akaike Information Criterion (AIC).

The ARIMA model has a number of disadvantages. Although the residuals of the ARIMA model may not be correlated, the variance might not be constant. Furthermore, ARIMA models cannot predict unusual movements in asset prices. Thus, ARCH/GARCH models were fitted to the residuals of the best ARIMA model to determine any nonlinear dependence in the time series which was not captured by the linear model.

3.5.2.2 Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Analysis

One of the stylized facts in the finance literature is that foreign exchange rates volatility is time varying and clustered. The fact that volatility changes and is clustered has implications for investors, since they need to be compensated for changing levels of exposure to risk. The models used to explain this heteroskedastic and correlated behavior of returns are the ubiquitous ARCH/GARCH models (Engle, 1982; Bollerslev, 1986).

A test for determining whether ARCH effects are present in the residuals of the estimated model was done using the following steps.

1. Run the postulated linear regression of the form given in equation (3.2.9) saving the residuals ε_t.

$$R_t = \alpha + \beta(L)R_{t-1} + \varepsilon_t. \tag{3.2.9}$$

2. Square the residuals and regress them on q own lags to test for ARCH of order m i.e. run the regression of the form:

$$\sigma_t^2 = \gamma_0 + \sum_{t=1}^{q} \gamma_t \varepsilon_{t-1}^2 + \eta_t. \tag{3.2.12}$$

The variable η_t is the regression error term. Obtain R-squared for this regression.

3. The test statistic is defined as TR^2 from the last regression and is distributed as a Chi-square with m degrees of freedom.

4. The null and alternate hypotheses are

H_0: $\gamma_0 = 0$ and $\gamma_1 = 0$ and $\gamma_3 = 0$ and ... and $\gamma_q = 0$

H_1: $\gamma_0 \neq 0$ and $\gamma_1 \neq 0$ and $\gamma_3 \neq 0$ and ... and $\gamma_q \neq 0$

The joint null hypotheses are that all coefficients in the regression equation are zero. If the value of the test statistic is greater than the critical value from the chi-square distribution, then the null hypothesis is rejected. This implies that the data displays an ARCH effect.

The ARCH model suffers from a number of problems. First, there are no clear criteria for selecting the number of lags m. Second, it may not be parsimonious since the number of lags m might be very large. Thirdly, it might violate the non-negativity constraint, that is, the more parameters there are, the higher the likelihood that one of the parameters could have a negative estimated value.

An extension to the ARCH (q) model that overcomes the above problems is a GARCH model. The GARCH (p, q) model is the dominant model in finance. It takes the form:

$$\sigma_t^2 = \gamma_0 + \sum_{t=1}^{p} \gamma_t \sigma_{t-1}^2 + \sum_{t=1}^{q} \lambda_t \varepsilon_{t-1}^2 + \eta_t. \qquad (3.2.11)$$

The GARCH model is nonlinear; therefore, ordinary least squares cannot be used to estimate its parameters. The maximum likelihood (MLE) method was used instead. This method works by seeking the most likely values of parameters given the data. A log-likelihood function was formed and the values of the parameters that maximize it were sought. In this study, first, the orders of the GARCH models without any seasonal or asymmetric effects were estimated for each sample. Then daily and monthly dummies were incorporated in the estimation of the models to capture the seasonal influences on volatility.

Many models in finance assume that investors should be compensated for taking additional risk by obtaining a higher return. This idea was implemented using the GARCH-in-Mean (GARCH-M) (Engle, Lilien and Robin, 1987) model. This model took the form:

$$R_t = \mu + \delta\sigma_{t-1} + \varepsilon_t, \varepsilon_t \approx N(0,\sigma_t^2) \qquad (3.2.12)$$

$$\sigma_t^2 = \omega + \sum_{t=1}^{p} \gamma_t \sigma_{t-1}^2 + \sum_{t=1}^{q} \lambda_t \varepsilon_{t-1}^2.$$

If δ is positive and statistically significant, then an increase in risk, measured by a rise in conditional variance, causes a rise in the mean return. Therefore, δ, measures the risk premium.

The GARCH model suffers from a number of limitations. First, the estimated model may violate the non-negativity constraint. Second, GARCH models cannot account for leverage effects. Thirdly, the model does not allow for any direct feedback between the conditional variance and the conditional mean. The above problems have been overcome by the use of asymmetric GARCH models. Empirical evidence shows that a negative shock to financial time series is likely to cause volatility to rise by more than a positive shock of the same magnitude. This is known as the leverage effect in financial markets. The two popular asymmetric models in the literature are the GJR (Glosten, Runkle and Jaganathan, 1993) and the exponential GARCH (Nelson, 1991). The GJR model extents the GARCH model by including an extra term to account for any asymmetry in the data. The conditional variance now takes the form:

$$\sigma_t^2 = \omega + \sum_{t=1}^{p} \gamma_t \sigma_{t-1}^2 + \sum_{t=1}^{q} \lambda_t \varepsilon_{t-1}^2 + \sum_{t=1}^{q} \lambda_t \varepsilon_{t-1}^2 I_{t-1}, \qquad (3.2.13)$$

where $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$, otherwise $I_{t-1} = 0$. $\gamma > 0$ for the leverage effect and the non-negativity condition now becomes $\omega \geq 0, \gamma_t \geq 0, \lambda_t \geq 0$ and $\gamma_t + \lambda_t \geq 0$.

In the EGARCH (Nelson, 1991) model there are several ways of modeling the conditional variance. The specification used in this study took the form:

$$\log_e(\sigma_t^2) = \omega + \sum_{t=1}^{p} \gamma_t \log_e(\sigma_{t-1}^2) + \sum_{t=1}^{q} \lambda_t \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \sum_{t=1}^{r} \alpha_t \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right]. \qquad (3.2.14)$$

This model has a number of advantages compared to the GARCH model. First, modeling $\log_e(\sigma_t^2)$ ensures that even if parameters are negative, the variance remains positive. This precludes the need for imposing artificial restrictions to ensure non-negativity on the parameters of the model. Second, exponential GARCH (E-GARCH) allows for asymmetry between returns and risks. For instance, since market volatility and returns are negatively related, γ, will be negative.

To estimate the parameters, the leptokurtosis conditional distribution of the data, common in financial data, was considered. This was achieved using the quasi-maximum likelihood approach. To select the best model the AIC was employed.

3.5.3 Analysis of Chaos the Existence and Occurrence of Chaos in the Market

To analyze chaos in the market, an ARIMA process was used to extract the linear structure and the GARCH process was used to extract the nonlinear structure in the data. Thus, the remaining nonlinear structure in the data was attributed to chaos. This section presents the two tests applied to examine the presence of chaos in foreign exchange rate changes. These are the Brock, Dechert and Scheinkman (BDS) test and the Lyapunov exponent test. Further, the analysis of chaos was examined through their occurrence, magnitude and duration.

3.5.3.1 Analysis of the Existence of Chaos in the Market

The BDS test and the Lyapunov exponent test are discussed below.

Brock, Dechert and Scheinkman (BDS) Test

Brock et al (1996) developed a powerful test for independence and identical distribution based on the correlation integral from chaos theory. The BDS test is an enhanced version of the Grassberg - Proccacia (GP) algorithm that corrects some of the weaknesses of the correlation dimension (CD) test. The BDS test was applied to the residuals of the GARCH process to determine whether they are independent and identically distributed (IID). The rejection of the null of IID indicates a general dependence in the residuals, which may be due to neglected nonlinearity (chaos) in the estimation process. The computation of BDS test follows the following steps:

i. Given a time series of N observations $x\ (t)$ (t = 1, 2, 3...N), which are the foreign exchange rate returns, select a value of m (embedding dimension), embed the time series into m-dimensional vectors, by taking each m successive points in the series. This scales into a series of overlapping vectors.

ii. Compute the correlation integral, which measures the spatial correlation among points by adding the number of points (i, j) where $1 \leq i \leq N$ and $1 \leq j \leq N$, in the m-dimensional space, which are close in the sense that the points are within a radius or tolerance ε of each other. Intuitively, the correlation integral measures the proportion of embedded vectors of dimension m lying within the ε-neighborhood of an initial embedding, X_t.

iii. Brock, Dechert and Scheinkman showed that under modest regularity conditions the correlation dimension $C\ (m,\ \varepsilon, N)$ has a limit $C\ (m, \varepsilon)$ as $N \to \infty$. Now if $x\ (t)$ is IID, then the m-dimensional correlation dimension is simply the one-dimension CD to the power m. If the ratio N/m is greater than 200, the values of

ε/σ range from 0.5 to 2 and the values of m are between 2 and 5. The quantity $\left[C_{\varepsilon,m} - (C_{\varepsilon,1})^m\right]$ has an asymptotic normal distribution with zero mean and variance, $V_{\varepsilon,m}$.

iv. The BDS test statistic is expressed as:

$$BDS(m,\varepsilon,N) = \sqrt{\frac{N}{V_{\varepsilon,m}}}\left[C(m,\varepsilon,N) - C(I,\varepsilon,N)^m\right] \tag{3.2.15}$$

The BDS is a two-tailed test, thus the null hypothesis is rejected if the BDS statistic is greater than or less than the critical values.

Lyapunov Exponent Test

One of the main characteristics of chaos is the sensitive dependence on initial conditions. Lyapunov exponents are used to measure the sensitivity of a dynamical system to its initial conditions. Therefore, Lyapunov exponents indicate the stability of a dynamical system. Lyapunov exponents reveal the existence of deterministic chaos in time series by measuring the degree of divergence of nearby trajectories of points in the phase space. A positive value of the largest Lyapunov exponent (LE) is a sign of deterministic chaos in the system. The computation of LE is based on dimensions in the phase space. There are as many LE as the dimensions. The procedure for calculating Lyapunov exponents is as follows:

i. Consider the matrix H of dimension $(T- m+1)*m$. T and m at the sample size and the embedding dimension, respectively.

ii. Choose any two arbitrary row vectors between which the Euclidean distance, r_0, is less than the preferred small value, ε. It can be demonstrated that in chaotic time series, at the next nth step forward, the two vectors H_{i+n} and H_{j+n} will be divergent.

iii. Define d_n as the ratio of the distance between the pairs of H in n time-step-ahead and initial time. Calculate d_n for different n values. If it exceeds one then the conclusion is that the system is chaotic, since by increasing the time step, close points in the m-dimensional space will be divergent.

iv. Calculate the Lyapunov exponent as follows:

$$LE(m,n) = \lim \frac{1}{T-n}\sum_n \log_e d_n(m,i,j). \tag{3.2.16}$$

A positive value of LE means that the points in m-dimensional space, in an attractor of a nonlinear process will be divergent as time increases. The system is characterized as chaotic if at least one of the Lyapunov exponents is positive.

3.5.3.2 Analysis of the Occurrence of Chaos in the Market

Chaos in the market is characterized by the occurrence of extremely high or extremely low returns and volatility in the market. Therefore, the focus in this section is on describing the occurrence of extremely high and extremely low volatility clusters in the foreign exchange market in Kenya across the year. The models used in this section were based on Markov chains in an attempt to incorporate some market microstructure ideas. The models were derived empirically, and economic significance was attached to the fitted parameters. The analysis was restricted to two state Markov chains. The states were labeled "Low" and "High". The model was in general fitted to the T days of the year from day t_l to t_T. The volatility on a given day was defined by the variable J (t) as follows:

$J(t) = 0$ if day t has low volatility, $t = t_l, \ldots, t_T$, (3.2.17)

$= 1$ if day t has high volatility

The magnitude of x, the foreign exchange return to be equaled or exceeded, is arbitrarily defined using threshold values of $x \le (E(X) - s)$ and $x \le (E(X) - 1.5s)$ for low volatility days and $x \ge (E(X) + 2s)$ and $x \ge (E(X) + 3s)$ for high volatility days, where $E(X)$ is the mean and s the standard deviation. These truncation values were chosen instead of actual absolute return amounts to facilitate comparison between different calendar periods.

The focus was restricted to second-order Markov chains but the analysis can be extended easily for higher order chains. The assumption that $J(t)$ forms a second-order Markov chain is the assumption that

$P[J(t)=1/J(t-1), J(t-2), J(t-3)\ldots] = P[J(t)=1/J(t-1), J(t-2)], t = t_1,\ldots,t_T$. To fit the Markov chain model involved estimating the 4T parameters $p_{hi}(t) = P[J(t)=1/J(t-1)=i, J(t-2)=h]$, $t = t_l, \ldots, t_T$, $h, i = 0, 1$.

The number of transitions are sufficient statistics for $p_{hi}(t)$, so the data may be reduced to a 2 x 2 x 2 x T table with entries $n_{h,i,j}(t)$ = Number of days with $J(t) = j$, $J(t-1) = i$, $J(t-2) = h$, $j = 0, 1$ and $t = t_l, \ldots, t_T$. The usual estimates of $p_{hi}(t)$ are the observed number of days $n_{h,i,j}(t)$ as a proportions of the total number of days, $\sum_{t=1}^{T} n_{hi}$, $h, i = 0, 1$. The assumption that a Markov chains is stationary implies that $p_{hi}(t) = p_{hi}$, $t = t_1 \ldots\ldots t_T$.

The approach used for curve fitting was based on the log-likelihood function below

$$l = \sum_{t=t_1}^{t_T} \sum_{h,i} \left[n_{hi1}(t)\log_e(p_{hi}(t)) + n_{hio}(t)\log_e(1 - p_{hi}(t)) \right]. \tag{3.2.18}$$

The model of time response used is expressed as follows

$$p_{hi}(t) = h(g_{hi}(t)), \tag{3.2.19}$$

where h is a known link function connecting the probabilities, $p_{hi}(t)$, to the function $g_{hi}(t)$ which is linear in unknown parameters. Since the binomial distribution is a member of the exponential family of distributions, the model is a generalized linear model (Nelder and Wedderburn, 1972) and hence the maximum likelihood estimates can be obtained easily. The link function h took the form,

$$h(t) = \exp(g_{hi}(t)) / [1 + \exp(g_{hi}(t))] \tag{3.2.20}$$

This ensured that the estimates of p lay between 0 and 1. The function $g_{hi}(t)$ may take many different forms and as a routine Fourier series were used,

$$g_{hi}(t) = a_{hio} + \sum_{k=1}^{m} \left[a_{hik}\sin(kt') + b_{hik}\cos(kt') \right], \; h,i = 0,1, \tag{3.2.21}$$

where $t' = 2\pi t / 12$. Fourier series have the desirable properties of modeling complex bi-modal data with few parameters. The required number of harmonics, m, was determined using multiple regression techniques in which the explanatory variables enter in a fixed order. Models with increasing values of m were fitted successively until no improvement in fit was gained by including additional terms. Maximum likelihood estimation was used, so likelihood ratio tests were used to assess the increase in goodness of fit. Thus for each model the deviance, G_m^2, was calculated and the difference in deviances, $G_m^2 - G_{m+1}^2$, measured the effect of including the *(m + 1)th* harmonic.

3.5.3.3 Analysis of the Distribution Characteristics of Chaos in the Market

The Gamma distribution and the Extreme Value Theory were applied to analyze the distributional nature of chaos in the market.

Gamma Distribution Model

The model for volatility magnitudes must describe the distribution of magnitudes on low volatility and high volatility days. This distribution may depend on the time of year and also on what has occurred on previous days. Let $X(t)$ be the magnitude of volatility on day t when $J(t) = 1$. $X(t)$ is undefined when $J(t) = 0$. The distribution of $X(t)$ is highly skewed and gamma distributions have been found to fit well. Let $x'(t) = X(t) - \delta$, with observations $x_i(t), i = 1, \ldots, n(t)$, where δ is some lower limit (equivalent to the standard deviation of the series $x(t)$) and $n(t)$ is the number of years in which volatility on day t is high or low. The distribution of $X(t)$ is then taken as the gamma with density function

$$f(x) = (\kappa / \mu(t))^{\kappa} x^{\kappa-1} \exp[-\kappa x / \mu(t)\Gamma(\kappa)] \qquad (3.2.22)$$

$E(x'(t)) = \mu(t)$ and the time dependence is taken to be of the form $\log(\mu(t)) = g(t)$. If $g(t)$ is linear in unknown parameters then this model is again a generalized linear model. Fourier series (3.2.32) are used as a routine. The methods of estimating parameters and assessing the goodness-of fit are essentially the same as when modeling the probability of a high/low clusters but are complicated by the second parameter, κ, which is the shape parameter of the gamma distribution.

As with the probability of volatility clusters, two related approaches to assessing goodness of fit of the Gamma distribution were applied. A graphical comparison of the observed and fitted values was probably the most useful. The second approach was to compare the residual between-day deviance with the "pure error" within-day deviance. The inter-day deviance was calculated as

$$D^2 = 2\Sigma n(t)[\log \bar{x}(t) - \log x(t)] \quad where \quad \log x(t) = [\Sigma \log x_j(t)] / n(t), \qquad (3.2.23)$$

where $\bar{x}(t)$ is the mean of $x(t)$.

In the gamma model the assumption made was that the coefficient of variation $(1/\sqrt{\kappa})$ is constant for all values of t. The $n(t)$ repeated observations on each day (or 5-day group) meant that an estimate of κ was available for each value of t. An estimate of κ was required to complete the model and maximum likelihood estimation was used. This is the solution of the equation

$$\log \kappa - \psi(k) = D^2 / 2n, \qquad (3.2.24)$$

where $n = \Sigma n(t)$ and $\psi(.)$ is the digamma function. Tables giving the solution of this are available or a rational approximation may be used (Greenwood and Durand, 1960).

Extreme Value Models

The L-moments Approach was used to estimate the parameters of the distribution of extreme returns. L-moments are linear combinations of probability-weighted moments. L-moments have got many advantages including unbiasedness, robustness, and consistency with respect to product moments. The method of L-moments was applied to estimate the mean or location, λ_1, the scale λ_2, the L-skewness, τ_3; and the L-kurtosis, τ_4. These L-statistics are similar to the ordinary moments, however, they are more efficient and tractable compared to the ordinary moments. There is a direct linear relationship between L-moments and probability weighted moments (PWM). Therefore, sample values of the L-moments can be obtained by exploiting these relationships via plotting position estimates of the probability weighted moments. The distribution were summarized by values of L-moments, λ_1 and λ_2 and L-ratios τ_3 and τ_4.

In order to determine the type of distribution that best describes foreign exchange returns the sample L-kurtosis were plotted against the sample L-skeweness. Then the underlying distribution was determined by choosing the distribution whose theoretical (L-kurtosis and L-skewness) curve passed close to plotted sample values. Specifically, a two-parameter distribution corresponds to a single point on this map (e.g. Gumbel, or Normal distribution); a three- parameter distribution to a curve (e.g. The Generalized Extreme Value (GEV), Generalized Logistic (GL), or Generalized Pareto (GP), or Log–Normal (L) distribution); and finally, a four-parameter distribution (e.g. the Generalized Lambda) referred to an area on the map. Sample L-moments were constrained to take on a specific range of values as follows: $\lambda_2 > 0, -1 < \tau_3 < 1, \frac{1}{4}\left(5\tau_3^2 - 1\right) \leq \tau_4 < 1$. The goodness of fit of the above models was tested using the Likelihood ratio statistic due to its power over the D-, V-, Z-, W^2, and U^2, statistics.

3.5.4 Analysis of the Duration of Chaos in the Market

The Neyman-Scott (NS) Model (1958) and the Bartlett-Lewis (BL) Model (1964) of volatility clustering were applied to analyze the duration of chaos in the market.

3.5.4.1 Neyman-Scott Model

The parameters of interest in fitting the NS (1958) model were the variance/mean ratio as captured by the variance-time curve, the recurrence times as measured by the survivor function, and the distribution of intervals between clusters as described by the hazard function. Data was divided into two classes – high volatility and low volatility clusters. The thresholds for low magnitudes were defined as before. Each category of data was analyzed separately from the rest to enable a comparison to be made about the duration of low and high volatility in the foreign exchange market in Kenya. The variance/mean ratio, *RV,* was calculated as follows,

$$R = E\{(1+M)^2\}/E(1+M), \tag{3.2.25}$$

M is the cluster size excluding the cluster centre. The asymptotic point on the variance-time curve and the hazard function determined the duration of the volatility cluster. The recurrence time for the NS model was computed as follows,

$$j(\tau) = \mu \frac{1 - e^{-\lambda\tau} II\left(e^{-\lambda\tau}\right)}{1 - e^{-\lambda\tau}} \rightarrow \mu(1 - p_0), \tag{3.2.26}$$

where μ is the intensity of the process of cluster centres, $e^{-\lambda\tau}$ is the probability of no cluster member in the interval (0, τ), *II (.)* is the empirical distribution of cluster members, τ is the interval length from the cluster centre and p_0 is the probability that the cluster is empty. The hazard function was obtained from the following formula,

$$h(\tau) = j(\tau) - j'(\tau) / j(\tau) \rightarrow \mu(1 - p_0), \tag{3.2.27}$$

where $j'(\tau)$ is the first derivative of $j(\tau)$ and p_0 is the probability that the cluster is empty.

3.5.4.2 Bartlett-Lewis Model

The parameters of interest in fitting the BL (1964) model are similar to those described by the NS model. Two types of clusters were analyzed – high volatility and low volatility clusters. The magnitudes for low and high volatility were defined as discussed in the Markov chain model, above. The variance/mean ratio, *RV*, was calculated as follows,

$$\psi(\omega) = |\ \hat{m}_1(\omega)\ |^2 \psi(\omega) + \frac{\mu}{\pi} \int_0^N (m_1(x) + c_2(x;\omega)) dx, \tag{3.2.28}$$

where $\psi(\omega)$ is the Bartlett spectrum for the process of cluster centers. N is the sample size, $\hat{m}_1(\omega)$is the spectral transform of the intensity, $m_1(x)$, of the process of cluster centers. $c_2(x;\omega)$ is the covariance density of the process of cluster members. The recurrence time of the BL model was calculated as,

$$j(\tau) = \lambda + \lambda a(1 - F(\tau)), \tag{3.2.29}$$

where τ is the length of the interval. The variable λ is the intensity of the process generating clusters. The hazard function was estimated as follows,

$$h(\tau) = \lambda + \lambda a\left(1 - F(\tau) + \frac{af(\tau)}{1 + a(1 - F(\tau))}\right), \tag{3.2.30}$$

where $a = \sum_1^\infty n\pi_n$ and $\sum \pi_n$ is the cumulative probability of clusters of size τ.

CHAPTER FOUR

DATA ANALYSIS, RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the results of data analysis and the discussion of the findings. Section 4.2 presents the results of analyzing market efficiency (objective 1). Section 4.3 examines the results of volatility analysis (objective 2). Section 4.4 discusses the results of analyzing chaos (objective 3) and section 4.5 is the summary.

4.2 Results of Analysis of Market Efficiency

This section presents the results of testing the EMH in the foreign exchange market in Kenya. The focus is on the assumptions of normally distributed returns, the absence of serial correlation in the error terms and a constant risk premium. The section also examines the existence of seasonal patterns in the returns.

4.2.1 Results of the Unit Root Tests

The first step in the analysis was to examine the time series characteristics of the data sets used to test for market efficiency. This was necessary because often the results of the tests are influenced by the characteristics of the data such as stationarity and seasonality. The optimal lag for the returns was one, hence the use of R_{t-1} in the analysis.

Figure 4 Daily Foreign Exchange Rates

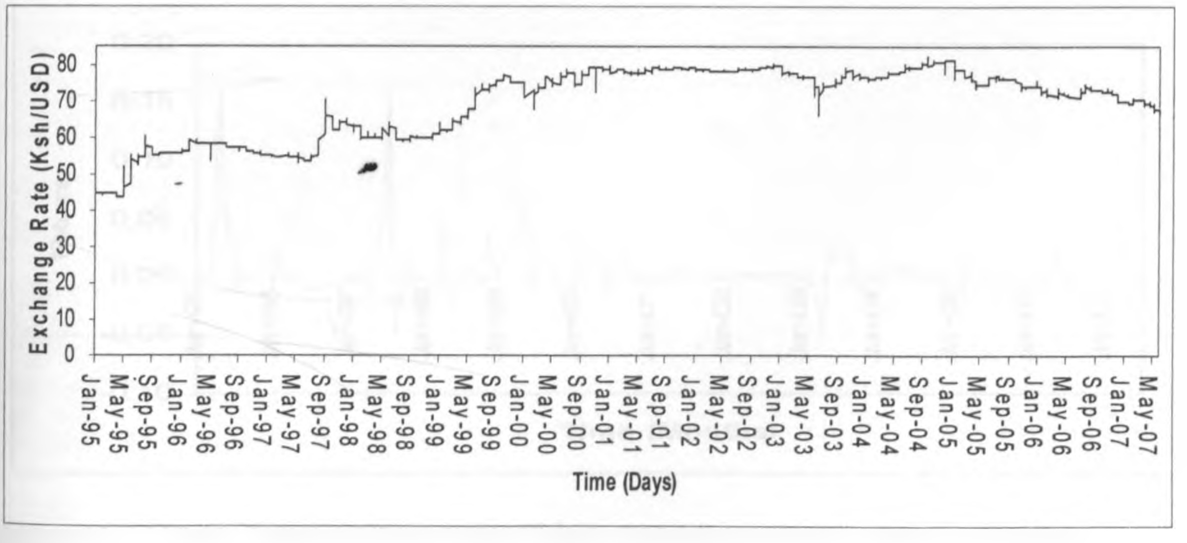


Figure 5 Daily Foreign Exchange Returns

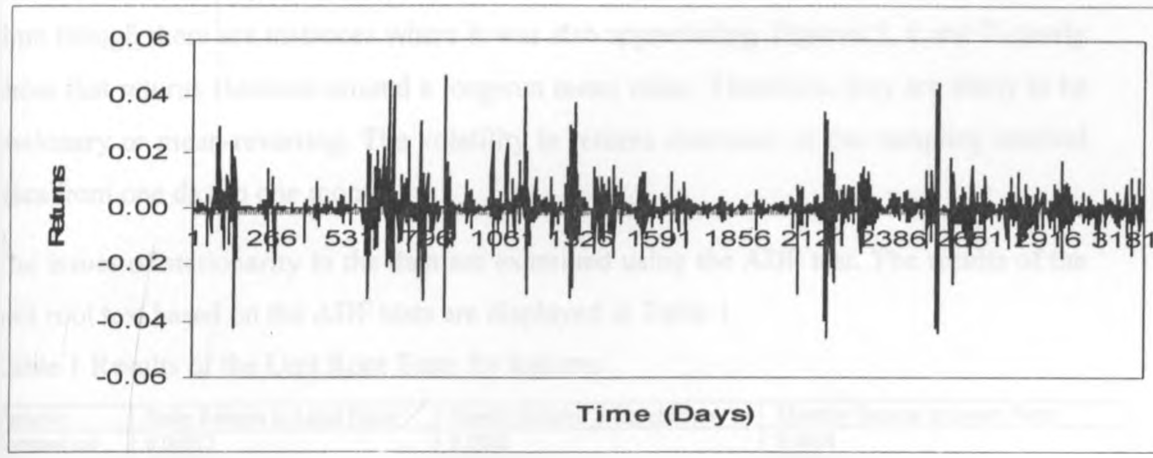


Figure 6 Weekly Foreign Exchange Returns

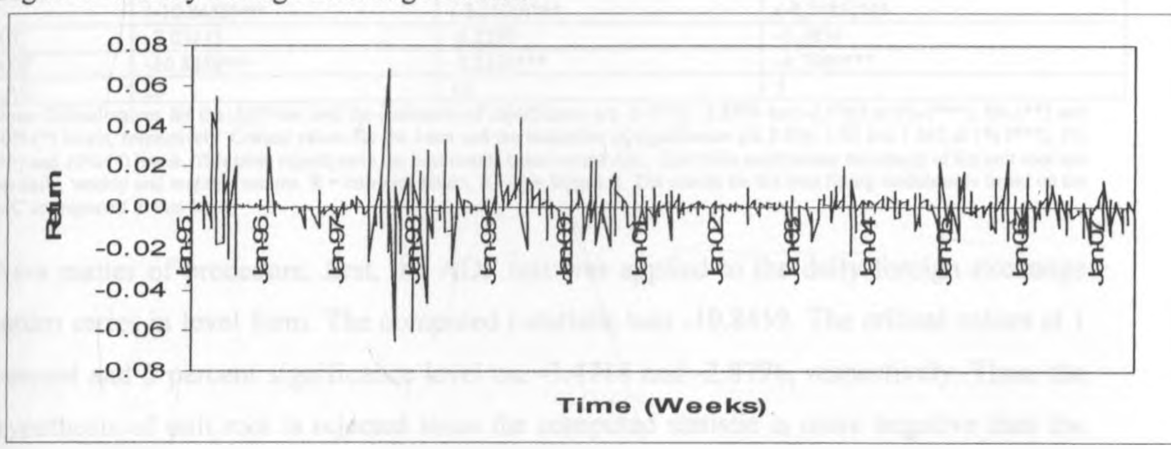
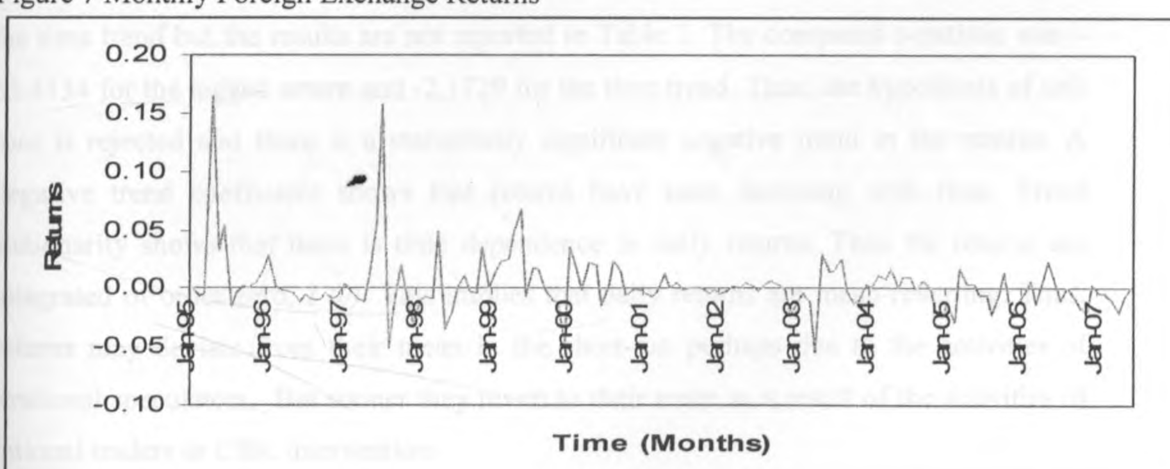


Figure 7 Monthly Foreign Exchange Returns



Figures 4, 5, 6 and 7 show the time series of daily exchange rates and returns at the daily, weekly and monthly intervals, respectively. In Figure 4 the exchange rates do not have a constant mean and variance. Therefore, the exchange rate is likely to be non-stationary.

This is confirmed by the unit root test. The exchange rate was depreciating most of the time though there are instances where it was also appreciating. Figures 5, 6 and 7 clearly show that returns fluctuate around a long-run mean value. Therefore, they are likely to be stationary or mean-reverting. The volatility in returns decreases as the sampling interval rises from one day to one month.

The issues of stationarity in the data are examined using the ADF test. The results of the unit root test based on the ADF tests are displayed in Table 1.

Table 1 Results of the Unit Root Tests for Returns

Variable	Daily Returns in Level Form	Weekly Returns in Level Form	Monthly Returns in Level Form
Constant (μ)	0.00013 (1.0546)	0.0002 (0.4791)	0.0004 (0.2476)
R(-1)	-1.0694 (-10.8459)***	-0.6985 (-5.2130)***	-0.7373 (-4.7985)***
AIC	-7.03115	-6.2220	-5.0834
ADF	-10.8459***	-5.2130***	-4.7985***
LAG	23	16	5

Note: Critical values for the *ADF*-test and the indication of significance are -3.4718, -2.8796 and -2.5765 at 1% (***), 5% (**) and 10% (*) levels, respectively. Critical values for the *t*-test and the indication of significance are 2.576, 1.96 and 1.645 at 1% (***), 5% (**) and 10% (*) levels. This table reports only the best results based on the AIC. This table summarizes the results of the unit root test for daily, weekly and monthly returns. R = currency return, R (-1) = lagged R. The results for the best fitting models only based on the AIC are reported in this table.

As a matter of procedure, first, the ADF test was applied to the daily foreign exchange return series in level form. The computed *t*-statistic was -10.8459. The critical values at 1 percent and 5 percent significance level are -3.4718 and -2.8796, respectively. Thus, the hypothesis of unit root is rejected since the computed statistic is more negative than the critical values. Then, the ADF test was applied to the daily return series in level form plus the time trend but the results are not reported in Table 3. The computed *t*-statistic was – 63.4134 for the lagged return and -2.1729 for the time trend. Thus, the hypothesis of unit root is rejected and there is a statistically significant negative trend in the returns. A negative trend coefficient shows that returns have been declining with time. Trend stationarity shows that there is time dependence in daily returns. Thus the returns are integrated of order zero, *I (0)*. This implies that daily returns are mean-reverting. Thus, returns may deviate from their mean in the short-run perhaps due to the activities of irrational speculators. But sooner they revert to their mean as a result of the activities of rational traders or CBK intervention.

Secondly, the ADF was applied to the level form of the weekly returns. The computed *t*-statistic was -5.2130. The critical values at 1 percent and 5 percent significance level are -3.4718 and -2.8796, respectively. Thus, the hypothesis of unit root is rejected since the computed statistic is more negative than the critical values. Then, the ADF test was applied to the foreign exchange weekly return series in level form plus the time trend but these results are not reported in Table 1. The computed *t*-statistic was -5.3749 for the lagged return and -1.3739 for the time trend. Thus, the hypothesis of unit root is rejected and there is no statistically significant trend in returns and therefore weekly returns are integrated of order zero, *I (0),* and have no statistically significant trend in time. The implications of these results are similar to those of daily returns except for the issue of trend stationarity.

Thirdly, the ADF was applied to the level form of the monthly returns. The computed *t*-statistic was -4.7985. The critical values at 1 percent and 5 percent significance level are -3.4718 and -2.8796, respectively. Thus, the hypothesis of unit root is rejected since the computed statistic is more negative than the critical values. Then, the ADF test was applied to the monthly return series in level form plus the time trend but the results are not reported in Table 3. The computed *t*-statistic was -5.6165 for the lagged return and -0.0506 for the time trend. Thus, the hypothesis of unit root is rejected and there is no statistically significant trend in the returns and hence monthly returns are integrated of order zero, I (0). The implications of these results are similar to those of weekly returns.

The same procedure for testing for unit roots in returns was applied to the interest rate differentials. Since the hypothesis of unit root could not be rejected in level form, first differences of the interest differentials were employed in the second stage. The results summarized in Table 3 indicate that interest rate differentials are integrated of order one, I (1). Thus, interest rate differentials are nonstationary and this implies that interest rate differentials have no tendency to return to their long run mean. Therefore, this suggests that interest rate differentials follow a random walk and cannot be accurately forecasted. Also further analysis involving the interest differential applied the first differences of the interest rate differential. Figure 8 and Figure 9, below, show the interest differentials. The mean is not constant and there is also a significant downward trend in time.

Table 3 Results of the Unit Root Tests for Interest Rate Differentials

Variable	Weekly Interest Rate Differentials			Monthly Interest Rate Differentials		
Constant (μ)	0.0275 (1.1156)	0.2128 (2.9860)***	-0.0132 (-0.4935)	0.2132 (1.3927)	0.6040 (1.2680)	-0.0912 (-0.4290)
IDIFF(-1)	-0.0039 (-1.8860)*	-0.0125 (-3.3615)***		-0.0398 (-2.3525)**	-0.0555 (-1.9359)**	
D(IDIFF(-1))			-0.3076 (-5.2992)***			-0.5426 (-5.1396)***
Trend(1)		-0.0003 (-2.7756)***	0.0000 (0.1918)		-0.00486 (-1.1227)	0.0005 (0.1899)
AIC	0.6019	0.5923	0.5237	1.3061	3.3716	3.1838
ADF	-1.8860	-3.3615	-5.2992***	-2.3525	-1.9356	-5.1396***
LAG	1	1	12	1	0	2

Note. Critical values for the *ADF*-test and the indication of significance are -3.4718, -2.8796 and -2.5765 at 1% (***), 5% (**) and 10% (*) levels, respectively. Critical values for the *t*-test and the indication of significance are 2.576, 1.96 and 1.645 at 1% (***), 5% (**) and 10% (*) levels.

Figure 8 Weekly Interest Rate Differentials

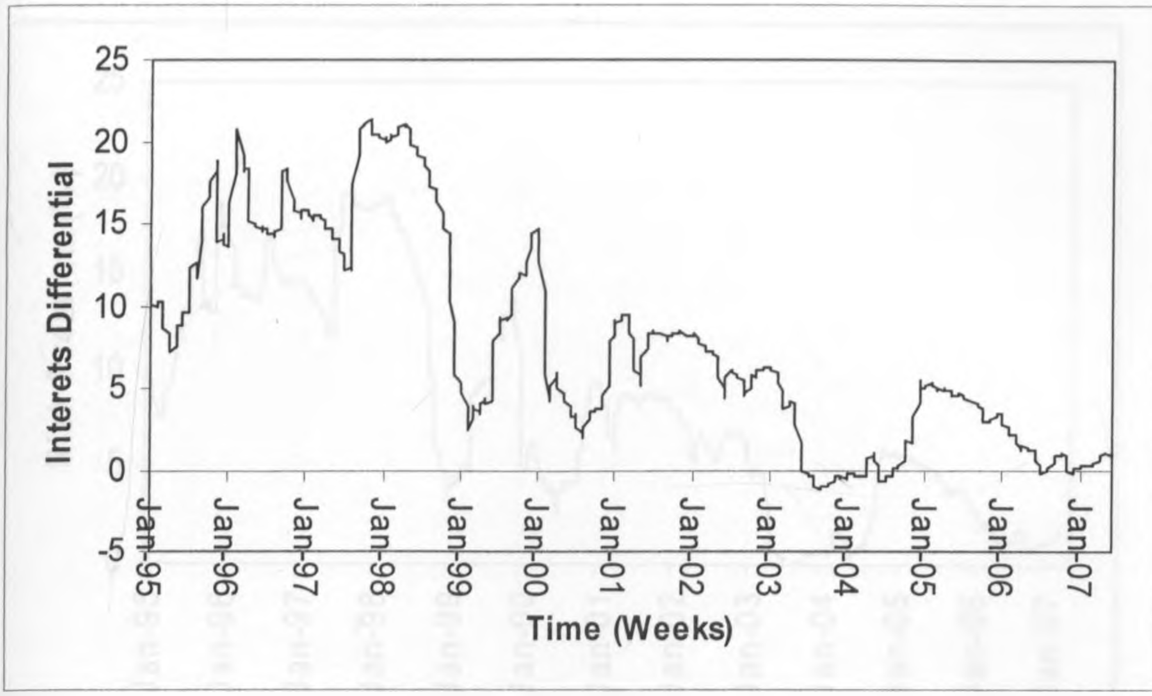
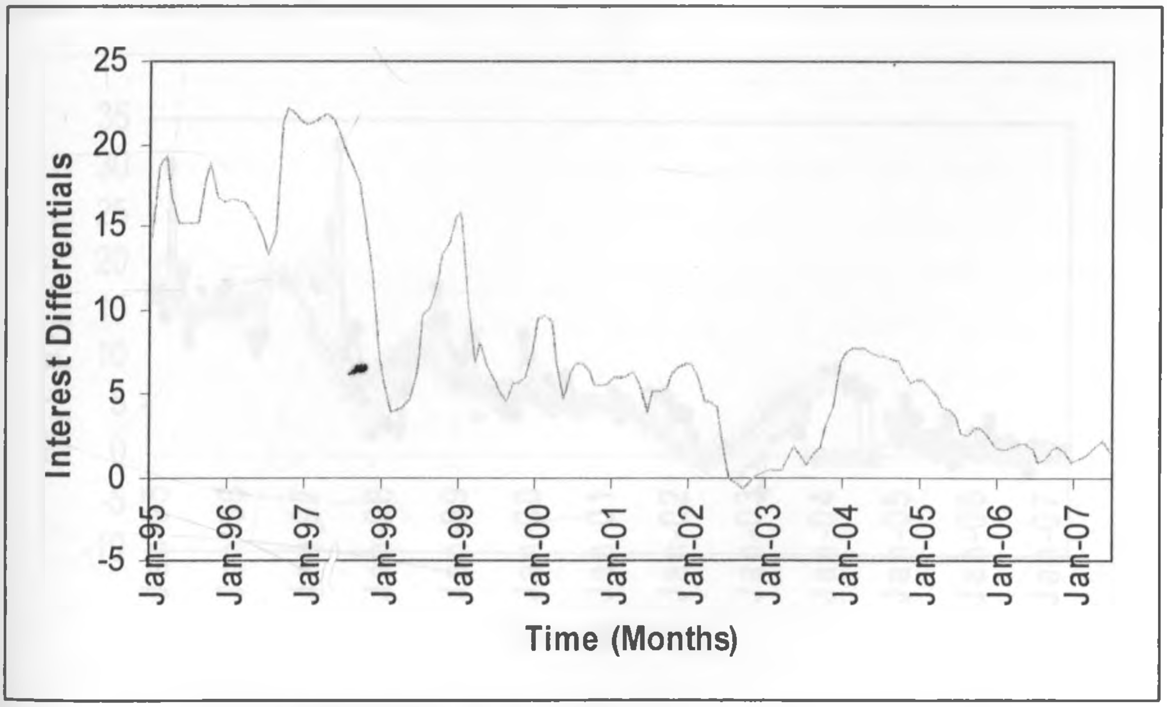


Figure 9 Monthly Interest Rate Differentials



Figures 10 and 11 show the risk premium at weekly and 1-, 3-, 6- , 12-monthly intervals. The mean of the risk premia is not constant. There are also downward trends in the risk premia over time.

Figure 10 Weekly Risk Premiums

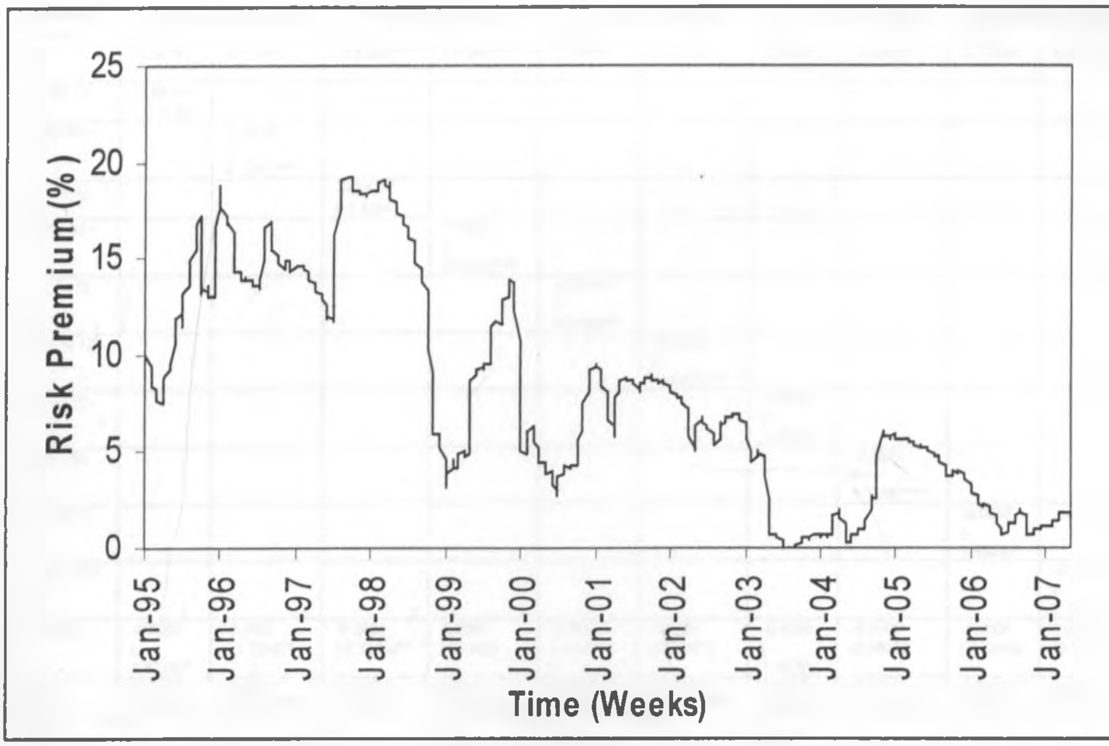


Figure 11 Monthly Risk Premiums

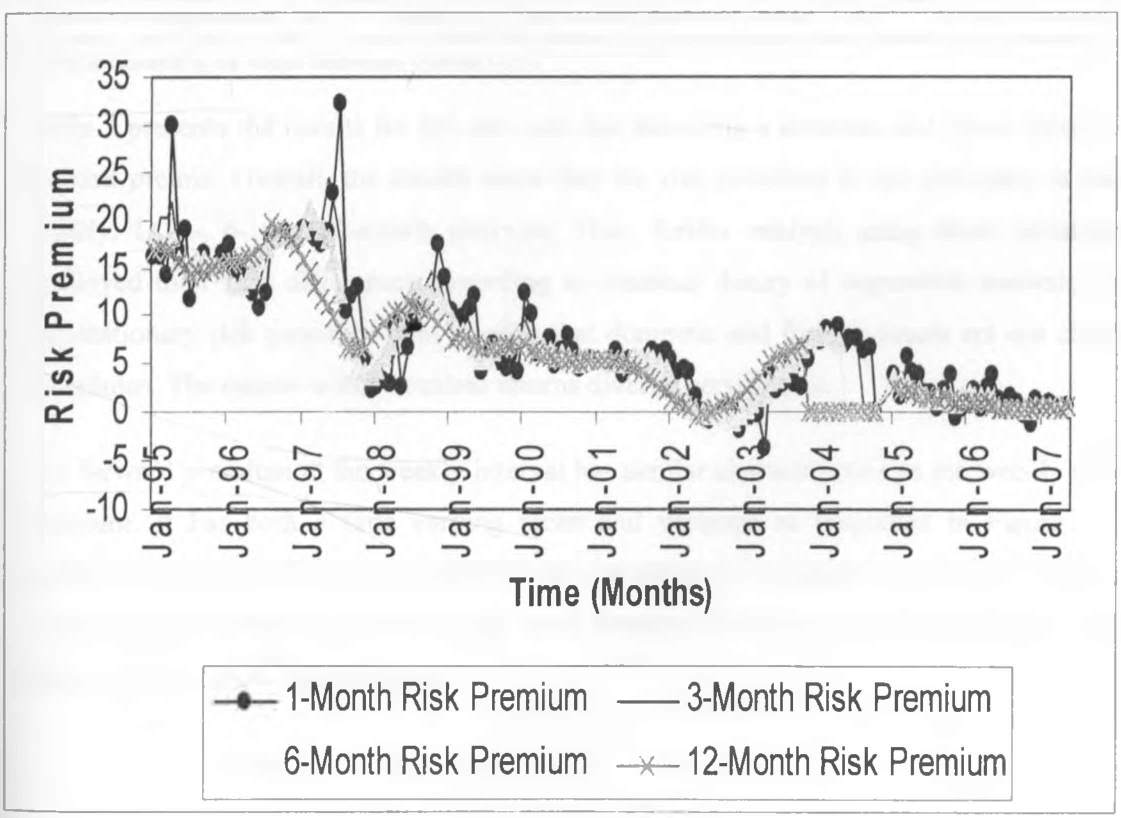


Table 4 Results of the Unit Root Tests for the Risk Premia

Variable	Weekly Risk Premium		1 Month Risk Premium		3 Month Risk Premium		6 Month Risk Premium		12 Month Risk Premium	
Constant (μ)	0.0259 (1.3196)	0.0150 (1.1000)	3.7833 (2.9546)**	-0.2007 (-0.3679)	1.0168 (1.5580)	-0.0385 (-0.2013)	0.3735 (1.0005)	-0.0788 (-0.6681)	0.2757 (1.2186)	-0.06101 (-0.9191)
RPW(-1)	-0.8844 (-0.8530)									
D(RPW(-1))		-1.6476 (-4.1042)***								
RP_1(-1)			-0.2472 (-3.4104)							
D(RP_1(-1))				-0.5362 (-5.0954)***						
RP_3(-1)					-0.0770 (-2.0146)**					
(RP_3(-1))						-0.5306 (-4.9051)***				
RP_6(-1)							-0.0319 (-1.4284)			
D(RP_6(-1))								-0.3531 (-4.7836)***		
RP_12(-1)									-0.0265 (-1.8828)*	
D(RP_12(-1))										-0.26258 (-3.7416)***
Trend(1)	-0.0001 (-1.8332)*	-0.0001 (-1.7246)*	-0.2824 (-2.7176)**	0.0007 (0.1162)	-0.0075 (-1.5403)	-0.0001 (-0.0261)	-0.0030 (-1.0879)	-0.0005 (0.3841)	-0.0020 (-1.1968)	0.0004 (0.5787)
AIC	-0.6121	-0.6959	5.1389	5.2190	2.8775	3.0380	1.7403	-9.5898	0.6324	0.9209
ADF	-0.8530	-4.1042***	-3.4104	-5.0954***	-2.0146	-4.9051***	-1.4284	-4.7836***	-1.8828	-3.7416***
LAG	3	0	2	0	13	0	12	1	13	2

Note: Critical values for the *ADF*-test and the indication of significance are -3.4718, -2.8796 and -2.5765 at 1% (***), 5% (**) and 10% (*) levels, respectively. Critical values for the *t*-test and the indication of significance are 2.576, 1.96 and 1.645 at 1% (***), 5% (**) and 10% (*) levels, respectively. [a] The results are based on the modified AIC. This table summarizes the results of the unit root test for the risk premia. RP_1= risk premium at one week horizon, D (RPW (-1)) = first difference of lagged RPW, RPW_1= risk premium at one month horizon, RP_1 (-1) = lagged RP_1. Other variables are similarly defined. D (RP_1* (-1)) = first difference of lagged RP_1, RP_3, RP_6 and RP_12, respectively. RP = Risk Premium. The results reported in this Table are for the best estimated models as indicated by the Akaike Information Criterion (AIC).

Table 5 presents the results for the unit root test assuming a constant and linear trend in the risk premia. Overall, the results show that the risk premium is not stationary at the weekly, 1-, 3-, 6- and 12-month intervals. Thus, further analysis using these variables employed their first differences according to classical theory of regression analysis. A non-stationary risk premium term implies that domestic and foreign assets are not close substitutes. The reason is that nominal returns diverge persistently.

The forward premium at the weekly interval has similar characteristics as the weekly risk premium. It has both a time varying mean and variance as displayed in Figure 12; therefore it is nonstationary as confirmed by the unit root test results in Table 5, below. There are also similarities between the term structure of the forward premium and the term structure of the risk premium.

Figure 12 Weekly Forward Premiums

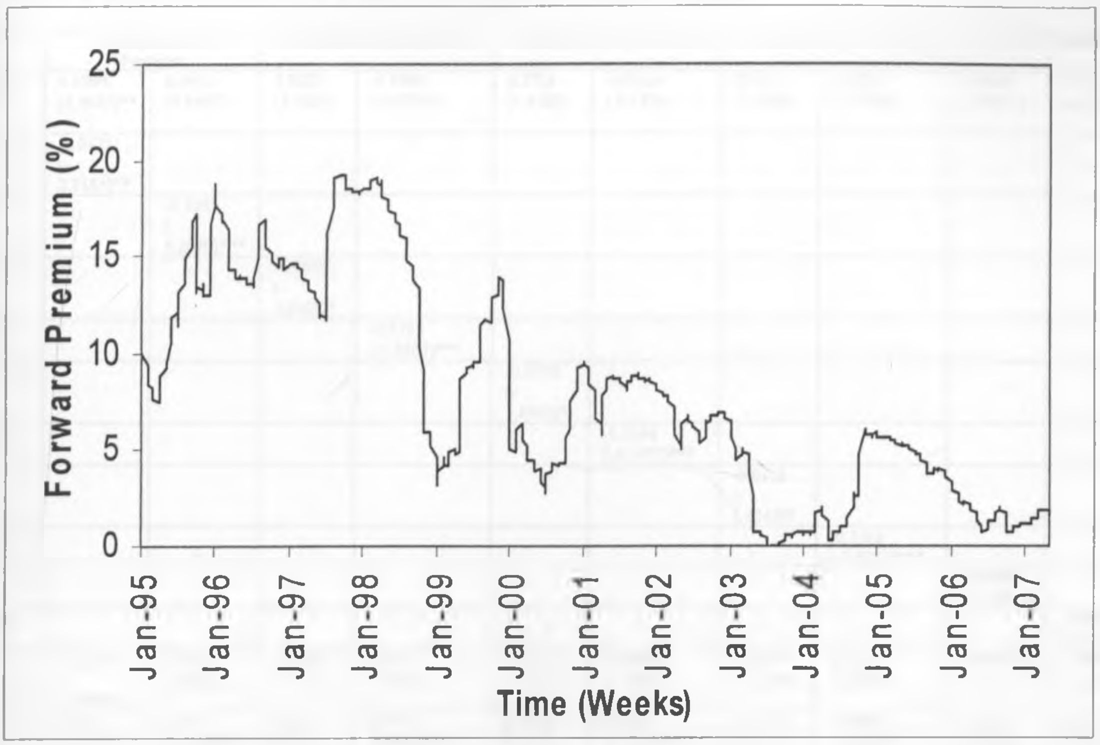


Figure 13 Monthly Forward Premiums

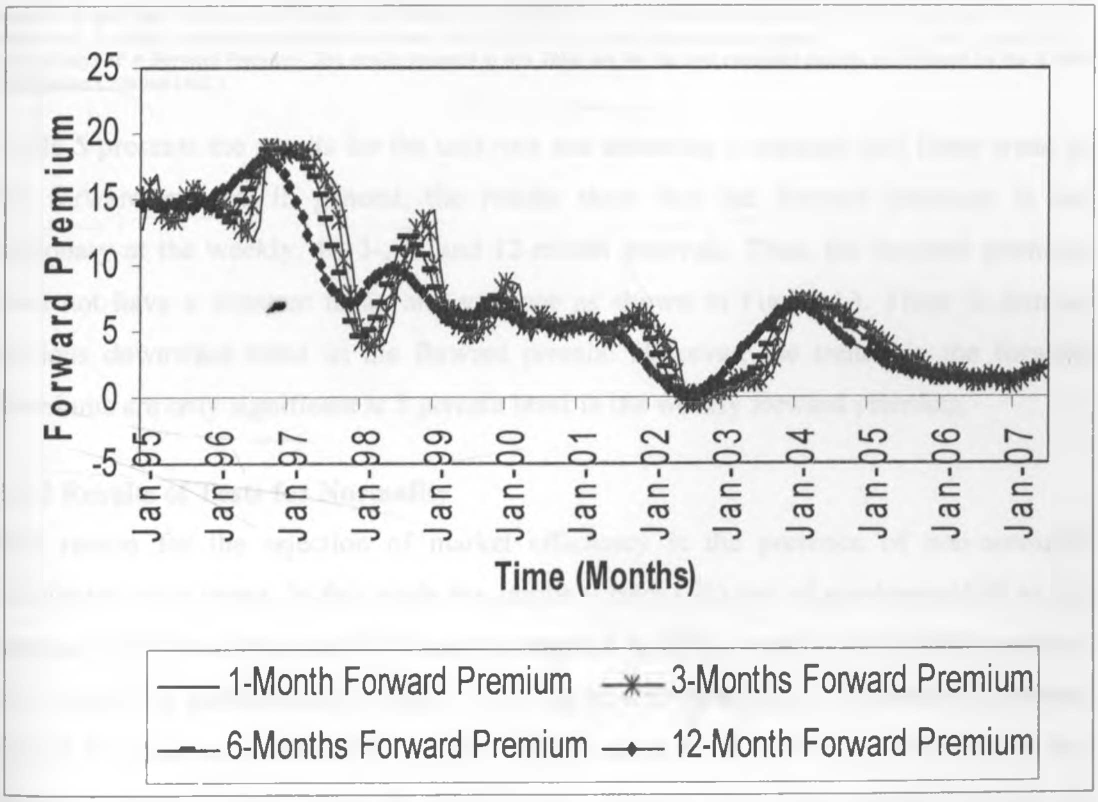


Table 5 Results of the Unit Root Tests for the Forward Premia

Variable	Weekly Forward Premium		1 Month Forward Premium		3 Month Forward Premium		6 Month Forward Premium		12 Month Forward Premium	
Constant (μ)	0.1909 (2.9621)**	0.0092 (0.3467)	0.8623 (1.5620)	-0.1491 (-0.8729)	0.2726 (1.4483)	-0.0364 (-0.5374)	0.1394 (1.2286)	-0.0333 (-0.9786)	0.0609 (1.0251)	-0.0103 (-0.5643)
FP(-1)	-0.01221 (-3.2154)**									
D(FP(-1))		-0.3581 (-5.2639)***								
FP_1(-1)			-0.0660 (-1.9499)*							
D(FP_1(-1))				-0.5786 (-7.9807)***						
FP_3(-1)					-0.0218 (-1.8562)*					
D(FP_3(-1))						-0.2144 (-4.1477)***				
FP_6(-1)							-0.0118 (-1.6547)*			
D(FP_6(-1))								-0.1568 (-3.6253)***		
FP_12(-1)									-0.0060 (-1.5262)	
D(FP_12(-1))										-0.0888 (-3.7801)***
Trend(1)	-0.0003 (-2.7458)**	-0.0004 (-0.5431)	-0.0062 (-1.5131)	0.0011 (0.5655)	-0.0020 (-1.4093)	-0.0002 (0.3015)	-0.0010 (-1.2186)	-0.0002 (0.6014)	-0.0005 (-1.0110)	0.0006 (0.2622)
AIC	0.5762	0.5930	2.8174	5.2190	0.6938	0.9728	-0.5510	-0.4972	-1.7336	-1.6325
ADF	-3.2154	-5.2639***	-1.9499	-7.9807***	-1.8562	-4.1477***	-1.6547	-3.6253**	-1.5262	-3.7801**
LAG	1	14	10	0	8	3	12	6	6	1

Note: Critical values for the *ADF*-test and the indication of significance are -3.4718, -2.8796 and -2.5765 at 1% (***), 5% (**) and 10% (*) levels, respectively. Critical values for the *t*-test and the indication of significance are 2.576, 1.96 and 1.645 at 1% (***), 5% (**) and 10% (*) levels, respectively. This table summarizes the results of the unit root test for the forward premia. FP_1= forward premium at one week horizon, D (FP (-1)) = first difference of lagged FP, FP_1 = forward premium at one month horizon, FP_1 (-1) = lagged FP_1. Other variables are similarly defined. D (FP_1* (-1)) = first difference of lagged FP_1, FP_3, FP_6 and FP_12, respectively. FP = Forward Premium. The results reported in this Table are for the best estimated models as indicated by the Akaike Information Criterion (AIC).

Table 5 presents the results for the unit root test assuming a constant and linear trend in the forward premia. In general, the results show that the forward premium is not stationary at the weekly, 1-, 3-, 6- and 12-month intervals. Thus, the forward premium does not have a constant mean and variance as shown in Figure 13. There is also an obvious downward trend in the forward premia. However, the trends in the forward premiums are only significant at 5 percent level in the weekly forward premium.

4.2.2 Results of Tests for Normality

One reason for the rejection of market efficiency is the presence of non-normally distributed error terms. In this study the Jarque – Bera (JB) test of goodness-of-fit to the normal distribution was used. The test was applied to daily, weekly and monthly returns. The results are summarized in Table 6. For the normal distribution the sample skewness should be close to zero and the sample kurtosis close to 3. The JB test shows that the sample skewness and kurtosis are significantly different from their expected values, as measured by the chi-square statistic. Therefore, the hypotheses that the daily, weekly and monthly returns are normally distributed are rejected. Hence daily, weekly and monthly returns are not normally distributed. Daily returns have a kurtosis of 89.3984 and a skewness of 1.3689. Weekly returns have a kurtosis of 50.0259 and a skewness of 4.0244. The excess kurtosis suggests that the market experiences large depreciations and appreciations in the exchange rates than is normal. Depreciations appear to be common at all intervals as indicated by a positive constant term for e^{μ} in Table 6.

Table 6 Results of the Normality Tests for Exchange Returns

Variable	Daily Returns	Weekly Returns	Monthly Returns
Constant(μ)	0.0001 (0.9824)	-0.0059 (-0.9033)	-0.0002 (-0.1188)
Mean	4.56E-18	-6.16E-17	2.75E-18
Stdev	0.0072	0.1654	0.0176
Skewness	0.1400	-25.1834	0.5155
Kurtosis	91.2008	639.1574	20.1554
Jarque-Bera	1057133	11012262	5.7297

Note: Critical values for the t-test and the indication of significance are 2.576, 1.96 and 1.645 at 1% (***), 5% (**) and 10% (*) levels, respectively. Stdev = standard deviation. This table summarizes the results for the normality test based on the constant returns model $R_t = \mu + e_t$ where μ is the constant mean return and e_t is the error term

Monthly returns have a kurtosis of 20.1554 and a skewness of 0.0594. The decline in the kurtosis and skewness implies that the returns tend toward the normal distribution as the sampling interval increases. In summary, the above results contradict one of the main assumptions of the EMH that returns are normally distributed. Therefore, the evidence adduced above shows that the returns are not normally distributed and suggests that the market is not efficient. The next step is to test the second major assumption of the EMH that the error terms in the constant returns model are not serially correlated.

4.2.3 Results of the Serial Correlation Tests

Another reason for the rejection of market efficiency is the presence of autocorrelation in the error terms. The results of the serial correlation test are displayed in Table 7 below. The regression results of the lagged returns, the holiday dummy, day-of-the-week dummies plus the month-of-the-year dummies are shown in Table 7. The variables were sequentially introduced in the model to allow the impact of each variable on the autocorrelated errors of the model to be isolated.

The results showed that the constant terms in the models are positive and not significant at the 5% level for the daily and weekly returns. Thus, when seasonal variables are included in the model the results show that the exchange rate has been depreciating most of the time especially at the monthly interval. The lagged returns are also significant at the 5% level in the models of daily and weekly returns. The results show that the problem of serial correlation is absent in the daily, weekly and monthly returns model after including seasonal dummies. The same procedure was repeated for weekly and monthly returns incorporating the interest rate differential. However, day of the week dummies were excluded due to differences in data sampling intervals.

Table 7 Results of the Serial Correlation Tests and Calendar Effects in the Market

Variable	Daily Returns	Weekly Returns	Monthly Returns
Constant (μ)	-0.0006 (-1.3200)	-0.0023 (-1.5862)	-0.0122 (-2.2812)**
R (-1)	-0.1144 (-6.5201)***	-0.0692 (-1.7381)*	0.1025 (1.0964)
R (-2)	-0.0702 (-4.0002)***	0.0926 (2.3332)**	
D(IDIFF (-1))		-0.0023 (-2.5949)**	0.0013 (0.9667)*
HOLIDAY	-0.0008** (-2.2915)		
MONDAY	0.0003 (0.6060)		
TUESDAY	0.0002 (0.4292)		
WEDNESDAY	0.0001 (0.2270)		
THURSDAY	0.0003 (0.6781)		
FRIDAY			
JANUARY	0.0006 (1.0777)	0.0023 (1 1755)	0.0121 (1.6815)*
FEBRUARY	0.0005 (0.8323)	0.0017 (0.8589)	0.0127 (1.6734)*
MARCH	0.0004 (0.7664)	0.0012 (0.5856)	0.0128 (1.6730)*
APRIL	0.0008 (1.6084)*	0.0044 (2.2427)**	0.0193 (2.5334)**
MAY	0.0014 (2.6578)**	0.0064 (3.2515)***	0.0217 (2.9161)**
JUNE	0.0006 (1.1732)	0.0006 (0.3178)	0.0158 (2.0810)**
JULY	0.000774 (1.4359)*	0.00371 (1.8467)*	0.01487 (1.9108)*
AUGUST	0.001064 (1.9419)*	0.00454 (2.2412)*	0.01131 (1.4858)
SEPTEMBER	0.0004 (0.7692)	0.0011 (0.5253)	0.0104 (1.3703)
OCTOBER	0.0005 (0.9627)	0.0013 (0.6495)	0.0098 (1.2735)
NOVEMBER	0.0003 (0.5109)	0.0013 (0.6586)	0.0054 (0.7482)
DECEMBER			
RESID (-1)	-0.2494 (-0. 9953)	0.0021 (0.0049)	-0.0233 (-0.0276)
AIC	-7.0391	-6.2633	-5.1110
LM	0.9961	0.0000	0.0009

Note: Critical values for the *t*-test and the indication of significance are 2.576, 1.96 and 1.645 at 1% (***), 5% (**), 10% (*) and 25% (°) levels, respectively. This table summarizes the results of the serial correlation test in returns R = currency return, R (-1) = lagged R. IDIFF = the interest differential, IDIFF (-1) = lagged IDIFF. D (IDIFF (-1)) = first difference of lagged IDIFF. RESID = residuals, RESID (-1) = lagged residuals. The results shown in this table are those of the best fitting models only as indicated by the AIC. The dummies for Friday and December were eliminated to avoid the dummy trap in regression analysis.

The results for the autocorrelation test shown in Table 7 indicate that there is statistically significant negative serial correlation in daily returns and monthly returns; and statistically significant positive serial correlation in the weekly and monthly returns. This implies that daily returns and monthly returns are mean-reverting while monthly returns are not mean-reverting.

In conclusion, daily and monthly returns are negatively autocorrelated while weekly returns are positively autocorrelated. Therefore, these results negate one of the main assumptions of the EMH that returns are not serially correlated.

4.2.4 Results of the Calendar Effects Tests

The next step in the analysis was to examine one main implication of the EMH that returns are random and therefore, do not display any pattern. This was analyzed by testing for the presence of calendar effects in the market. Four calendar effects were tested – the weekend effect, the day-of-the-week effect, the holiday effect, and the January effect. The results in Table 8 show that the holiday dummy is significant at 5% level in models of daily returns. This shows the presence of the holiday effect in the foreign exchange market. However, the results also show the absence of the day-of-the-week effect and the weekend effect in the market. Further, the results of the monthly returns model indicate the presence of the January effect. The results in Table 7 also indicate that there are significant seasonal patterns in April, May, June, July and August at the daily, weekly and monthly intervals. The coefficients of the seasonal dummies are all positive and increase in magnitude as the sampling interval increases. The coefficient for the holiday dummy is negative and statistically significant. This means that returns actually decline over holidays probably due to a decline in demand for the US dollar by the tourists.

In summary, the foreign exchange market displays seasonal patterns around holidays, in April, May, June, July and August. This shows that returns are not random as implied by the EMH. Therefore, this strongly suggests that the market in not efficient in the weak form.

4.2.5 Results of Testing for the Time Varying Risk Premia in the Market

The last assumption of the EMH that was tested is that the risk premium in the market is constant. Figure 11 and Figure 13, above, display the term structure of the risk premiums and the forward premiums, respectively. Evidently, the risk premia and the forward premia appear to be nonstationary and cointegrated. Therefore, the first step in testing for the risk premia in the market was to examine whether the risk premia and the forward premia are cointegrated. This was achieved using the Johansen cointegration test. The results are shown in Table 8.

The results indicate that the risk premiums and the forward premiums are cointegrated at all horizons. There are four cointegrating vectors for each risk premium horizon. However, at the 6-month and 12-month horizon there is only one cointegrating equation compared to the two shorter horizons.

Table 8 Results of the Cointegration Tests

Variable	RP 1 vs FP 1	RP 3 vs FP 3	RP 6 vs FP 6	RP 12 vs FP 12
Trace Statistic	46.2864**	31.6483	24.8172	8.3015
Critical Value	15.4947	15.4947	15.4947	15.4947
No CE(s)	Reject	Reject	Reject	Accept
At most 1 CE	Reject	Reject	Accept	Accept
CVs	4	4	4	4

Note: **denotes rejection of the hypothesis at 5 percent level This table provides a summary of the cointegration test between the risk premium and the forward premium. RP_1 is the one month risk premium, RP_3 is the one month risk premium, RP_6 is the one month risk premium, and RP_12 is the one month risk premium. FP_1 is the one month forward premium, FP_3 is the one month forward premium, FP_6 is the one month forward premium, and FP_12 is the one month forward premium. CE = Cointegrating Equations. CV = Cointegrating Vectors.

Engle and Granger (1987) showed that if variables such as the risk premium (RP_t) and the forward premium (FP_t) are integrated of order one, I (1), and $\eta_t = RP_t - \alpha FP_t$ and $\vartheta_t = FP_t - \gamma RP_t$ are both integrated of order zero, I (0), that is, if long-run relationships exist between these two variables, then RP and FP are said to be cointegrated.

Such variables may be considered to be generated by a vector autoregressive error-correction model (VECM). In this model the error correction terms are expected to capture the adjustments in RP and FP toward the long run equilibrium, while the lagged differenced terms of these variables are expected to capture the short run dynamics in of the model.

The results for estimating the error correction models for 1-, 3-, 6- and 12-month horizons are shown in Table 9. In the short-run the 1-, 3-, 6- and 12-months risk-premiums and forward premiums and their first and second differences are not mean-reverting. This means that in the short-run both the risk premiums and forward premiums are non-stationary. These results agree with those reported in section 4.2.1 that both the risk premiums and the forward premiums have unit roots. In the long-run the results of the *F*-test at optimum lags show that the *F*-statistics are greater than the critical values. Also the error-correction term is negative and statistically significant. These results indicate that the risk premium and the forward premium are cointegrated. The negative coefficient of the error-correction term shows that in the long-run the risk premiums are mean-reverting.

Table 9 Results of Vector Error-Correction Estimates of the Risk Premia

Variable	1-Month Risk Premium		3-Month Risk Premium		6-Month Risk Premium		12-Month Risk Premium	
CE	RP_1		RP_3		RP_6		RP_12	
RP(-i)	1.0000		1.0000		1.0000		1.0000	
FP(-i)	-1.1002 (-26.2733)***		-1.0670 (-37.2085)***		-1.0615 (-32.3811)3***		-1.0343 (-26.2733)***	
μ	0.5203		0.3125		0.333567		0.197887	
EC	D(RP_1)	D(FP_1)	D(RP_3)	D(FP_3)	D(RP_6)	D(FP_6)	D(RP_12)	D(FP_12)
ECT	-0.7945 (-5.1734)***	0.1192 (2.2988)**	-0.4396 (-5.8441)***	0.0547 (2.2140)**	-0.2176 (-3.9086)***	0.0308 (1.7016)	-0.1321 (-3.0754)**	0.0035 (0.27437)
D(RP(-1))	0.0260 (0.2024)	0.0042 (0.0969)	0.4245 (4.8973)***	0.0886 (3.1101)**	0.4029 (4.5198)***	0.1213 (4.1905)***	0.2587 (2.9129)**	0.1385 (5.1851)***
D(RP(-2))	0.0023 (0.0239)	0.0060 (0.18761)	0.2496 (2.7659)**	-0.0338 (-1.1408)	-0.0113 (-0.1190)	-0.07248 (-2.3421)**	-0.1265 (-1.3132)	-0.0924 (-3.1912)
D(FP(-1))	0.4587 (1.8438)*	0.5086 (6.0552)***	0.6229 (3.0392)**	1.1660 (17.3145)***	1.1182 (4.9991)***	1.3292 (18.2941)***	1.4416 (5.7466)***	1.3689 (18.1501)***
D(FP(-2))	-0.0468 (-0.2023)	-0.1699 (- 2.1756)**	-0.5544 (-2.8399)**	-0.5178 (-8.0730)***	-0.5978 (-3.1265)**	-0.5327 (-8.5774)***	-0.5181 (-2.4771)**	-0.5033 (-8.0038)***
μ	-0.0499 (-0.2112)	-0.0628 (-0.7872)	-0.0438 (-0.4699)	-0.0163 (-0.5317)	-0.0257 (-0.5064)	-0.0084 (-0.5095)	-0.0146 (-0.5440)	-0.0048 (-0.5948)
F-statistic	15.735***	12.225***	15.181***	120.71***	31.8111***	271.2793***	50.6456***	446.9343***
AIC	7.6443		3.7183		1.2883		-1.4008	

Note: Critical values for the t-test and the indication of significance are 2.576, 1 96 and 1 645 at 1% (***), 5% (**), 10% (*) and 25% (*) levels, respectively. The null hypothesis of market efficiency is analyzed by testing the restrictions that ECT = 1; D (FP (-1)) = 1and D (RP (-1)) = D (RP (-2)) = D (FP (-2)). This table summarizes the results of estimating the error correction models for the term structure of the risk premium. CE = Cointegration Equation, EC = Error Correction, ECT = Error Correction Term, RP_1 = Error correction term for the cointegration equation for the 1-month risk premium, RP_3 = Error correction term for the cointegration equation for the 3-month risk premium, RP_6 = Error correction term for the cointegration equation for the 6-month risk premium, and RP_12 = Error correction term for the cointegration equation for the 12-month risk premium. D (RP_1) = the difference of the error correction term RP_1. Other error correction terms are defined in the same way. RP (-i) = RP lagged i times. FP (-i) = FP lagged i times. RP = Risk Premium, D (RP (-1)) = First difference of RP lagged once and D (FP (-1)) = First difference of FP lagged once. Other variables are defined in similar manner. μ = Constant.

In summary, the results of the error-correction model reveal that both the risk premiums and forward premiums are non-stationary in the short-run. The F-statistics indicate that all coefficients of the error-correction models are jointly significant at 5 percent level. Therefore, this strongly suggests that the foreign exchange rate market is not efficient. Thus, evidence adduced in this study support the argument that the risk premium is time varying. Furthermore, the results show that the term structure of the risk premia contain significant information that can be exploited to forecast the future spot exchange rates.

In conclusion, returns are not normally distributed even after taking into account other relevant variables since they have high kurtosis compared to the normal distribution. The returns are serially correlated. There are also seasonal patterns in the market such as the January effect. Furthermore, the risk premium is not constant. Indeed, the term structure of the risk premia contains information that can improve the forecasting of future spot exchange rates. Therefore, when taken together the evidence provided above strongly suggests that the foreign exchange market is not efficient in the weak form.

4.3 Results of Analysis of Volatility Clustering in the Foreign Exchange Market

One important assumption of the EMH is that returns have a constant variance. However, the results presented in the previous section have shown that the risk premium is not constant. This finding implies that the variance of returns is heteroskedastic. This section presents the results obtained from analysis of volatility in the market. The analysis proceeded as follows.

4.3.1 Results of the Heteroscedasticity Tests

First, the heteroscedasticity test was performed on the error terms of best fitting linear models estimated in the analysis of efficiency. The results of the heteroscedasticity test are reported in Table 10. The results indicate the presence of heteroscedasticity in the residuals of the estimated linear models. However, the ARCH effect declines as the sampling interval increases. This forms the justification for conducting GARCH analysis.

Table 10 Results of the Heteroscedasticity Tests

Variable	Daily Returns	Weekly Returns	Monthly Returns
μ	0.0000 (4.1222)***	0.0001 (6.7767)***	0.0003 (4.7349)***
ARCH (1)	0.3984 (24.7981)***	0.1386 (4.841)***	0.1292 (2.5111)**
F-Statistic	614.9438***	16.6802***	6.3057***

4.3.2 Results of the ARCH Analysis

Second, the ARCH (1) model was fitted to the daily, weekly and monthly returns. The results in Table 11 Appendix C show that daily, weekly and monthly returns display significant ARCH effects. The coefficient of the daily lagged squared error is greater than one indicating that the variance of daily returns is likely to be explosive. The coefficients for the weekly and monthly lagged squared errors in the ARCH models show that 92 percent and 90 percent of past volatility for weekly and monthly returns, respectively, is carried over into the next period. Therefore, volatility in daily, weekly and monthly returns is persistent or clustered. This means that once the market becomes highly volatile it is likely to remain so than to calm down.

The ARCH-LM statistic indicates that all the models can explain the nonlinear dependence in the standardized squared residuals. Thus, there is no second order dependence in the standardized residuals of all the models. Therefore, there is no evidence of the ARCH effect in the residuals. This means that the models can capture properly the variance displayed by the returns. Overall, the AIC shows that GARCH models perform better than other nonlinear models in describing the nonlinear dependence in returns.

The same procedure for estimating the nonlinear models of returns was applied to the risk premium at 1-, 3-, 6- and 12-months horizons. The results are presented in Table 15 to Table 18. The results in Table 15 below show that volatility in the risk premia is persistent. The results also indicate the presence of an ARCH effect. Thus, once the market becomes volatile it is likely to remain volatile than to calm down.

Table 15 Results of Estimating ARCH Models of the Risk Premia

Variable	ARCH 1-Month RP	ARCH 3-Months RP	ARCH 6-Months RP	ARCH 12-Months RP
Mean Equations				
Constant (μ)	0.1761 [1.6849]*	-0.0247 [-0.4124]	-0.0669 [-1.9111]*	-0 0419 [-2 0265]**
D(RP_i(-1))	-0.5980 [-16.2254]***	-0.2316 [-1.9686]**	0.2145 [2.4321]**	0.0967 [1.1194]
D(RP_i(-2))	-0.2962 [-10.5448]***	-0.3594 [-3.9914]***	-0.4327 [-4.7608]	-0.0230 [-0.2411]
D(FP_i(-1))	0.8582 [6.7842]***	1.1708 [5.5591]***	1.10083 [5.8975]***	1.3465 [7.7903]***
D(FP_i(-2))	0.0270 [0.3573]	-0.2396 [-1.5427]	-0.1420 [-0.8004]	-0.6307 [-3.0677]***
ECT	1.0681 [57.2212]***	0.5657 [9.7121]***	0.2007 [4.9552]***	0.1331 [3.4804]***
Variance Equations				
Constant	0.7577 [3.9566]***	0.1407 [2.7354]***	0.0675 [3.0128]***	0.0262 [3.8356]***
ARCH (-1)	0.5107 [3.5723]***	0.4130 [2.2980]**	0.4598 [2 4259]**	0.4322 [2.1735]**
ARCH (-2)	-0.0653 [-1.0799]	0.1409 [1.0758]	0.5104 [3.5279]***	
ARCH (-3)	0.2297 [2.4596]**	0.2688 [1.9634]**		
ARCH (-4)		0.1996 [1.6476]*		
AIC	3.5818	2.7026	1.5577	0.3536
ARCH-LM	0.4701	0.1084	0.1611	0.0035

Note: Critical values for the z-test and the indication of significance are 2.576, 1.96 and 1.645 at 1% (***), 5% (**), 10% (*) and 25% (*) levels, respectively. This table summarizes the results of fitting nonlinear models to the 1-, 3-, 6- and 12-months risk premiums. RP_1 = Error correction term for the cointegration equation for the 1-month risk premium, RP_3 = Error correction term for the cointegration equation for the 3-month risk premium, RP_6 = Error correction term for the cointegration equation for the 6-month risk premium, and RP_12 = Error correction term for the cointegration equation for the 12-month risk premium. D (RP_1) = the difference of the error correction term RP_1. Other error correction terms are defined in the same way. RP (-i) = RP lagged i times. FP (-i) = FP lagged i times (i = 1, 3, 6, 12 for 1-, 3-, 6-, and 12- months intervals, respectively). RP = Risk Premium, D (RP (-1)) = First difference of RP lagged once and D (FP (-1)) = First difference of FP lagged once. Other variables are defined in similar manner. C (1) = the coefficient of the standardized absolute error term. C (2) = coefficient of the asymmetry term The values in square brackets are z-statistics. ECT = Error-Correction Term.

4.3.3 Results of the GARCH Analysis

Third, the GARCH models were estimated to determine the presence of the GARCH effect in returns. The results displayed in Table 12 in Appendix C, indicate that only daily and weekly returns show a GARCH effect. The coefficients for the lagged conditional variance in the GARCH models show that 88 percent, 80 percent and 6 percent of past volatility for daily, weekly and monthly returns, respectively, is carried over into the next period. These findings confirm the presence of volatility clustering in the returns.

Table 16 Results of Estimating GARCH Models of the Risk Premia

Variable	GARCH 1-Month-RP	GARCH 3-Months RP	GARCH 6-Months RP	GARCH 12-Months RP
Mean Equations				
Constant (μ)	5.1771 [16.3424]***	5.5537 [24.390]***	-0.0311 [0.0367]	-0.0335 [-1.8605]*
D(RP_i(-1))	-0.0323 [-0.1815]	0.3803 [2.2414]**	0.1238 [1.0923]	0.1473 [1.6575]*
D(RP_i(-2))	-0.1644 [-1.0965]	0.635346 [3.4742]***	-0.2371 [-2.1212]**	-0.1814 [-1.5599]
D(FP_i(-1))	0.5784 [1.4848]	-1.1007 [-2.1868]**	0.9073 [4.6714]***	1.7752 [9.3761]***
D(FP_i(-2))	0.5123 [1.6203]	1.1873 [2.2470]**	-0.1241 [-0.6524]	-0.9798 [-7.2524]
Variance Equations				
Constant	2.3534 [1.6896]	1.7417 [0.4606]	0.0125 [1.6413]	0.0009 [0.7326]***
ARCH (-1)	0.6110 [2.35368]**	1.1201 [2.6403]***	0.3205 [2.9852]***	0.1208 [4.6266]***
ARCH (-2)		0.3091 [0.0991]		
GARCH (-1)	0.1963 [0.4445]	-0.3355 [-0.1218]	0.0370 [0.2956]	-0.0624 [-3.7603]***
GARCH (-2)	0.0125 [0.0396]	-0.2590 [-0.6581]	0.5657 [3.4194]***	
GARCH (-3)	-0.0043 [-0.0267]	0.1117 [0.2212]		
GARCH (-4)	-0.0187 [-0.3930]	-0.0590 [-0.1194]		
GARCH (-5)	-0.0053 [-0.2639]	-0.0189 [-0.0842]		
GARCH (-6)	-0.0057 [-0.4223]	0.0077 [0.0573]		
GARCH (-7)	-0.0040 [-0.0889]	-0.0223 [-0.2663]		
GARCH (-8)	0.0315 [0.4020]	0.0260 [0.2824]		
GARCH (-9)		-0.0031 [-0.0389]		
AIC	5.8023	5.3996	1.4594	0.2602
ARCH-LM	1.6330	1.0609	0.5065	1.3677

Note: Critical values for the z-test and the indication of significance are 2.576, 1.96 and 1.645 at 1% (***), 5% (**), 10% (*) and 25% (') levels, respectively. This table summarizes the results of fitting nonlinear models to 1-, 3-, 6- and 12-months risk premiums. RP_1 = Error correction term for the cointegration equation for the 1-month risk premium, RP_3 = Error correction term for the cointegration equation for the 3-month risk premium, RP_6 = Error correction term for the cointegration equation for the 6-month risk premium, and RP_12 = Error correction term for the cointegration equation for the 12-month risk premium. D (RP_1) = the difference of the error correction term RP_1. Other error correction terms are defined in the same way. RP (-i) = RP lagged i times. FP (-i) = FP lagged i times (i = 1, 3, 6, 12 for 1-, 3-, 6-, and 12- months intervals, respectively). RP = Risk Premium, D (RP (-1)) = First difference of RP lagged once and D (FP (-1)) = First difference of FP lagged once. Other variables are defined in similar manner. C (1) = the coefficient of the standardized absolute error term. C (2) = coefficient of the asymmetry term. The values in square brackets are z-statistics. ECT = Error-Correction Term.

The results in Table 17 below indicate the presence of a GARCH effect in the risk premiums at all horizons except the 3-month interval. This means that volatility in the risk premia is persistent except at the 3-months horizon. Therefore the market is not likely to calm down once it becomes volatile with respect to 1-, 6- and 12-months risk premia.

Indeed, the results show that the level of persistence increases with the time horizon. For instance, the coefficients for the lagged conditional variance in the GARCH models show that 33 percent, 52 percent, and 60 percent of past volatility for 1-, 3- and 6-monthly risk premium, respectively, is carried over into the next period. However, at the 12-months horizon this effect wears out considerably dropping to 6 percent suggesting reversion to the mean.

4.3.4 Results of E-GARCH Analysis

Fourthly, the leverage effect was tested by estimating the E-GARCH models for the returns. The results in Table 14 in Appendix C show that only daily and weekly returns are asymmetrical.

Table 17 Results of Estimating the E-GARCH Models of the Risk Premia

Variable	E – GARCH 1-Month RP	E – GARCH 3-Months RP	E – GARCH 6-Months RP	E – GARCH 12-Months RP
		Mean Equation		
Constant	0.0558 [0.7913]	-0.0188 [-0.3063]	-0.0444 [-2.2490]**	-0.0301 [-1.1888]
D(RP_i(-1))	-0.5767 [-27.250]***	-0.1398 [-1.2323]	0.1535 [1.8094]*	0.1359 [1.2791]
D(RP_i(-2))	-0.3284 [-16.518]***	-0.3360 [-4.1509]***	-0.1147 [-1.7130]*	-0.2353 [-2.2138]**
D(FP_i(-1))	0.8788 [12.906]***	1.1049 [5.7971]***	1.3530 [9.6563]***	1.3909 [7.6843]***
D(FP_i(-2))	-0.0049 [-0.0990]	-0.1861 [-1.2594]	-0.6379 [-6.7424]***	-0.4132 [-2.3794]**
ECT	1.0142 [78.772]***	0.4893 [8.7967]***	0.1065 [4.3949]***	0.1456 [3.9767]***
		Variance Equations		
Constant	-0.1993 [-0.8018]	-0.4825 [-4.9058]***	-6.6160 [-11.906]***	-0.7086 [-3.8058]***
C (1)	0.9895 [11.339]***	0.5795 [4.6353]***	0.9923 [3.3497]***	0.4826 [3.5506]***
C (2)	-0.2497 [-2.4901]**	0.0215 [0.2712]	1.0035 [3.1634]***	0.1725 [1.8596]*
C (3)	-0.6529 [-25.4126]***	0.9146 [24.321]***	0.0693 [0.8922]	0.3403 [1.3611]
C (4)			-0.8332 [-13.608]***	0.5389 [2.2119]**
AIC	3.5486	2.6610	0.3012	0.3245
ARCH-LM	0.5899	0.1973	0.0038	1.3014

Note: Critical values for the z-test and the indication of significance are 2.576, 1.96 and 1.645 at 1% (***), 5% (**), 10% (*) and 25% (°) levels, respectively. This table summarizes the results of fitting nonlinear models to 1-, 3-, 6- and 12-months risk premiums. RP_1 = Error correction term for the cointegration equation for the 1-month risk premium, RP_3 = Error correction term for the cointegration equation for the 3-month risk premium, RP_6 = Error correction term for the cointegration equation for the 6-month risk premium, and RP_12 = Error correction term for the cointegration equation for the 12-month risk premium. D (RP_1) = the difference of the error correction term RP_1. Other error correction terms are defined in the same way. RP (-i) = RP lagged i times. FP (-i) = FP lagged i times (i = 1, 3, 6, 12 for 1-, 3-, 6-, and 12- months intervals, respectively). RP = Risk Premium, D (RP (-1)) = First difference of RP lagged once and D (FP (-1)) = First difference of FP lagged once. Other variables are defined in similar manner. C (2) = coefficients of the asymmetry term in the 1- and 3-months risk premia. C (3) = coefficients of the asymmetry term in the 6- and 12-months risk premia. The values in square brackets are z-statistics. ECT = Error-Correction Term.

Thus a positive shock to the market contributes to a smaller increase in volatility in the market compared to a negative shock of equal magnitude on a daily and weekly basis. The asymmetrical response to news in the market is absent at the monthly interval. This means that both negative and positive shocks of equal magnitude increase volatility equally in the market. Therefore, this suggests that the market efficiently prices risk only at the monthly interval. This conjecture is confirmed by fitting the GARCH-M model to the returns.

The results in Table 18 indicate the presence of asymmetry in the risk premiums at all horizons, except at the 3-month interval. This means that a positive shock in the market is likely to cause a small change in the magnitude of the risk premium compared to a negative shock of equal magnitude except at the 3-month horizon.

4.3.5 Results of the GARCH-M Analysis

Fifthly, the GARCH-M model was estimated for daily, weekly, and monthly returns. The objective was to determine the efficiency of the market in pricing of exchange risk.

Table 18 Results of Testing the GARCH-M Models of the Risk Premia

Variable	GARCH – M 1- Month RP	GARCH – M 3- Months RP	GARCH – M 6-Months RP	GARCH – M 12 Months RP
Mean Equations				
Constant	0.2664 [2.4533]**	1.0546 [3.0357]***	-0.0358 [-0.7227]	0.0075 [0.4447]
D(RP_i(-1))	-0.6167 [-18.341]***	-0.0925 [-1.0541]	0.1202 [1.0497]	0.1873 [2.1761]**
D(RP_i(-2))	-0.2492 [-9.7260]***	-0.2981 [-3.2274]***	-0.2367 [-2.1242]**	-0.1736 [-1.6605]*
D(FP_i(-1))	0.7726 [6.8480]***	1.1066 [6.7444]***	0.9073 [4.6903]***	1.4683 [107.38]***
D(FP_i(-2))	0.0517 [1.0124]	-0.3882 [-3.0096]***	-0.1211 [-0.6325]	-0.6840 [-7.4003]***
ECT	1.0632 [64.111]***	0.5021 [9.3687]***	0.2971 [5.6011]***	0.1659 [5.4721]***
GARCH	-0.1026 [-1.6775]*	-1.1738 [-2.9107]***	0.0305 [0.1317]	-0.6020 [-2.6409]***
Variance Equations				
Constant	0.3166 [2.6858]***	0.2367 4.3193	0.0126 [1.6451]*	0.0009 [0.6036]
ARCH (-1)	0.5601 [4.3242]***	0.1554 [2.8538]***	0.3273 [2.8602]***	0.1571 [4.3424]***
GARCH (-1)	-0.0912 [-1.9165]*	1.0606 [6.2633]***	0.0367 [0.3042]	-0.1173 [-3.7299]***
GARCH (-2)	0.3979 [3.4179]***	-0.4872 [-3.4864]***	0.5604 [3.3610]***	0.9073 [45.965]***
AIC	3.5158	2.7269	1.4730	0.2335
ARCH-LM	1.1499	0.8374	0.4572	0.0298

Note: Critical values for the z-test and the indication of significance are 2.576, 1.96 and 1.645 at 1% (***), 5% (**), 10% (*) and 25% (') levels, respectively. This table summarizes the results of fitting nonlinear models to 1-, 3-, 6- and 12-months risk premiums RP_1 = Error correction term for the cointegration equation for the 1-month risk premium, RP_3 = Error correction term for the cointegration equation for the 3-month risk premium, RP_6 = Error correction term for the cointegration equation for the 6-month risk premium, and RP_12 = Error correction term for the cointegration equation for the 12-month risk premium. D (RP_1) = the difference of the error correction term RP_1. Other error correction terms are defined in the same way RP (-i) = RP lagged i times FP (-i) = FP lagged i times (i = 1, 3, 6, 12 for 1-, 3-, 6-, and 12- months intervals, respectively). RP = Risk Premium, D (RP (-1)) = First difference of RP lagged once and D (FP (-1)) = First difference of FP lagged once. Other variables are defined in similar manner. The values in square brackets are z-statistics. ECT = Error-Correction Term.

The results displayed in Table 14 in Appendix C show that the market does not price risk efficiently except at monthly interval. The coefficient of the variance term (GARCH) is positive at all intervals. However, the variance coefficient is only significant at 1 percent level for monthly returns. Therefore, returns increase (decrease) as the risk increases (decreases) but only significantly so, in a statistical sense, at the monthly interval. The GARCH-M model shows that 74 percent and 80 percent of past daily and weekly volatility in returns, respectively, is carried over to the next period.

Therefore, the market is likely to respond to volatility asymmetrically at all horizons except at the 3-month horizons. The next step was to test the efficiency of the market in pricing currency risk. The results in Table 18 indicate that the coefficient of the variance (GARCH) is negative and significant at all horizons except at the 6-month interval. This means that the market is efficient in the pricing of risk at all horizons. Though the coefficient of the variance is positive at the 6-month horizon, it is not statistically significant. Therefore, participants in the market are fully compensated for their risk exposure except at the 6-months horizon.

Another test of the efficiency of the market was done by testing whether the term structure of interest rates contains any information that can be exploited to predict the forward premium. The results in Table 18 indicate that the coefficient of the risk premium lagged twice is negative and significant at all horizons. Thus, the information in the term structure of the risk premia can be used to improve the prediction of the risk premium and the exchange rate. Therefore, the market is not efficient. The ARCH-LM statistic indicates that all the models can explain the nonlinear dependence in the standardized squared residuals of the risk premium. Thus, there is no second order dependence in the standardized residuals of all the models. Therefore, there is no evidence of the ARCH effect in the residuals. This means that the models can capture well the variance displayed by the risk premium. Overall, the AIC shows that GARCH models perform better than other nonlinear models in describing the nonlinear dependence in the risk premiums.

The implications of these results are that returns are nonlinear and have a time varying variance. Therefore, including nonlinear terms in the regression equation of daily, weekly and monthly returns can increase prediction accuracy of the model. The response of daily returns to market shocks is asymmetrical. The results also indicate that there is no heteroskedasticity in the squared residuals of the GARCH models. Therefore, including the variance in the regression model of returns improves the predictability of returns.

Asymmetry in volatility of returns is likely to be associated with the behavior of importers in the market. When the economic fundamentals improve, the Kenya shilling appreciates against the dollar perhaps increasing the imports. Therefore, the demand for the dollar will rise but only marginally. However, when the reverse occurs, there is a steep demand for dollars to meet the imports bill by the importers. This causes the Kenya shilling to depreciate significantly against the US dollar. The possible explanation for this is that importers are risk averse.

In summary, the evidence provided above indicates that the variance of returns is not constant. It is time varying. Therefore, these results contradict one of the major assumptions of the EMH that the variance of returns is constant. The term structure of the risk premia also contains information that can be used to improve prediction of returns. However, the market is efficient in the pricing of risk. Thus, market participants are not exposed to exchange risk for which they are not fully compensated. Thus, when the results of this section and the previous section are taken together the evidence adduced strongly suggest that the foreign exchange market in Kenya is not efficient in the weak form.

4.4 Results of the Analysis of Chaos in the Foreign Exchange Market

This section presents the results of two tests applied to examine the presence of any patterns in the errors of the GARCH models. Such patterns are attributed to chaos in foreign exchange rate market. These tests are the Brock, Dechert and Scheinkman (BDS) test and the Lyapunov exponent test. These tests showed the presence of chaos. Thus, the results on the occurrence, distribution of magnitudes and duration of chaos are also discussed.

4.4.1 Results of the Analysis of the Existence of Chaos in the Market

The results of the BDS test and the Lyapunov exponent test are presented below.

4.4.1.1 Results of the BDS Tests

The BDS test was applied to the error terms of the best fitting GARCH models of returns, risk premia and the forward premia. The hypothesis of IID error terms was rejected as indicated by significant computed z-statistics in Table 19 below compared to the critical value $z = 2.638$ at 5 percent significance level. Therefore the patterns in the errors, which are not captured by linear and nonlinear models, could be attributed to chaos. The z-statistics decline in magnitude as the sampling interval increases. This shows that the rejection of the IID hypothesis weakens as the sampling interval increases. Therefore, chaotic dynamics are more likely to be observed at shorter sampling intervals than at longer sampling intervals.

Table 19 Results of the BDS Tests for Chaos in Returns

Dimension	BDS Statistic	Std. Error	Z-statistic	Probability
		Daily Returns		
2	0.0534	0.0020	25.9739***	0.0000
3	0.0972	0.0032	29.6585***	0.0000
4	0.1269	0.0039	32.4040***	0.0000
5	0.1433	0.0040	34.9667***	0.0000
6	0.1500	0.0039	37.8045***	0.0000
		Weekly Returns		
2	0.0472	0.0047	10.0024***	0.0000
3	0.0863	0.0075	11.4494***	0.0000
4	0.1141	0.0090	12.6357***	0.0000
5	0.1286	0.0094	13.5786***	0.0000
6	0.1343	0.0091	14.6159***	0.0000
		Monthly Returns		
2	0.0713	0.0101	7.0217***	0.0000
3	0.1150	0.0163	7.0525***	0.0000
4	0.1368	0.0196	6.9672***	0.0000
5	0.1483	0.0207	7.1651***	0.0000
6	0.1531	0.0201	7.5817***	0.0000

Note: The results in this table are based on the error terms of the best fitting model for estimating the returns. Critical values for the z-test and the indication of significance are 2.576, 1.96 and 1.645 at 1% (***), 5% (**), 10% (*) and 25% (ª) levels, respectively

Hence, the likely cause of chaos can be ascribed to the risk aversion or speculative behavior of economic agents. Market participants shorten their decision horizons in response to increased market volatility. This finding is rather counter-intuitive since it means that the more risk averse or speculative the market participants are, the more likely the market is to become volatile, rather than quiescent.

Table 20 Results of the BDS Tests for Chaos in the Risk Premiums

Dimension	BDS Statistic	Std. Error	Z-statistic	Probability
One Month Risk Premium				
2	0.0214	0.0055	3.8476***	0.0001
3	0.0310	0.0088	3.5139***	0.0004
4	0.0386	0.0105	3.6695***	0.0002
5	0.0407	0.0109	3.7166***	0.0002
6	0.0388	0.0105	3.6729***	0.0002
Three Months Risk Premium				
2	0.0008	0.0071	0.1128	0.9101
3	0.0095	0.0114	0.8351	0.4037
4	0.0132	0.0136	0.9692	0.3324
5	0.0125	0.0142	0.8763	0.3809
6	0.0133	0.0137	0.9699	0.3321
Six Months Risk Premium				
2	0.0046	0.0067	0.6811	0.4958
3	0.0090	0.0108	0.8368	0.4027
4	0.0103	0.0129	0.7994	0.4240
5	0.0088	0.0134	0.6556	0.5120
6	0.0073	0.0130	0.5609	0.5748
Twelve Months Risk Premium				
2	0.0076	0.0076	1.0018	0.3164
3	0.0213	0.0121	1.7512*	0.0799
4	0.0249	0.0145	1.7180*	0.0858
5	0.0275	0.0151	1.8112*	0.0701
6	0.0232	0.0146	1.5852	0.1129

Note: The results in this table are based on the error terms of the best fitting model for estimating the risk premia. Critical values for the z-test and the indication of significance are 2.576, 1.96 and 1.645 at 1% (***), 5% (**), 10% (*) and 25% (ª) levels, respectively

Table 21 Results of the BDS Tests for Chaos in the Forward Premiums

Dimension	BDS Statistic	Std. Error	Z-statistic	Probability
One Month Forward Premium				
2	0.1776	0.0054	32.7652***	0.0000
3	0.2991	0.0086	34.6510***	0.0000
4	0.3783	0.0102	36.7527***	0.0000
5	0.4280	0.0107	39.8512***	0.0000
6	0.4592	0.0103	44.2794***	0.0000
Three Months Forward Premium				
2	0.1854	0.0055	33.4164***	0.0000
3	0.3108	0.0088	35.0899***	0.0000
4	0.3938	0.0105	37.1986***	0.0000
5	0.4479	0.0110	40.4404***	0.0000
6	0.4816	0.0107	44.9281***	0.0000
Six Months Forward Premium				
2	0.1915	0.0058	32.6617***	0.0000
3	0.3223	0.0093	34.4260***	0.0000
4	0.4106	0.0112	36.6625***	0.0000
5	0.4687	0.0117	39.9702***	0.0000
6	0.5055	0.0113	44.4952***	0.0000
Twelve Months Forward Premium				
2	0.2006	0.0069	28.9227***	0.0000
3	0.3395	0.0110	30.6901***	0.0000
4	0.4349	0.0132	32.8825***	0.0000
5	0.4991	0.0138	36.0739***	0.0000
6	0.5415	0.0133	40.4252***	0.0000

Note: The results in this table are based on the direct application of the BDS test to raw data. Critical values for the z-test and the indication of significance are 2.576, 1.96 and 1.645 at 1% (***), 5% (**), 10% (*) and 25% (ª) levels, respectively

The BDS test was also applied to the errors of the best fitting E-GARCH models for risk premiums. Table 20 below shows that the null hypothesis of IID errors in the risk premiums can only be rejected at the one-month horizon. Therefore, these results reinforce the argument above that chaos are more likely to be caused by risk aversion or speculation. The BDS test was further applied to the forward premiums at 1-, 3-, 6- and 12-months intervals. The results in Table 21 indicate that the null hypothesis of IID errors in forward premiums is rejected at all horizons. The BDS statistics are larger in magnitude compared to those in Table 20 since both linear and nonlinear structures had not been filtered from the forward risk premiums.

4.4.1.2 Results of the Lyapunov Exponent Tests

Table 22 Results of Lyapunov Exponent Tests for Chaos in Returns

Lyapunov Exponent	Daily Returns	Weekly Returns	Monthly Returns
λ_1	0.9064	0.9032	0.9054
λ_2	-0.0019	-0.0098	-0.0063
λ_3	-14.5711	-14.5600	-14.5657

Table 23 Results of Lyapunov Exponent Tests for Chaos in the Risk Premia

Lyapunov Exponent	1-Month Risk Premium	3-Months Risk Premium	6-Months Risk Premium	12-Months Risk Premium
λ_1	0.9072	0.9212	0.8800	0.8955
λ_2	-0.0084	-0.0190	0.0017	-0.0071
λ_3	-14.5654	-14.5689	-14.5484	-14.5550

To examine further the presence of deterministic dependence Lyapunov exponents were computed for the foreign exchange returns and the risk premia. Tables 22 and 23 summarize the results. Consistent with the assertion above, the results indicate the presence of positive first Lyapunov exponents in daily, weekly and monthly returns. There are also positive Lyapunov exponents in the term structure of the risk premiums and the term structure of the forward premiums. Thus, the results of the Lyapunov exponent test indicate deterministic chaos in the data.

In conclusion, the results show that the rejection of the null hypothesis of IID error terms at 5% significance level could be due to deterministic chaos in the returns, in the risk premiums and the in the forward premiums. This is likely to be caused by the risk aversion behavior of market participants or speculation in the foreign exchange market.

4.4.2 Risk Aversion, Speculation and the Likelihood of Chaos in the Market

In this section, the behavior of market participants towards risk and speculation are used to show how it leads to chaos in the market. The degree of risk aversion is measured by the agent's investment horizon. A short investment horizon corresponds to risk-aversion while a long investment horizon corresponds to high risk tolerance. The number of extreme observations was calculated for different investment horizons and the results are shown in Figures 14, 15, 16 and 17 below. As the investment horizon decreases from one year to one week (5 days), there is a corresponding increase in the number of extreme observations of returns/volatility per unit time. Beyond one week, the number of exceedances per unit time decline steeply.

Figure 14 Frequency of Exceedances Over Threshold Volatility in the Market

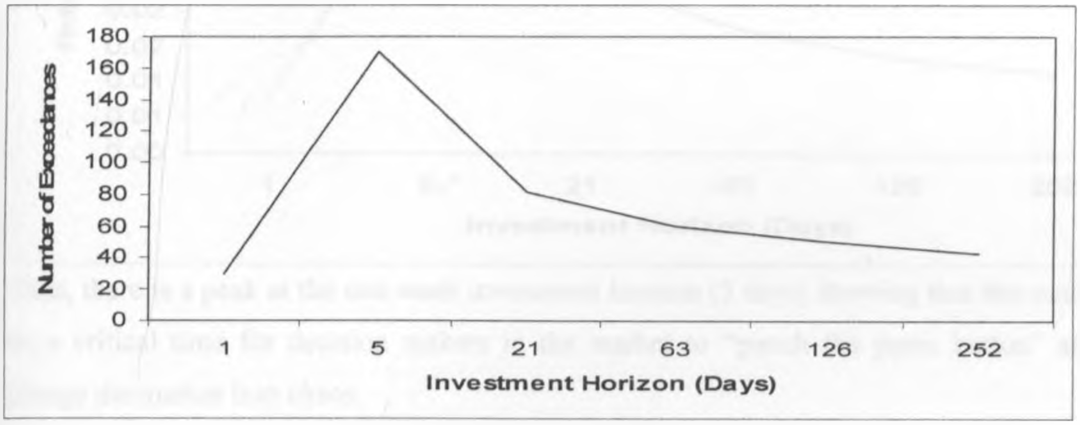


Figure 15 Frequency of Exceedances Below Threshold Volatility in the Market

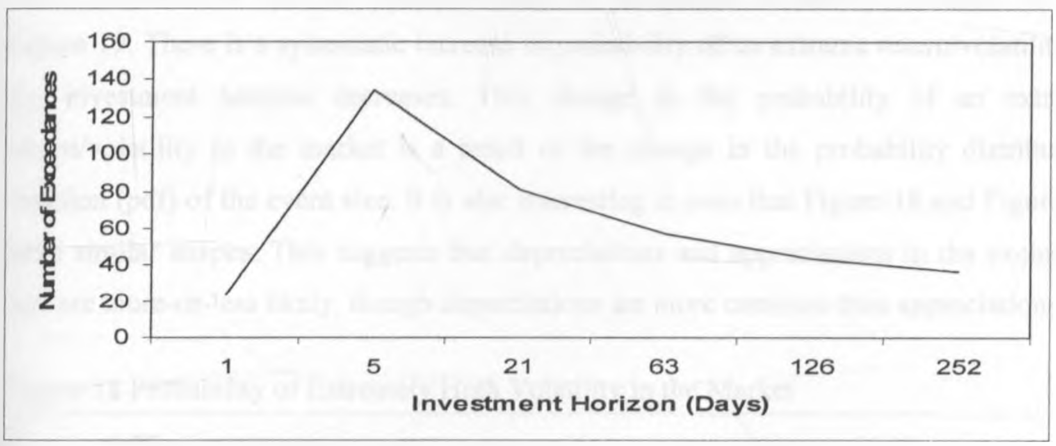


Figure 16 Probability of Exceedances Over Threshold Volatility in the Market

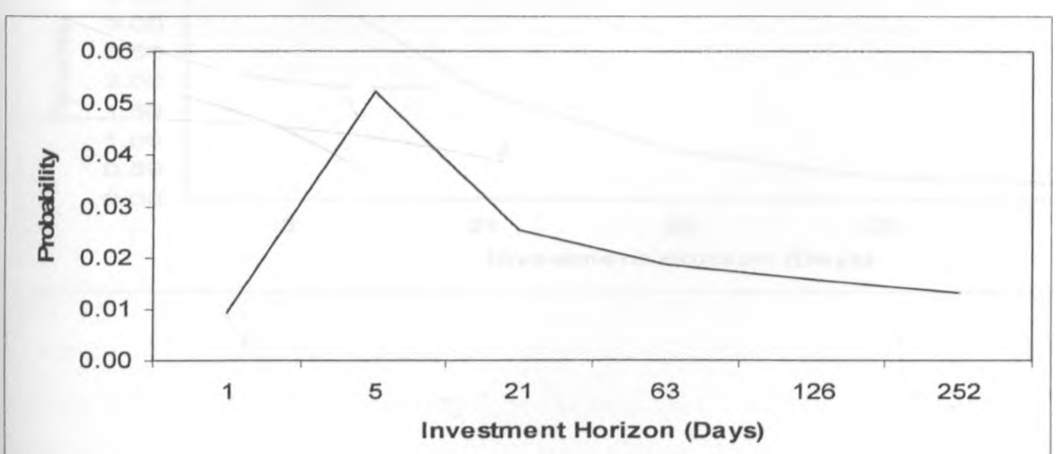
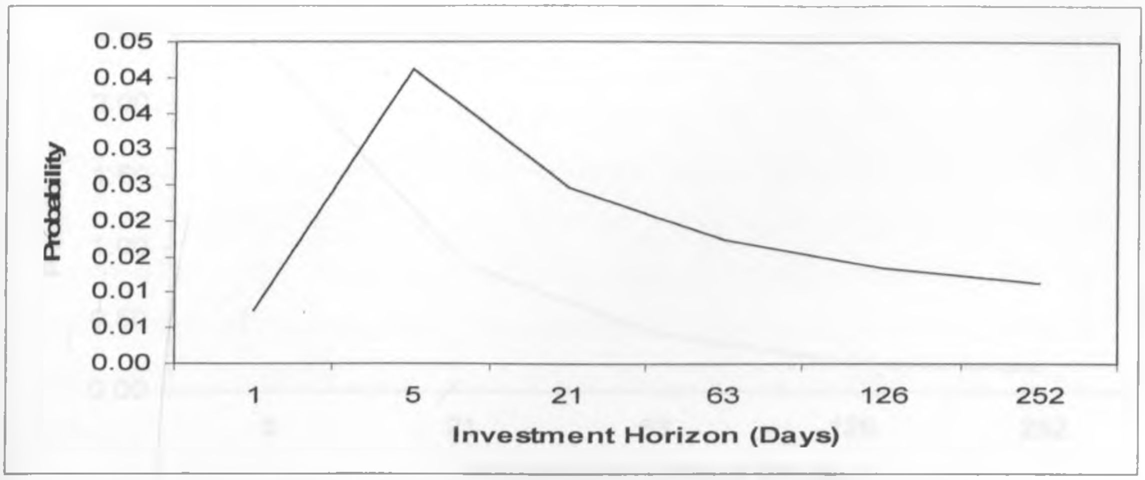


Figure 17 Probability of Exceedances Below Threshold Volatility in the Market



Thus, there is a peak at the one week investment horizon (5 days) showing that this could be a critical time for decision makers in the market to "punch the panic button" and plunge the market into chaos.

The probability of extreme return/volatility in the market is shown in Figure 18 and Figure 19. There is a systematic increase in probability of an extreme return/volatility as the investment horizon decreases. This change in the probability of an extreme return/volatility in the market is a result of the change in the probability distribution function (pdf) of the event size. It is also interesting to note that Figure 18 and Figure 19 have similar shapes. This suggests that depreciations and appreciations in the exchange rate are more-or-less likely, though depreciations are more common than appreciations.

Figure 18 Probability of Extremely High Volatility in the Market

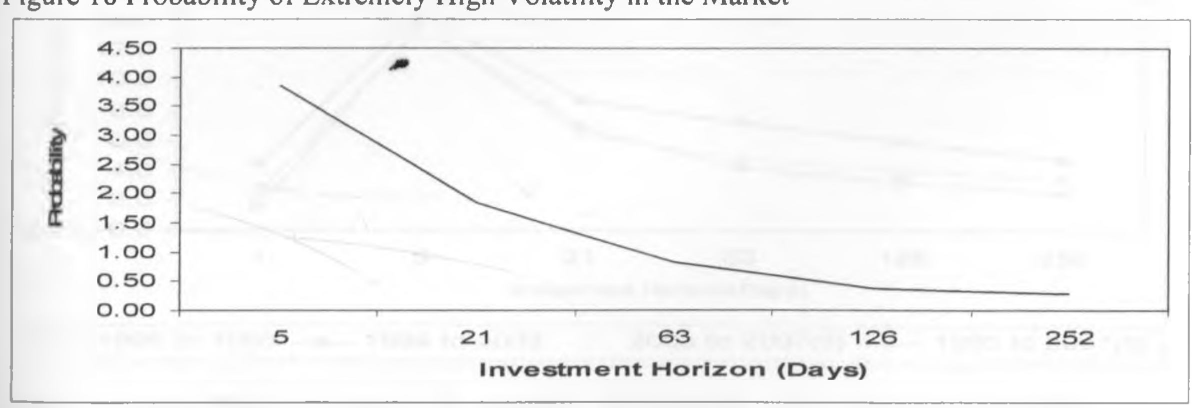


Figure 19 Probability of Extremely Low Volatility in the Market

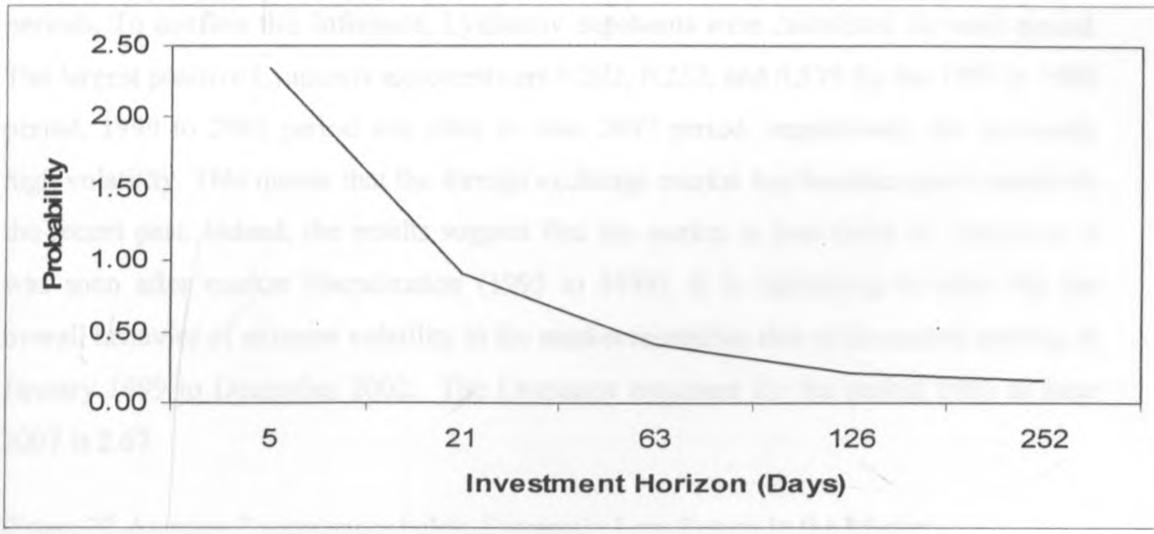


Figure 20 Average Exceedances Over Extremely High Volatility in the Market

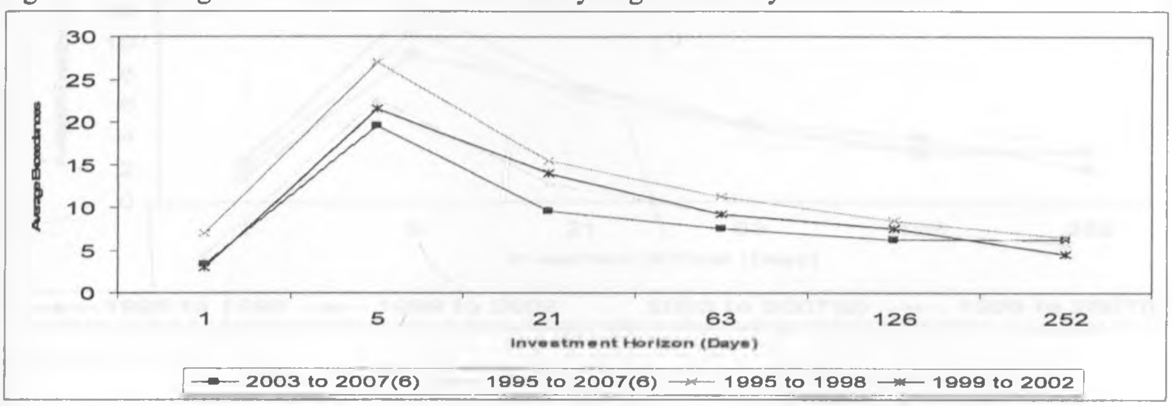


Figure 21 Average Exceedances Over Extremely High Return in the Market

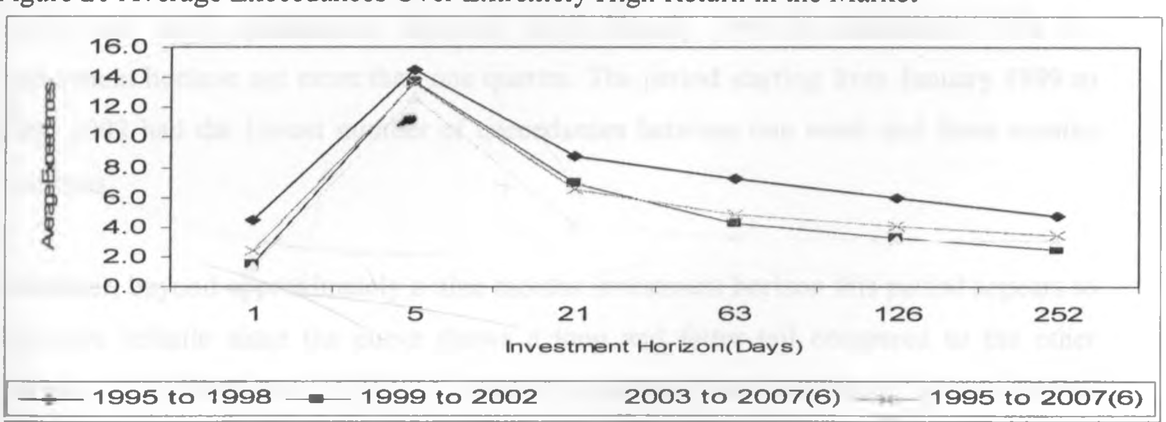


Figure 20 and Figure 21 show the average exceedances over different investment horizons. The results show that most exceedances occurred from January 1995 to December 1998. The period starting from January 2003 to June 2007 had the lowest number of exceedances compared to the previous years. However, this period appears to be more volatile since the curve shows a long and fatter tail compared to the other periods. To confirm this inference, Lyapunov exponents were calculated for each period. The largest positive Lyapunov exponents are 0.292, 0.232, and 0.579 for the 1995 to 1998 period, 1999 to 2002 period and 2003 to June 2007 period, respectively, for extremely high volatility. This means that the foreign exchange market has become more volatile in the recent past. Indeed, the results suggest that the market is now twice as volatile as it was soon after market liberalization (1995 to 1998). It is interesting to note that the overall behavior of extreme volatility in the market resembles that of the period starting in January 1999 to December 2002. The Lyapunov exponent for the period 1995 to June 2007 is 2.67.

Figure 22 Average Exceedances below Extremely Low Return in the Market

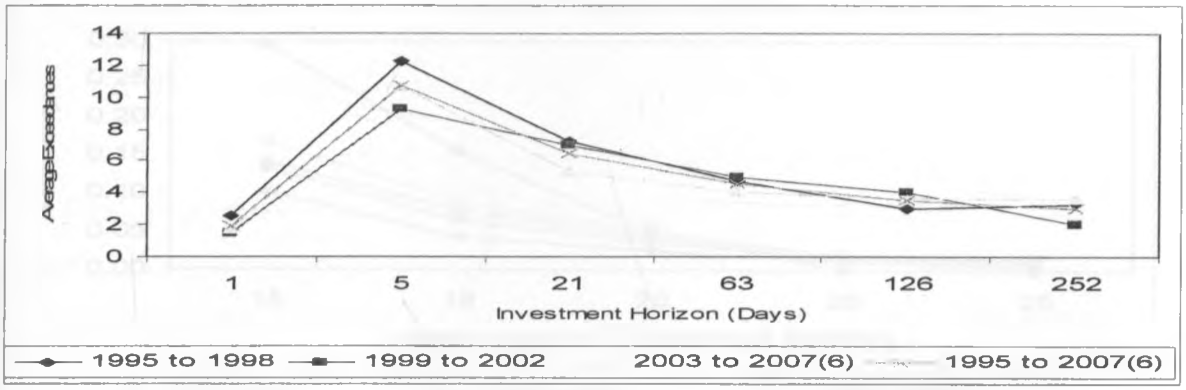


Figure 22 shows the average exceedances over different investment horizons. The results show that most exceedances occurred from January 1995 to December 1998 for investment horizon not more than one quarter. The period starting from January 1999 to June 2002 had the lowest number of exceedances between one week and three months horizons.

However, beyond approximately a nine months investment horizon this period appears to be more volatile since the curve shows a long and fatter tail compared to the other periods. To confirm this inference, Lyapunov exponents were calculated for each period. This finding confirms the previous assertion that the market has become more volatile over time.

Figure 23 Probability Distribution of Extremely High Returns in the Market

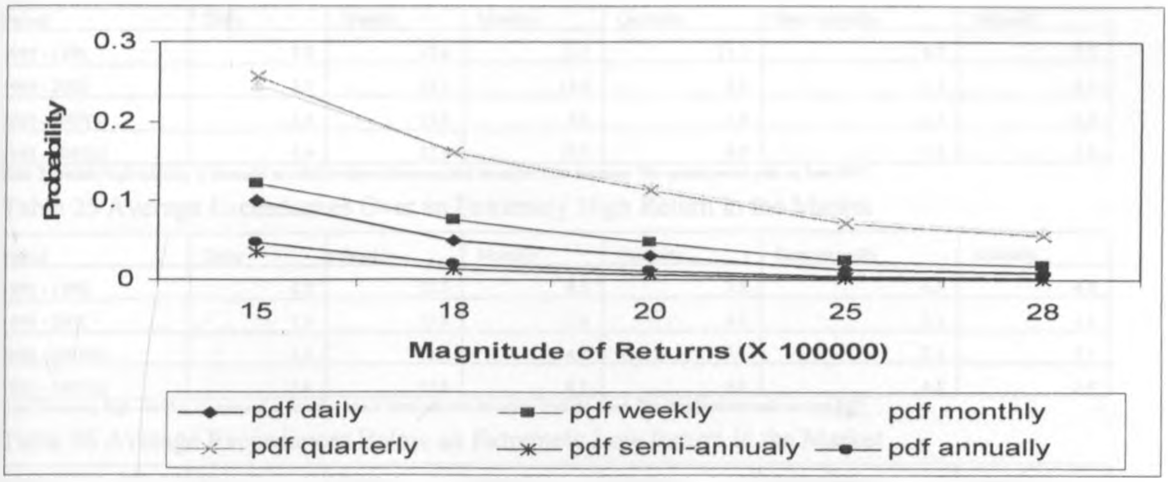


Figure 24 Probability Distribution of Extremely Low Returns in the Market

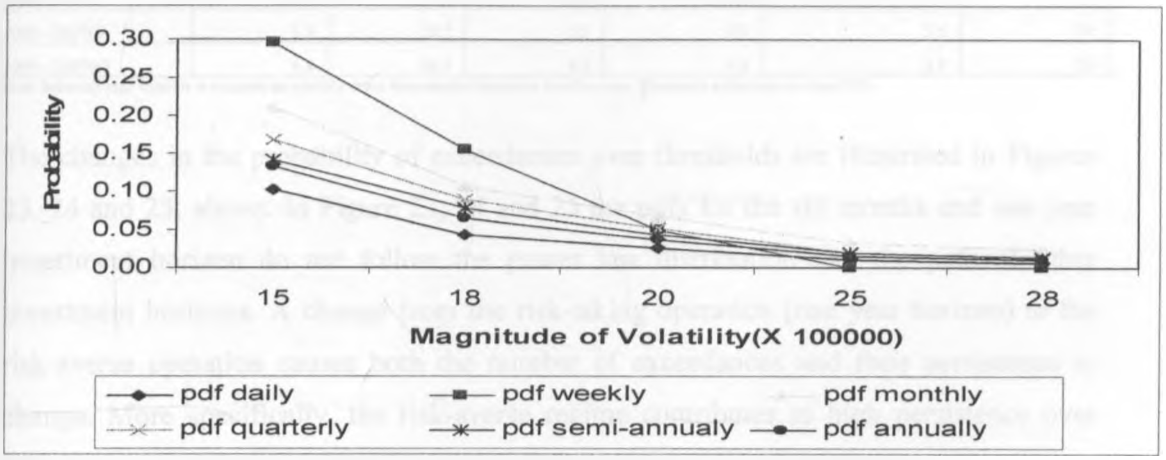


Figure 25 Probability Distribution of Extremely High Volatility in the Market

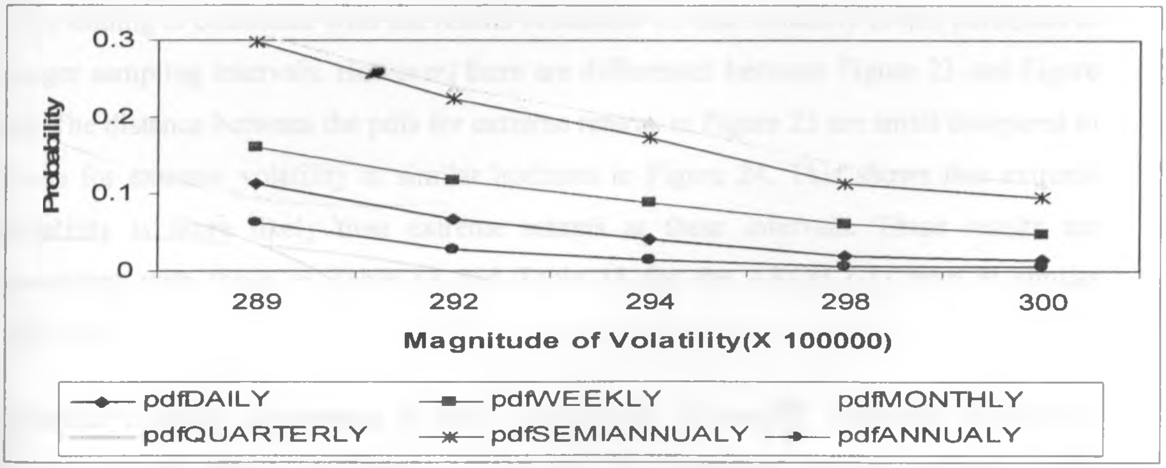


Table 24 Average Exceedances Over Extremely High Volatility in the Market

Period	Daily	Weekly	Monthly	Quarterly	Semi-annually	Annually
1995 - 1998	7.0	27.0	15.5	11.3	8.5	6.5
1999 - 2002	3.0	21.5	14.0	9.3	7.5	4.5
2003 - 2007(6)	3.3	19.6	9.6	7.6	6.2	6.2
1995 - 2007(6)	4.4	22.6	12.9	9.3	7.4	5.8

Note: Extremely high volatility is measured as volatility above three standard deviations from the mean. The sample period ends on June 2007

Table 25 Average Exceedances Over an Extremely High Return in the Market

Period	Daily	Weekly	Monthly	Quarterly	Semi-annually	Annually
1995 - 1998	4.5	15.3	8.5	7.5	6.5	4.8
1999 - 2002	1.5	13.8	7.0	4.3	3.3	2.5
2003 - 2007(6)	1.3	12.7	4.2	3.3	3.1	3.1
1995 - 2007(6)	2.4	13.8	6.5	5.0	4.2	3.4

Note: Extremely high volatility is measured as volatility above three standard deviations from the mean. The sample period ends on June 2007.

Table 26 Average Exceedances Below an Extremely Low Return in the Market

Period	Daily	Weekly	Monthly	Quarterly	Semi-annually	Annually
1995 - 1998	2.5	12.3	7.3	4.8	3.0	3.3
1999 - 2002	1.5	9.3	7.0	5.0	4.0	2.0
2003 - 2007(6)	1.8	10.7	5.3	4.0	3.6	3.6
1995 - 2007(6)	1.9	10.7	6.5	4.6	3.5	3.0

Note: Extremely high volatility is measured as volatility above three standard deviations from the mean. The sample period ends on June 2007.

The changes in the probability of exceedances over thresholds are illustrated in Figures 23, 24 and 25, above. In Figure 23, 24 and 25 the pdfs for the six months and one year investment horizon do not follow the power law distribution like the pdfs of other investment horizons. A change from the risk-taking operation (one year horizon) to the risk-averse operation causes both the number of exceedances and their persistence to change. More specifically, the risk-averse regime contributes to high persistence over long horizons while the risk-seeker regime causes reduced or no persistence.

This finding is consistent with the results of section 4.3 that volatility is less persistent at longer sampling intervals. However, there are differences between Figure 23 and Figure 24. The distance between the pdfs for extreme returns in Figure 23 are small compared to those for extreme volatility at similar horizons in Figure 24. This shows that extreme volatility is more likely than extreme returns at these intervals. These results are consistent with those in Table 14 and Table 18 for the ARCH (-1) term at similar horizons.

Extreme volatility persistence is more pronounced at monthly sampling intervals as shown by the results in Figures 23, 24 and 25. Therefore, further analysis of the occurrence of chaos employed the monthly interval. The distribution of extremely high returns and extremely high volatility are all fat–tailed at the monthly, quarterly and semi-annual horizons. This suggests that market participants herd together in reaction to new information in the market at these horizons. Figure 25 suggests that the herding tendency is greatest at the monthly horizon. This means that the market is not memory-less and there is speculation in the market. It also implies that market participants do not react instantaneously to new information released in the market. They may be taking time to collect opinions and build consensus before taking action.

Therefore, the risk-averse operation/speculation, or worse a risk-averse policy in response to extreme volatility in the market, increases the probability of extreme volatility. This causes an increase in the number of exceedances (extreme volatility) if the risk-aversion behavior is already prevalent in the market. Therefore, there could be a critical level of speculation or risk aversion that triggers chaos in the market. The results of this study suggest that this critical point corresponds to a one week (5 days) investment horizon.

4.4.3 Results of the Occurrence of Chaos in the Foreign Exchange Market

The results of section 4.4.2 indicate that chaos is more likely at the monthly investment horizon. Therefore, Fourier series were fitted to the data on the monthly Ksh/USD spot rate in order to study the seasonal occurrence of chaos. The deviances obtained are shown in Table 27 below. The decline in deviances can be compared with appropriate χ^2 distributions. The harmonics, *m*, required for each curve are indicated by an asterisk. For instance, the results indicate that five harmonics are required for extreme low volatility (L) $\Re <= m - 1.5\sigma$ where the volatility/return magnitude is $\Re$, m is the mean and σ is the standard deviation. However, only one harmonic is required for extreme high volatility, $\Re >= m + 3\sigma$.

Figure 26 shows the persistence of extremely high and extremely low volatility clusters in the market. The results show that both high and low volatility regimes are highly persistent. If there is low volatility in the market there is a 0.49 probability on average that the market will remain quiescent. Moreover, if the market is volatile there is a 0.67 probability on average that the market will not calm down. Thus, extremely high volatility is more persistent than extremely low volatility.

Table 27 Number of Harmonics required to Fit Extreme Volatility and Extreme Returns

Panel A: Extreme Volatility: Summary and Test of Goodness of Fit																
	L	HL	L	HL	L	LH	H	HL	H	HL	H	HL	H	HL	H	HL
m	1	1	1	1	5	1	3	1	1	1	1	1	1	1	1	1
G	0.0270*	0.0110*	0.0320*	0.0080*	0.1210	0.0240*	0.3700	1.0500*	0.0170*	0.0110*	0.7200*	0.0050*	0.0070*	0.0070*	0.0020*	0.0030*
X	7.8100	12.590	7.8200	12.590	7.8200	7.8200	7.8200	12.590	7.8200	7.8200	7.8200	7.8200	7.8200	12.590	12.590	12.590
d	10	10	10	10	2	10	6	10	10	10	10	10	10	10	10	10
Panel B Extreme Returns: Summary and Test of Goodness of Fit																
	L	HL	L	HL	L	LH	H	HL	H	HL	H	HL	H	HL	H	HL
m	1	1	1	1	5	1	3	1	1	1	1	1	1	1	1	1
G	0.0270*	0.0110*	0.0320*	0.0080*	0.1090*	0.0240*	0.1090*	0.8100*	0.0140*	0.0030*	0.4200*	0.0019*	0.0002*	0.0002*	0.0030*	0.0008*
X	7.8100	12.590	7.8200	12.590	7.8200	7.8200	7.8200	12.590	7.8200	7.8200	7.8200	7.8200	7.8200	12.590	12.590	12.590
d	10	10	10	10	2	10	6	10	10	10	10	10	10	10	10	10
R	R<= (m − 0.5s.d.)		R<= (m − 1.0s.d.)		R<= (m − 1.5s.d.)		R>= (m + 1.0s.d.)		R>= (m + 1.0s.d.)		R>= (m + 1.5s.d.)		R>= (m + 2.5s.d.)		R>= (m + 3.0s.d.)	

Note: L = Probability of Extreme low volatility. LH = Probability of changing from a Low volatility regime to a High volatility regime. Deviances (G) and degrees of freedom (d.f.) HL = Probability of changing from a High volatility regime to a Low volatility regime. In order to fit a curve to extremely high volatility one (m) harmonic is required. To fit curves to extreme returns only one harmonic is required

Figure 26 Results of the Analysis of the Persistence of Extremely Low and Extremely High Volatility

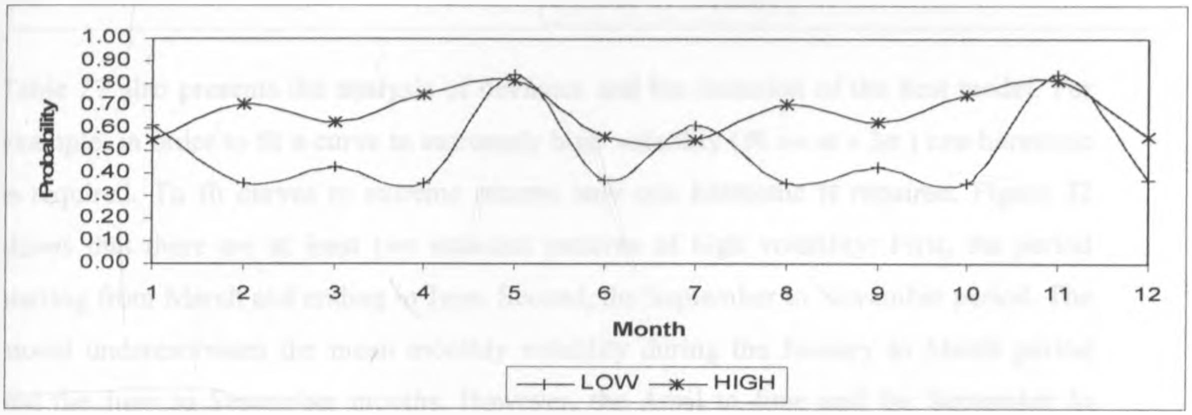
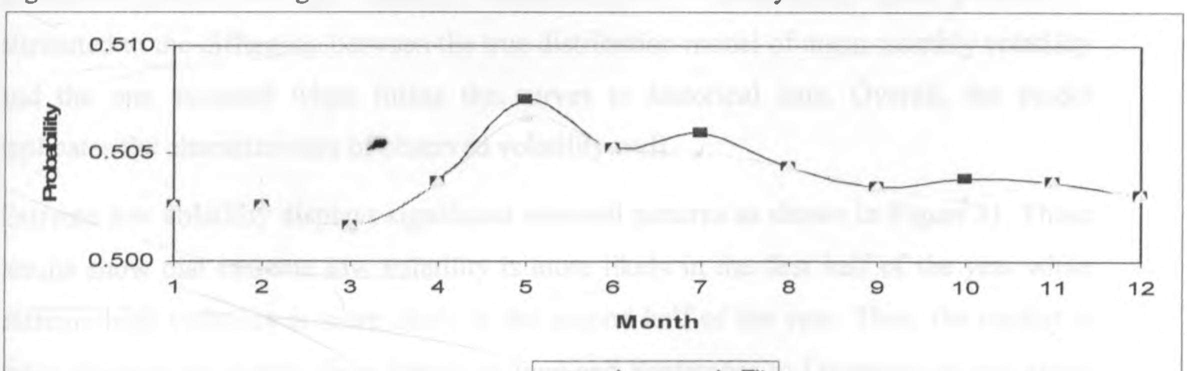


Figure 27 Results of Fitting Markov Chains to Extreme Low Volatility in the Market



A formal goodness of fit for the finally selected model is given in Table 27 Panel A and Panel B. G^2 is approximately χ^2 if the model is correct. The values of χ^2 for the selected models are all lower than the critical value and indicate that the models adequately fit the data. Further tests for goodness of fit were obtained by comparing the observed and the fitted values of extreme volatility as illustrated in Figures 27 and 28. Markov chains fit very well extremely low magnitudes of volatility in the market as indicated in Figures 27. But for extremely high magnitudes of volatility the Markov chains do not fit well as shown in Figure 28.

Figure 28 Results of Fitting Markov Chains to Extremely High Volatility in the Market

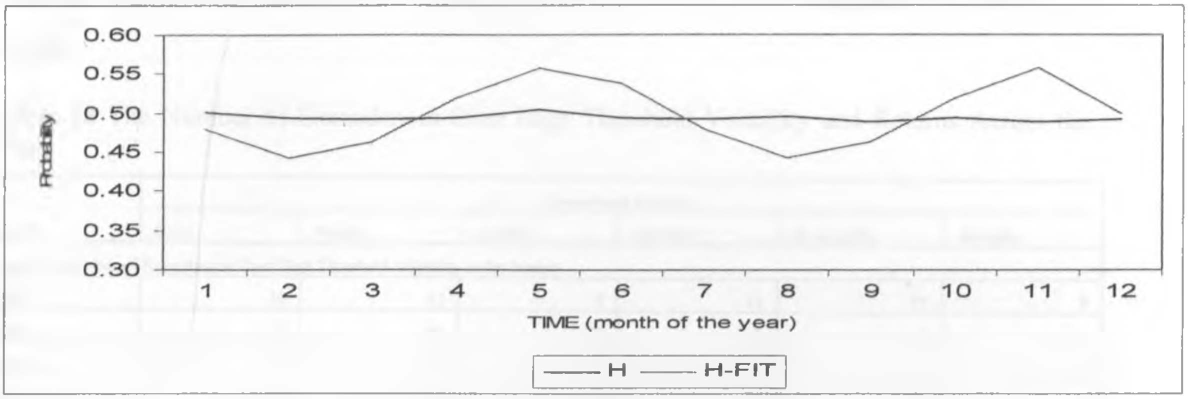


Table 27 also presents the analysis of deviance and the selection of the best model. For example, in order to fit a curve to extremely high volatility ($\Re >= m + 3\sigma$) one harmonic is required. To fit curves to extreme returns only one harmonic is required. Figure 32 shows that there are at least two seasonal patterns of high volatility: First, the period starting from March and ending in June. Second, the September to November period. The model underestimates the mean monthly volatility during the January to March period and the June to September months. However, the April to June and the September to December period average monthly volatilities are overestimated. This problem is attributed to the difference between the true distribution model of mean monthly volatility and the one assumed when fitting the curves to historical data. Overall, the model replicates the characteristics of observed volatility well.

Extreme low volatility displays significant seasonal patterns as shown in Figure 31. These results show that extreme low volatility is more likely in the first half of the year while extreme high volatility is more likely in the second half of the year. Thus, the market is more likely to be chaotic from March to June and September to December in any given year. This finding can be ascribed to a number of factors. Among them is the IMF PRGF evaluation of the performance of the government which occurs around this time of the year; government borrowing to finance the budget deficit that influences interest rates; the level of inflation in the economy; the inflows of revenue from tourism, horticulture, tourism, coffee and tea exports; and the level of interest rates in the economy that determine the flow of short term investment funds.

4.4.4 Results of the Analysis of the Distribution of Chaos in the Market

This section is divided into two parts, the first part presents the results of fitting the Gamma distribution on extreme volatility and the second part examines the results of fitting

Table 28 The Number of Exceedances Over High Threshold Volatility and Returns Across the Year

	Investment Horizon					
Month	Daily	Weekly	Monthly	Quarterly	Bi-annually	Annually
Panel A: Number of Exceedances Over High Threshold Volatility in the Market						
JAN	10	15	9	15	13	9
FEB	2	22	10	4	5	1
MAR	0	26	11	5	0	0
APR	3	30	18	11	10	9
MAY	16	27	17	19	17	19
JUN	3	34	11	7	7	9
JUL	3	22	13	3	5	3
AUG	7	22	14	7	8	8
SEP	0	21	5	6	4	2
OCT	6	18	12	11	6	6
NOV	1	21	15	7	4	2
DEC	4	24	26	21	13	4
Panel B: Number of Exceedances Over High Threshold Return in the Market						
JAN	4	15	5	8	7	6
FEB	1	13	6	3	4	1
MAR	0	14	9	1	0	0
APR	2	18	10	9	5	5
MAY	10	17	7	10	8	9
JUN	1	17	7	4	5	8
JUL	2	11	4	0	2	1
AUG	5	12	6	6	7	7
SEP	0	16	4	3	2	1
OCT	3	11	6	4	3	3
NOV	1	13	7	2	1	1
DEC	1	16	10	12	9	1

Extreme Value Models to extreme returns and extreme volatility. The number of exceedances over threshold returns and volatility at different investment horizons are displayed in Table 28.

There is a high exceedances rate in January, April, May, June, August, October and December on average compared to other months of the year. At the one week investment horizon, the exceedances rate is highest in June. The month of May is the most volatile month across the years. These patterns in returns and volatility are discussed in the following sections.

4.4.4.1 Results of Estimating the Gamma Distribution Model

The estimate of the shape parameter k of the gamma distribution for the Ksh/USD spot market in Table 29 indicates that the between-day values are marginally different from the maximum likelihood values.

Table 29 Parameter Estimates of the Gamma Distribution in the Spot Market

Month	1	2	3	4	5	6	7	8	9	10	11	12
K	0.1170	0.1140	0.1110	0.1110	0.1190	0.1200	0.1160	0.1160	0.1160	0.1140	0.1120	0.1160
A	0.0580	0.0540	0.0470	0.0550	0.0550	0.0480	0.0440	0.0440	0.0433	0.0580	0.0500	0.0500

Note: *k0* and *a* are the maximum likelihood estimates of the shape and scale parameters of the Gamma distribution

The between-day estimate (using rational approximation) is the easiest to obtain and is used as a routine. The estimates of k are far much less than 1, so the exponential distribution, used by several authors for its algebraic simplicity is not suitable for modeling extreme volatility as demonstrated in subsequent sections. The estimate of the variance of mean monthly returns, s^2, compares well with the actual variance.

Figure 29 Results of Estimating the Monthly Shape Parameters of the Gamma Distribution

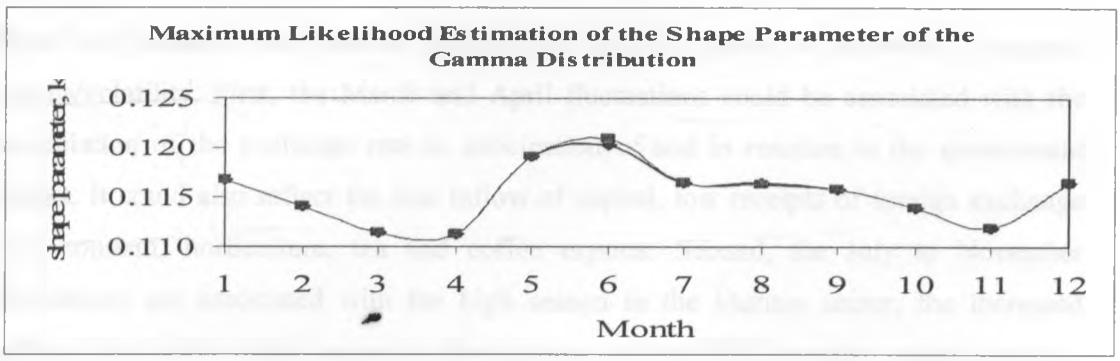
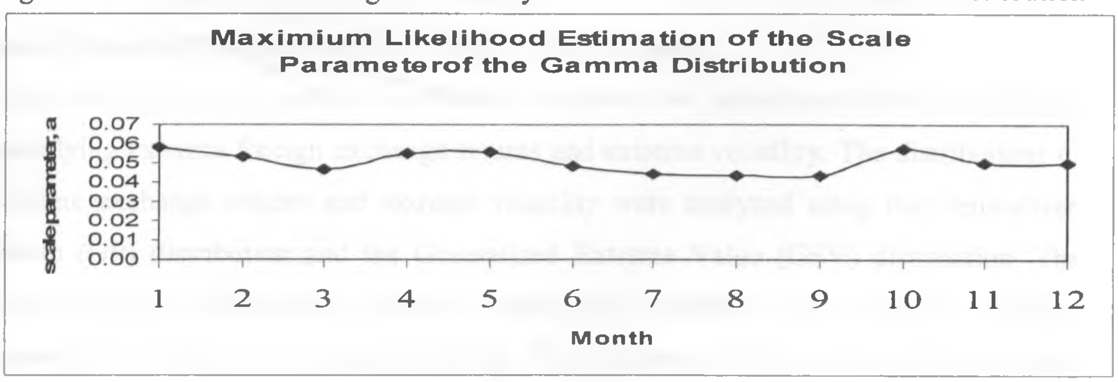


Figure 30 Results of Estimating the Monthly Scale Parameters of the Gamma Distribution



Thus the gamma distribution captures well the skewness of the extreme volatility in the foreign exchange market and the January Effect as indicated by the highest value of the scale parameter, α, in January.

Figure 29 and Figure 30 show the seasonal variations in the estimates of the parameters of the gamma distribution. Evidently, the scale and shape parameters are not stationary. The shape parameter is highest during the May to July months of the year. However, it is lowest during the March, April and November months of the year. This means that extreme high returns and volatility are less likely to be observed between May and July in any given year. Thus, the Kenya shilling is likely to be stable over this period. Extreme returns and volatility are more likely in the months of March, April, and August to November. These findings are consistent with those in section 4.2.4 on the impact of seasonality on the predictability of returns. The scale parameter of the Gamma distribution also displays seasonality. There are two distinct high volatility regimes. The first starts in March and ends in June while the second commences in September and ends in December. These two regimes correspond to the relatively low volatility regime and the relatively high volatility regimes, respectively, as discussed above.

There are probably two possible explanations for this pattern of behavior in extreme returns/volatility. First, the March and April fluctuations could be associated with the depreciation of the exchange rate in anticipation of and in reaction to the government budget. It could also reflect the low inflow of capital, low receipts of foreign exchange from tourism, horticulture, tea and coffee exports. Second, the July to November fluctuations are associated with the high season in the tourism sector, the increased inflows from horticulture, tea and coffee exports, and the PRFG positive reports from the World Bank.

4.4.4.2 Results of Estimating the Extreme Value Models

This study applied extreme value theory to estimate the parameters of the distribution underlying extreme foreign exchange returns and extreme volatility. The distributions of extreme exchange returns and extreme volatility were analyzed using the Generalized Pareto (GP) distribution and the Generalized Extreme Value (GEV) distribution. The distributions of maxima and minima returns were examined over weekly, monthly, quarterly, semi-annual and annual intervals. The goodness of fit test was performed using the Log likelihood ratio (LLR) statistic for each data set. The results are reported in Tables 30 to 33 below.

Table 30 Results of Parameter Estimates and Goodness of Fit for Maxima Extreme Returns

Panel A: GP Distribution						
Interval	N	Observations	Location	Scale	Shape	LLR
Weekly	652	30		0.0029 (0.0001)	0.4689 (0.0570)	-2667.9600
Monthly	150	170		0.0086 (0.0009)	0.2022 (0.0818)	-532.5580
Quarterly	50	82		0.0183 (0.0035)	0.0988 (0.1372)	-145.0390
Semiannually	20	61		0.0385 (0.0122)	-0.1336 (0.2293)	-47.8120
Annually	12	51		0.0558 (0.0262)	-0.3712 (0.3789)	-24.8250
Panel B: GEV Distribution						
Interval	N	Observations	Location	Scale	Shape	LLR
Weekly	652	30	0.0018	0.0030	0.2190 (0.0154)	-2647.9100
Monthly	150	170	0.0045 (0.0003)	0.0041 (0.0000)	0.5699 (0.1479)	-537.0890
Quarterly	50	82	0.0091 (0.0010)	0.0068 (0.0006)	0.6390 (0.2056)	-152.5980
Semiannually	20	61	0.0161 (0.0031)	0.0112 (0.0029)	0.7102 (0.3364)	-50.4360
Annually	12	51	0.0283 (0.0080)	0.0220 (0.0065)	0.2235 (0.3747)	-25.3190

Notes: This table shows a comparison of parameter estimates and goodness of fit for the GP and GEV distributions fitted by PWM to extremes of daily returns over various selection intervals both for the whole 13-year period and over certain sub-periods. N is the number of observations. LLR denotes the log-likelihood statistic. The values in brackets are standard errors.

The results in Tables 30 and 32 indicate that the location and scale parameters for maximal returns are all positive. The values for shape parameter are negative for the semi-annual and annual intervals for the GP distribution. Based on the LLR statistic the GEV distribution fits the extreme returns best as the sampling interval increases. The GP distribution fits the data better than the GEV distribution at the weekly interval. This is consistent with the results in section 4.4.2 that indicated that the one week horizon is a critical point in the market. It marks the transition to chaos. Therefore, the distribution of extreme maxima returns and extreme maxima and minima volatility are not fat-tailed at one week horizon. However, in Tables 31 and 33 the GEV distribution fits better than the GP distribution at all intervals.

In conclusion, this section has presented the results of an investigation of extreme exchange rate returns and extreme volatility for the period January 1995 to June 2007. The statistical distributions that have been suggested in the literature as capable of describing the behavior of maximal and minimal returns have been estimated over the sample period by applying the extreme value theory. In general, the GEV distribution fits the data well compared to the GPD as the sampling interval increases from one week to one year.

Table 31 Results of Parameter Estimates and Goodness of Fit for Minima Extreme Returns

Panel A: GP Distribution						
Interval	N	Observations	Location	Scale	Shape	LLR
Weekly	652	24		0.0003 (0.0000)	0.6600 (0.2187)	-256.4370
Monthly	150	134		0.0009 (0.0000)	-1.3188 (0.0007)	-51.2207
Quarterly	50	81		0.0107 (0.0000)	-1.6677 (0.0005)	-101.4790
Semiannually	20	57		0.1539 (0.0000)	-1.2427 (0.0008)	-10.9446
Annually	12	44		0.1179 (0.0000)	-1.3734 (0.0006)	-37.3720
Panel B: GEV Distribution						
Interval	N	Observations	Location	Scale	Shape	LLR
Weekly	652		-0.0078 (0.0000)	0.0123 (0.0000)	-0.4306 (0.0000)	-2082.50
Monthly	150	134	-0.0112 (0.0000)	0.0124 (0.0000)	-1.1304 (0.0000)	-525.2450
Quarterly	50	81	-0.0158 (0.0000)	0.0151 (0.0000)	-1.2344 (0.0008)	-158.1100
Semiannually	20	57	-0.0419 (0.0083)	0.0344 (0.0056)	-0.0432 (0.1055)	-36.6940
Annually	12	44	-0.0050 (0.0000)	0.0445 (0.0000)	-1.2122 (0.0008)	-33.4990

Notes: This table shows a comparison of parameter estimates and goodness of fit for the GP and GEV distributions fitted by PWM to extremes of daily returns over various selection intervals both for the whole 13-year period and over certain sub-periods N is the number of observations LLR denotes the log-likelihood statistic

Table 32 Results of Parameter Estimates and Goodness of Fit for Maxima Extreme Volatility

Panel A: GP Distribution						
Interval	N	Extreme Observations	Location	Scale	Shape	LLR
Weekly	652	52		0.0047 (0.0002)	0.3177 (0.0464)	-2632.8400
Monthly	150	278		0.0107 (0.0011)	0.1543 (0.0768)	-506.6900
Quarterly	50	166		0.0224 (0.0043)	0.0371 (0.1357)	-137.9600
Semiannually	20	119		0.0526 (0.0160)	-0.3207 (0.2207)	-45.3040
Annually	12	93		0.0956 (0.0391)	-0.7509 (0.4128)	-25.1700
Panel B: GEV Distribution						
Interval	N	Extreme Observations	Location	Scale	Shape	LLR
Weekly	652	52	0.00236	0.0024	0.7107	-2631.0600
Monthly	150	278	0.00577 (0.00041)	0.0050 (0.0001)	0.4985 (0.1046)	-513.5000
Quarterly	50	166	0.01090 (0.00136)	0.0078 (0.0010)	0.6378 (0.2048)	-145.5400
Semiannually	20	119	0.02095 (0.00368)	0.0130 (0.0035)	0.6699 (0.3358)	-47.9260
Annually	12	93	0.03505 0.00830)	0.0225 (0.0067)	0.1882 (0.3870)	-25.2630

Notes: This table shows a comparison of parameter estimates and goodness of fit for the GP and GEV distributions fitted by PWM to extremes of daily returns over various selection intervals both for the whole 13-year period and over certain sub-periods. N is the number of observations. LLR denotes the log-likelihood statistic. The values in brackets are standard errors.

In this study the classical EVT has been directly applied to maxima and minima extreme returns and extreme volatility in the market. However, from a modern perspective, the classical approach is too narrow. An alternative approach employed in this study is based on exceedances over thresholds (Leadbeatter, 1991). In this approach an upper bound is defined then all exceedances above this threshold are sought. Theory suggests that the distribution of exceedances over thresholds follows the GP distribution. Therefore, in this study the GP distribution was fitted to the exceedances over thresholds. However, a more modern and substantive approach is to take the point process perspective of exceedances over thresholds. From a point process perspective, the number of exceedances and the magnitude of exceedance over threshold are viewed as a two-dimensional point process.

Table 33 Results of Parameter Estimates and Goodness of Fit for Minima Extreme Volatility

Panel A: GP Distribution					
Interval	N	Location	Scale	Shape	LLR
Weekly	652		0.0002=4 (0.0000)	0.5513 (.01903)	-4426.5300
Monthly	150		0.0000 (0.0000)	0.1406 (0.0694)	-1244.5700
Quarterly	50		0.0000 (0.0000)	0.0932 (0.1067)	-457.9180
Semiannually	20		0.0000 (0.0000)	1.7660 (0.5145)	-168.0700
Annually	12		0.0000 (0.0000)	-0.8095 (0.0465)	-127.6100

Panel B: GEV Distribution					
Interval	N	Location	Scale	Shape	LLR
Weekly	652	0.00011 (0.000002)	0.0001 (0.0000)	0.9935 (0.0371)	-4414.8700
Monthly	150	0.00004 (.000002)	0.0000 (.00000)	0.6364 (.0920)	-1244.9700
Quarterly	50	0.00002 (0.000002)	0.0000 (0.0000)	0.8247 (0.1789)	-462.3560
Semiannually	20	0.00004	0.0001 (0.0000)	0.1003	-81.3920
Annually	12	0.00001 (0.000002)	0.0000 (0.0000)	0.8056 (0.4373)	-133.6760

Notes. This table shows a comparison of parameter estimates and goodness of fit for the GP and GEV distributions fitted by PWM to extremes of daily returns over various selection intervals both for the whole 13-year period and over certain sub-periods. N is the number of observations. LLR denotes the log-likelihood statistic. The values in brackets are standard errors.

The results based on the point process perspective are displayed in Table 34 and Table 35 in Appendix C. Using the LLR statistic to compare the GP distribution and the Point Process model shows that generally the latter fits the data better than the GP distribution using different thresholds and sampling intervals.

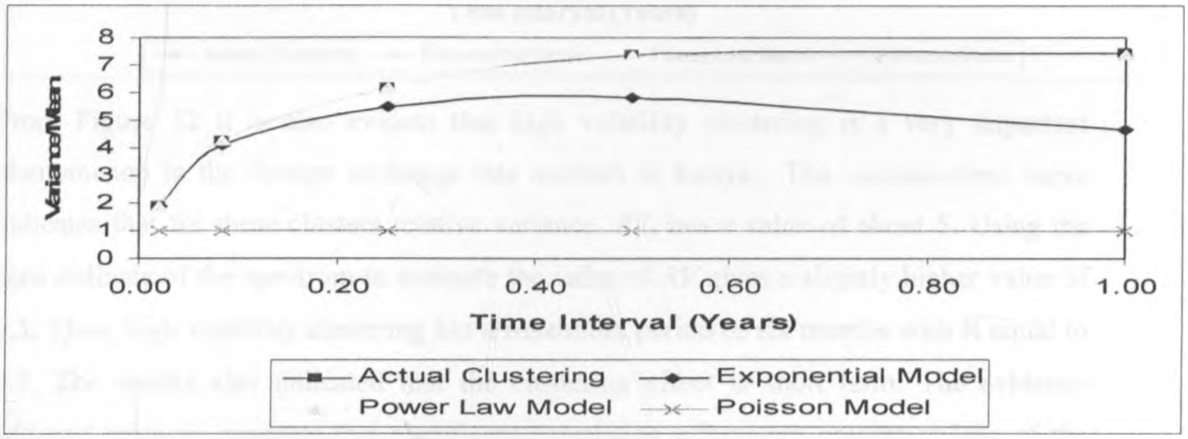
4.4.5 Results of the Analysis of the Duration of Chaos in the Foreign Exchange Market

The main limitation of the analysis in the previous section is that it does not take into account time dependence in extreme returns and extreme volatility. It is a fact that volatility in the market is clustered. Thus, the first and second parts of this section present the results based on the Neyman-Scott (NS) Model and the Bartlett-Lewis (BL) Model of volatility clustering, respectively. The aim in this section is to estimate the time it takes the market to regain equilibrium after a random shock. This is equivalent to the duration of chaos in the market.

4.4.5.1 Results of Estimating the Neyman-Scott Model

The spectrum for volatility clusters in the KSh/USD spot market is given in Figures 35 and 36. It is based on the analysis of the number of exceedances over a given threshold at weekly intervals (5 days). The choice of the weekly interval is based on the results in section 4.4.2. From second order analysis it was apparent that no significant periodic weekly effects are present in foreign exchange rate returns in Kenya. Since there are no major weekly periodic effects, the information about the second order structure of the clustering process is best displayed using the variance-time curve in Figures 31 and 32.

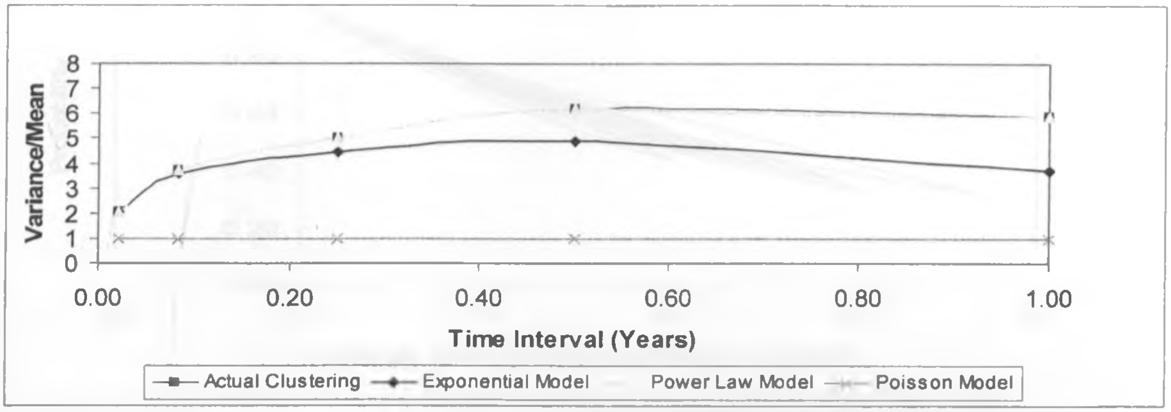
Figure 31 Variance - Time Curve for Low Volatility in the Market



The rate of convergence to the asymptotic form gives an idea about the time-scale of the clustering effects. The asymptotic slope of the variance-time curve gives the approximate duration of each cluster, which is about 120 days or 0.5 years for both extremely low and extremely high volatility clusters.

From Figure 31 it is evident that low volatility clustering is a very important phenomenon in the foreign exchange rate markets in Kenya. The variance-time curve indicates that for these clusters relative variance, *RV,* has a value of about 6. Using the zero ordinate of the spectrum to estimate the value of *RV* gives a slightly higher value of 7.5. Thus, low volatility clustering has a maximum period of six months with R equal to 7.5. The results also indicated that the clustering effect is short term. Though not much reliance can be attached to the variance-time curve, especially the last few points, the evidence adduced strongly suggests that significant correlation effects are present at lags of the order of months (up to six months). Thus the distribution of extreme low volatility clusters is fat-tailed. This finding is confirmed by the steep rise of the spectrum at the origin of the curve. Further analysis of clustering processes in the foreign exchange market focused on high volatility clustering. High volatility clustering has a maximum duration of 6 months with RV approximating a value of 6.5 as shown in Figure 36.

Figure 32 Variance - Time Curve for High Volatility in the Market



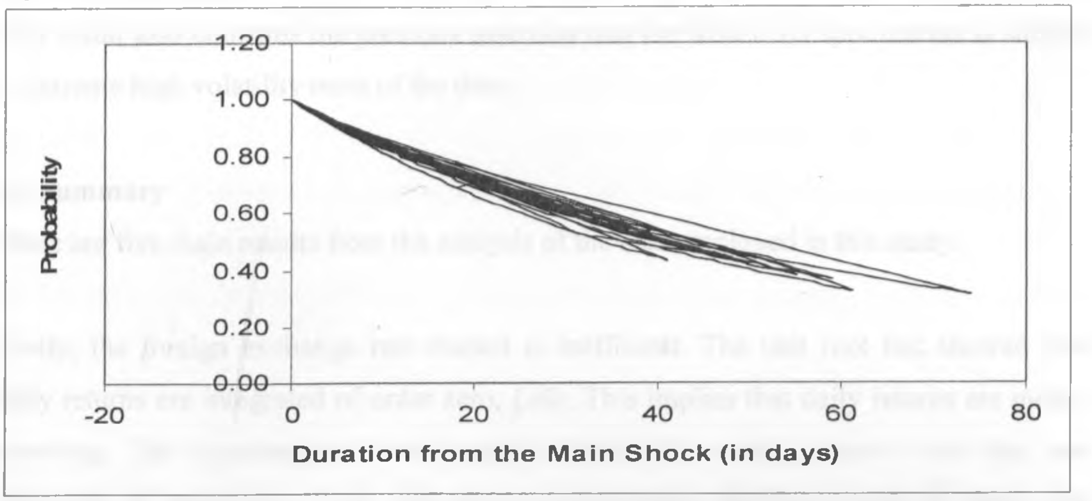
From Figure 32 it is also evident that high volatility clustering is a very important phenomenon in the foreign exchange rate markets in Kenya. The variance-time curve indicates that for these clusters relative variance, RV, has a value of about 5. Using the zero ordinate of the spectrum to estimate the value of RV gives a slightly higher value of 6.5. Thus, high volatility clustering has a maximum period of six months with R equal to 6.5. The results also indicated that the clustering effect is short term. The evidence adduced strongly suggests that significant correlation effects are present at lags of the order of months (up to six months). Thus, the distribution of extreme high volatility clusters is fat-tailed. This finding is confirmed by the steep rise of the spectrum at the origin of the curve.

In summary, extremely low volatility clusters show a higher tendency to cluster (RV = 7.5) compared to extremely high volatility clusters (RV = 6.5). However, both types of volatility clusters in the market have the same asymptotic duration of six months.

4.4.5.2 Results of Estimating the Bartlett-Lewis Model

The parameters of interest in fitting the BL model are similar to those described by the NS model. The results obtained for the BL model are similar to those of the NS model thus they are not presented. The temporal distribution of extreme low volatility exceedances in a volatility cluster are given in Figure 33. The cluster members are concentrated near the centre of the cluster (main shock) and the number of cluster members decreases significantly with the increase in the duration from the main shock.

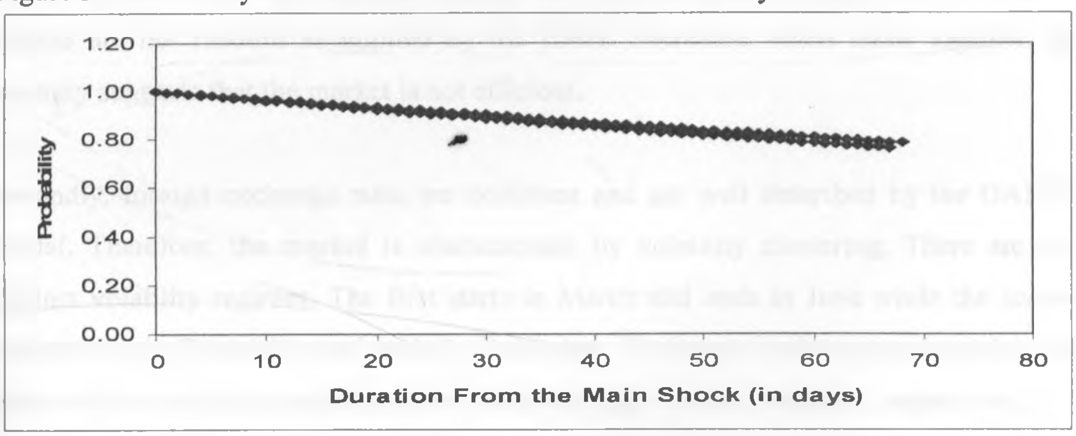
Figure 33 Probability of Exceedances Below Threshold Volatility in the Market



Therefore, the exceedances over a give threshold in a volatility cluster follow the inverse power law distribution away from the main shock. This illustrates the singular nature of the renewal process at the origin, a sharp decrease in replication and a long fat-tail.

The probability of extreme high volatility exceedances after a given duration from the main shock is shown in Figure 34. The probability decreases at a slower rate compared to the probability of extreme low volatility clusters. The results also indicate a possible long fat-tail in the death process of high volatility clusters. The characteristic fat-tail is also evident even at very low probabilities of regeneration. The death process can be best described by the inverse power law than by the exponential distribution.

Figure 34 Probability of Exceedances Over Threshold Volatility in the Market



Thus, the mechanism generating the exceedances over a given threshold in a volatility cluster after a random shock in the market are best described by the inverse power law as illustrated in Figure 38. Furthermore, while 60 percent of extremely low volatility cluster members would have died-out by the 40th day from the main volatility shock, only 20 percent of extremely high volatility cluster members would have died out by this time. This result also confirms the previous assertion that the KSh/USD spot market is subject to extreme high volatility most of the time.

4.5 Summary

There are five main results from the analysis of the data employed in this study.

Firstly, the foreign exchange rate market is inefficient. The unit root test showed that daily returns are integrated of order zero, *I (0)*. This implies that daily returns are mean-reverting. The hypothesis of unit root is rejected for weekly returns thus they are integrated of order zero, *I (0)*, and have no statistically significant trend in time. The results also showed that the risk premium is not stationary at the weekly, 1-, 3-, 6- and 12-month intervals. In general, the results show that the forward premium is not stationary at the weekly, 1-, 3-, 6- and 12-month intervals. The evidence adduced also showed that the returns are not normally distributed. The results also indicated that both daily and monthly returns are negatively autocorrelated while weekly returns are positively autocorrelated. Therefore, these results negate one of the main assumptions of the EMH that returns are not serially correlated. Furthermore, the risk premium is not constant. Indeed, the term structure of the risk premia contains information that can improve the forecasting of future spot exchange rates. The foreign exchange market also displays seasonal patterns around holidays, in April, May, June, July and August. This shows that returns are not random as implied by the EMH. Therefore, when taken together, the strongly suggests that the market is not efficient.

Secondly, foreign exchange rates are nonlinear and are well described by the GARCH model. Therefore, the market is characterized by volatility clustering. There are two distinct volatility regimes. The first starts in March and ends in June while the second commences in September and ends in December. These two regimes correspond to the relatively low volatility regime and the relatively high volatility regimes, respectively.

Thirdly, the results show that the foreign exchange market is chaotic. The results of the BDS tests indicate that the rejection of the null hypothesis of IID error terms from the best fitting GARCH model at 5% significance level could be due to deterministic chaos in the returns, in the risk premiums and the in the forward premiums. Chaos in the market are caused by the risk aversion behavior of market participants or speculation in the foreign exchange market. Therefore, speculation, or worse a risk-averse policy in response to extreme volatility in the market, increases the probability of extreme volatility. This causes an increase in the number of exceedances (extreme volatility) if the risk-aversion behavior is already prevalent in the market. Therefore, there could be a critical level of speculation or risk aversion that triggers chaos in the market. The results of this study suggest that this critical point corresponds to a one week (5 days) investment horizon.

Fourthly, the distribution of the magnitudes of the chaos follows the GEV distribution. The statistical distributions that have been suggested in the literature as capable of describing the behavior of maximal and minimal returns were estimated over the sample period by applying the extreme value theory. In general, the GEV distribution fits the data well compared to the GPD as the sampling interval increases from one week to one year. Both extremely low and extremely high volatility cluster member distributions are well described by the inverse power law distribution than the exponential distribution.

Fifthly, the occurrence of chaos in the market displays a distinct seasonal pattern. There is a high exceedances rate in January, April, May, June, August, October and December on average compared to other months of the year. At the one week investment horizon, the exceedances rate is highest in June. The month of May is the most volatile month across the years. There are two distinct extreme volatility regimes. The first starts in March and ends in June while the second commences in September and ends in December. These two regimes correspond to the relatively low volatility regime and the relatively high volatility regimes, respectively, as discussed above.

Sixth, the duration of chaos in the foreign exchange market is about six months. Extremely low volatility clusters showed a higher tendency to cluster (RV = 7.5) compared to extremely high volatility clusters (RV = 6.5). However, both types of volatility clusters in the market have the same asymptotic duration of six months. Moreover, high volatility clusters are very persistent and are more common compared to low volatility clusters. This implies that the exchange rate was depreciating most of the time over the sample period.

CHAPTER FIVE

SUMMARY AND CONCLUSIONS

5.1 Introduction

This chapter presents the summary of the results of the study and the main conclusions drawn from the analysis of the data in Chapter Four. The chapter is organized as follows. Section 5.2 presents the summary of the findings of the study while section 5.3 is the conclusion. Section 5.4 discusses the policy implications arising from the results of this study. Lastly, section 5.5 presents the recommendations for further research.

5.2 Summary of the Study

The liberalization of the foreign exchange rate market in Kenya was meant to increase market efficiency. However, this does not seem to be the case as evidence by high and persistent volatility in the market. Excess volatility increases the cost of doing business and the prices of essential goods and services to consumers. This reduces allocation efficiency of economic resources and consequently affects economic growth and development in Kenya. Thus it becomes necessary for the Central Bank of Kenya (CBK) to intervene in the foreign exchange market. Attempts by the Central Bank of Kenya (CBK) to intervene in the market to reduce excessive volatility have either been too little or too late. Often such interventions have even contributed to increased market volatility. For effective intervention the CBK must understand the data generating process (d.g.p.) for the observed exchange rates and volatility clusters. However, no such model is currently available and CBK interventions more often than not fail to meet expectations of market participants and citizens in general. This study contributed to the filling of this gap by examining the data generating process for exchange rates and volatility in the KSH/US$ market. The study used data for daily, weekly and monthly closing prices of the KSH/US$ exchange rates; the 1-month, 3-, 6- and 12- months forward and risk premia; the daily, weekly and monthly Government of Kenya (GoK) and the USA government Treasury Bills rate. The study covered the period starting January 1995 to June 2007.

The general objective of this study was to analyze market efficiency, volatility, and nonlinearity and chaos in the foreign exchange market in Kenya for the period starting January 1995 to June 2007. There were three specific objectives: first, to test the efficiency of the foreign exchange market in Kenya; second, to examine the volatility structure in the foreign exchange market; and third, to determine the presence, occurrence, distribution and duration of chaos in the market. The motivation was to determine the data generating process for the observed returns and volatility clusters in the market. The results are summarized below.

Firstly, the results from the data analysis strongly suggest that the foreign exchange market is not efficient in the weak form. The spot market is characterized by foreign exchange rates that are non-stationary and returns that are not normally distributed. Therefore, the hypothesis that foreign exchange rates are stationary and the hypothesis that returns are normally distributed are rejected. The returns are positively serially correlated implying that the exchange rate has been depreciating most of the time. Returns are also mean- reverting. The results also showed the existence of a time varying risk premium. The term structure of the risk premia contains significant information that can be used to predict the future spot exchange rate. Thus, the hypothesis that returns are not serially correlated and the hypothesis that the risk premium is constant are rejected.

Secondly, there are seasonal patterns in returns and volatility in the foreign exchange market. Foreign exchange returns display seasonal patterns around holidays, in April, May, June, July and August. Volatility also revealed significant seasonal patterns in March to June, and September to December. Seasonality may reflect the economy-wide events such as reading of the government budget and the tourism season, as well as the institutional arrangements within the market.

Thirdly, these results strongly suggest that the foreign exchange market is highly volatile. Both extremely low and extremely high volatility are clustered and are well described by the ARCH/GARCH model. Thus, volatility in the foreign exchange market is predictable, at least in the short run. Consequently, the hypothesis that exchange rates do not display the ARCH effect and the hypothesis that exchange rates do not display the GARCH effect are rejected. The GARCH models best described the behavior of volatility in the market compared to other linear and nonlinear models. The results revealed that the ARCH/GARCH effects in returns tended to decline with the increase in the sampling interval. The ARCH/GARCH effects in returns were more pronounced at the daily and weekly sampling intervals. However, the ARCH/GARCH effects for the risk premia displayed increasing persistence at the 1-, 3-, 6- and 12-months intervals. The results indicated that significant asymmetries exist in the returns, the risk premiums and the forward premiums. Hence, the null hypothesis that foreign exchange rates are symmetrical is rejected. The results of the GARCH-M models indicate that the foreign exchange market correctly prices risk, thus, the hypothesis that the foreign exchange market does not correctly price risk is rejected.

Fourthly, the evidence strongly indicates that the foreign exchange rate market is nonlinear and chaotic. The results of the BDS test showed that significant patterns could be remaining in the errors of GARCH models for returns at all relevant intervals. Thus, the error terms are not independent and identically distributed. However, the findings showed that significant patterns are only present in the errors of the 1-month risk premiums. This suggests that the error terms are not independent and identically distributed at the monthly interval for the risk premiums. The results indicated that the forward premia are not independent and identically distributed. The remaining patterns in returns, the risk premia and the forward premia are ascribed to chaos in the market. The results of the Lyapunov test revealed the presence of a positive Lyapunov exponent in returns, the forward premiums and the risk premiums at all the relevant intervals. This strongly suggests the presence of nonlinearity and chaos in the returns, the forward premia and the risk premia. Therefore, the hypothesis that the foreign exchange market is not chaotic is rejected. The distribution of extreme returns and extreme volatility over thresholds at particular time intervals strongly suggests that they are well described by the same distribution - the GEV distribution. Further, the results strongly suggest that the distribution of volatility cluster members follows the inverse power law, irrespective of the scale at which these are examined. Extreme low volatility displays significant seasonal patterns. Thus, the market is more likely to be chaotic from March to June and September to December in any given year. Therefore, the hypothesis that the distribution of chaos in the market is random is rejected.

Fifthly, the results show that the term structure of the risk premiums rises with the investment horizon. Thus, as the investment horizon rises from one month to twelve months, the risk premiums demanded also increase to reflect the increasing exposure to risk at longer maturities. This suggests that the yield curve is upward sloping. When short-term risk premiums are rising, longer-term risk premiums are also rising. Therefore, the yield curve typically shifts upward or downward each week or month instead of twisting or rotating about some point along the yield curve.

5.3 Conclusions

Several conclusions can be drawn from the findings of this study in section 5.2 above. Firstly, the evidence strongly suggests that the foreign exchange market in Kenya is not efficient in the weak form. The foreign exchange market inefficiency is ascribed to significant serial correlation, non-normal distribution and a non-constant variance in returns. Inefficiency in the foreign exchange market is also attributable to seasonal patterns in foreign exchange returns and volatility. Both returns and volatility in the market can be predicted, at least in the short-run.

Secondly, the results indicate that the foreign exchange market is highly volatile most of the time. Volatility clusters are well described by the Poisson distribution while the cluster members follow the inverse power law distribution. Thus, the volatility clusters arise from random shocks to the market and are likely to persist in the market. This suggests that new information in the market is not instantaneously incorporated into exchange rates. Hence, there are irrational market participants and/or market participants hold heterogeneous expectations.

Thirdly, the foreign exchange market is characterized by seasonal patterns in returns and volatility. There appears to be two significant seasonal patterns in returns and volatility across the year. The first season begins in March and ends in June while the second seasonal pattern starts in August and ends in December.

Fourthly, the term structure of the risk premium is upward sloping. The risk premiums increase with the investment horizon. The risk premiums are also pro-cyclical, rising and falling with economic booms and recessions, respectively. Premiums of various maturities move in the same direction. However, short term risk premiums are more volatile compared to long term risk premiums.

Fifthly, the behavior of returns and volatility in the foreign exchange market are nonlinear and chaotic. This result confirms those of Peters (1991), De Grauwe, et al (1993), Serlertis and Dormaar (1994), Bask (1996, 2002) and Brzozowska-Rup and Orlowski (2004) among others who studied nonlinear behavior of exchange rates in other countries. The forward premiums and the risk premiums in the foreign exchange market could also be nonlinear and chaotic.

5.4 Policy Implications

There are several economic implications of these results for both business policy and public policy. Firstly, when the market is inefficient in processing information, it implies that there are significant lags between dissemination of information and market participants' reaction to news. These information lags could arise from market segmentation and/or poor utilization of information communication technologies in the market. Therefore, to improve the information efficiency in the foreign exchange market, the government should consider using information technology infrastructure to provide information on exchange rates to the wider public. This is already happening with respect to the stock market. For individuals and businesses, this implies that they can profitably utilize their sophisticated IT infrastructure to gather information and exploit it to earn profits in the foreign exchange market.

Secondly, persistence and nonlinearity in volatility also suggest inefficient information processing in the market. This could be attributed to irrationality or heterogeneous expectations or risk aversion in the market that causes participants to herd together. Therefore, the CBK needs to intervene in the market to reduce information asymmetry and speculation, which could be contributing to nonlinearity and persistence in volatility. The results also imply that forward contracts and other derivative instruments for hedging against risk should be introduced in the market. This will enable participants to bear only that risk they are willing to carry in the highly volatile market. This can increase market liquidity and information efficiency.

Thirdly, the two seasons in returns and volatility in the market are characterized by extreme movements in the exchange rates, especially in January, May and December. This suggests increased speculation in the foreign exchange market around these dates. Again, this suggests that intervention by the CBK may reduce the pronounced volatility around these seasons. For dealers, forex bureaus, and portfolio managers this represents an opportune time to take positions in the market and reap profits. However, farmers expecting cash inflows from export of their products should consider hedging their expected cash flows around these months. The importers of goods and raw materials should also consider using derivatives to hedge against currency risk around these periods in the year.

Fourthly, the results in this study suggest that effective intervention in the market by the CBK should occur at most five days after gyrations begin in the exchange rates and the interest rates at different maturities. Any delay beyond five days after the market has become volatile, given risk averse and irrational market participants, could plunge the market deep into chaos.

Lastly, nonlinearity and chaos in exchange rates have important implications for portfolio insurance, stop-loss trading strategies and determination of the minimum capital requirements for dealer banks and foreign exchange bureaus. The Central Bank can use the results of this study to set the minimum capital for dealers and forex bureaus. Portfolio managers also need to hedge their open positions in the market, since extreme exchange rate changes are more common in the market than suggested by popular normal distribution. Thus, derivative products should be introduced and popularized in the market to help participants to manage foreign exchange rate risk.

5.5 Recommendations for Further Research

There are at least four areas where this study can be extended. First, the efficiency, nonlinear and chaotic behavior of the foreign exchange market over time needs to be examined. This may shed light on the impact of specific reforms and CBK interventions in the market on efficiency and complexity. A similar study can be done for other currencies vis-à-vis the Kenya shilling. This will allow a comparison to be made between markets based on information efficiency and the degree of nonlinearity and complexity. Secondly, there is need to study the issue of volatility forecasting in the foreign exchange market in Kenya. Specifically, it should be examined whether the models fitted to the data in the current study offer any improvement over the extant models in forecasting returns and volatility in the foreign exchange market. At the moment, the ability of existing models to predict the future, even over the short-run, is poor.

Thirdly, the results presented with respect to the KSh/USD market could be gainfully replicated in other currency markets. This will provide an opportunity to compare results in this study with those of other markets and thereby enable one to make general statements concerning the efficiency and volatility clustering in all foreign exchange markets in Kenya.

Fourthly, future studies could employ high frequency data to re-examine the issues raised and addressed by the current study. The motivation would be to study market activity almost in real time.

5.6 Contributions of the Study to Theory, Policy and Practice of Finance

The results of this study have a number of implications for the theory, practice and policy of Finance. For the theory of Finance, the results show that using the Theory of Point Processes enriches the repertoire of models available for the study of market volatility. This model captures well the time dependency in the distribution of volatility magnitudes.

For the practice of Finance, the findings indicate that investors can earn abnormal profits in the market only in the long run. Evidence adduced shows that market fundamentals influence the behavior of exchange rates only in the long run. The results also indicate that CBK intervention in the market is necessary whenever the market becomes extremely volatile to be justified by the fundamentals.

Three key policy implications are worthy noting. First, to be effective, CBK intervention in the market should be no later than five days after the start of excessive volatility in the market. Second, the CBK should among other things focus on reducing speculation in the foreign exchange market since this is what increases volatility.

Thirdly, the CBK should encourage the development of derivatives such as forward contracts and futures contracts. These instruments are important for foreign exchange risk management in the market. Fourthly, once the market becomes volatile it is likely to remain so for about six months. This implies that there are no quick fixes to the problem of foreign exchange rate instability. Therefore, joint action by all the players in the market can effectively manage the demand and supply forces and thus tame the volatile shilling.

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APPENDICES

APPENDIX A

Table 2 Summary of Studies on Chaos and Nonlinear Dynamics in the Foreign Exchange Markets

	AUTHOR	YEAR	CONTEXT	DATA	TESTS	FINDINGS
1	Hsieh, D.A.	1989	**USA**	**Daily:** CAD/USD, JPY/USD, SFr/USD, BP/USD, DM/USD	**CD, LE and BDS**	Significant non-linearity No chaos
2	Lui & Peasnell	1989		**Daily:** HKD/USD **Sample:** 4 Jan. 1982 – 31 Dec. 1984	**DF, CD**	High serial correlation Poor predictability
3	BajoRubio, et al	1992	**Spain**	**Daily:** PST/USD **Sample:** 1985 - 1991	**CD & LE**	Strong indications of chaos
4	De Grauwe et al	1993		**Daily:** DM/USD, JPY/USD, BP/USD, **Sample: 1973 - 1982**	**CD & LE**	Strong indications of chaos in BP/USD and JPY/USD
5	Serlertis and Dormaar	1994	**Australia**	**Daily:** USD/JPY,USD/ZL, USD/LEV, USD/CKR, USD/RBL, USD/DM spot-month futures	Correlation. Dimension **(CD)**, Lyapunov Exponent **(LE)**	Significant indications of chaos
6	Koutmos, G.	1994	**Greece**	**Daily:** DRC/USD, DRC/DM, DRC/FFr, DRC/JPY, DRC/Lr **Models:** E-GARCH	**CD & LE**	Volatility is predictable Significant nonlinearities
7	Cecen & Erkal	1996		**Hourly:** BP, DM, SFr and JPY **Sample:** 2 Jan 1986 and 15 Jul 1986	**CD & LE**	Significant nonlinearities No chaos
8	Bask	1996	**Sweden**	**Daily:** KR/USD, KR/BP, KR/JPY, KR/DM, KR/EUR **Sample:** 13 Jan 1986 to August 1998	**LE**	Strong indications of chaos
9	Creedy, Lye, & Martin	1996	**UK**	**Monthly:** US/UK **Sample:** Mar 1973 – May 1990	**ECM & MLE**	Nonlinear model performs better than the linear model
10	Brooks	1998	**UK**	**Daily:** 10 BP denominated exchange rates	**LE, ANN & BDS**	No chaos
11	Schmitt, Schertzer, & Lovejoy	1999	**EMS**	**Daily:** FFR/SFR, FFR/BP, FFR/JPY, FFR/DM, FFR/USD	Multifractal Analysis, **CD**	Significant nonlinearities in the data
12	Richards	2000	**Australia, Canada, UK, Japan, etc**	**Daily:** CAD, ASD, BP, JPY	**CD & LE**	No chaos
13	Bask	2002	**Sweden**	**Daily:** KR/USD, KR/BP, KR/JPY, KR/DM, KR/EUR **Sample:** May 1991 to August 1995	**CD & LE**	Strong indications of chaos
14	Brzozowska-Rup & Orlowski	2004	**Poland**	**Daily:** USD/ZL **Sample:**1993- 2003	**CD & LE**	Strong indications of chaos
15	Serletis & Shahmoradi	2004	**Canada**	**Daily:** CAD/USD **Sample:**1974-2002	**CD & LE**	No Chaos
16	Weston & Premachandran	2005	**New Zealand**	**Daily:** NZD/USD **Sample:** 1985 - 2004	**CD, LE, BDS, Kurtosis**	Strong indications of chaos
17	Vandrovych	2006	**USA**	**Daily:** USD/BP, JPY/USD, SFr/USD, CAD/USD **Sample:** Jan. 1975 – Jun 2006 **Variables:** returns, volatility, and FX rates	**CD and LE**	Significant nonlinearities No chaos
18	Guillaume	1995, 2000		**Intra-day:** USD/DM, SD/BP, USD/JPY, SD/FFr **Sample:**1987- 1992	**CD & LE**	No Chaos

APPENDIX B

FOREIGN CURRENCIES TRADED IN KENYA

1	United States dollar
2	Sterling pound
3	Euro
4	South Africa Rand
5	Uganda shilling
6	Tanzania shilling
7	AE Dirham
8	Deutch Mark
9	Canadian dollar
10	French franc
11	Swiss franc
12	Dutch guilder
13	Italian lira
14	Belsium franc
15	Japanese yen (100)
16	Swedish kroner
17	Norwegian kroner
18	Danish kroner
19	Austrian schilling
20	Finn marka
21	Spanish peseta
22	Indian rupee
23	Hong kong dollar
24	Singapore dollar
25	Saudi riyal
26	Australian dollar
27	US dollar per SDR
28	Zambian kwacha
29	Ethiopian barr
30	Rwanda franc
31	Burundi franc
32	Uapta

APPENDIX C

Table 11 Results of Estimating ARCH Models of Returns

Variable	ARCH Daily Returns	ARCH Weekly Returns	ARCH Monthly Returns
μ	-0.0024 [-28.71802]***	-0.0052 [-6.6580]***	-0.0098 [-2.3429]**
D(IDIFF(-1))		-0.0011 [-1.1744]	0.0015 [1.3027]
HOLIDAY	0.0019 [11.7520] ***		
MONDAY	-0.0005 [-5.5966] ***		
TUESDAY	-0.0003 [-2.3783 **		
WEDNESDAY	-0.0005 [-5.4976] ***		
THURSDAY	-0.0004 [-4.7476] ***		
JANUARY	0.0029 [26.8091] ***	0.0052 [3.5283] ***	0.0078 [1.1290]
FEBRUARY	0.0026 [26.7463] ***	0.0056 [3.0578] ***	0.0094 [1.4088]
MARCH	0.0025 [38.0375] ***	0.0033 [2.4330] **	0.0152 [3.0722]**
APRIL	-0.0019 [-24.0308] ***	0.0089 [7.4147] ***	0.0171 [3.1008]**
MAY	0.0024 [28.2878] ***	0.0064 [4.4927] ***	0.0098 [1.8125]*
JUNE	0.0020 [31.0300] ***	0.0054 [2.4938] **	0.0117 [1.6082]
JULY	0.0025 [19.0462] ***	0.0041 [2.8812] ***	0.0132 [2.0182]**
AUGUST	0.0028 [27.5131]***	0.0060 [3.5247] ***	0.0131 [2.2940]**
SEPTEMBER	0.0030 [28.1509]***	0.0052 [3.9330] ***	0.0122 [1.6598]**
OCTOBER	-0.0013 [-19.6061]***	0.0045 [2.4827] **	0.0107 [1.6905]**
NOVEMBER	0.0028 [23.9251]***	0.0039 [3.1394] ***	0.0088 [2.3354]**
R (-1)	0.0841 [5.6549]***	0.0182 [0.4230]	0.1688 [1.4884]
R (-2)	-0.15171 [-8.2751]***	0.1021 [2.3280] **	
Variance Equations			
Constant	1.52E-06 [18.3245]***	2.99E-05 [10.3789] ***	0.0001 [3.5801]**
ARCH (-1)	1.6860 [24.7588]***	0.4634 [6.1094] ***	0.8985 [2.5726]**
ARCH (-2)	0.1719 [7.5495]***	0.0420 [1.1064]	
ARCH (-3)	0.13918 [7.1267]***	0.0755 [2.1714] **	
ARCH (-4)	0.0663 [5.1730]***	0.0732 [3.0724] ***	
ARCH (-5)	0.0423 [3.6681]***	0.1256 [3.0724] ***	
ARCH (-6)	0.0671 [6.2430]***	0.1346 [3.6842] ***	
ARCH (-7)	-0.0131 [-2.0031]**	-0.0302 [-3.5531] ***	
ARCH (-8)	0.0591 [9.2363]***		
ARCH (-9)	0.0538 [8.7882]***		
AIC	-7.9723	-6.6504	-5.2932
ARCH-LM	0.5300	0.0914	0.0222

Note: Critical values for the *z*-test and the indication of significance are 2.576, 1.96 and 1.645 at 1% (***), 5% (**), 10% (*) and 25% ([a]) levels, respectively. This table summarizes the results of fitting ARCH models to daily, weekly and monthly returns. R= currency return, R (-1) = lagged R. IDIFF = the interest differential, IDIFF (-1) = lagged IDIFF. D (IDIFF (-1)) = first difference of lagged IDIFF. RESID = residuals, RESID (-1) = lagged residuals. The results shown in this table are those of the best fitting models as indicated by the AIC. The dummies for Friday and December were eliminated to avoid the dummy trap in regression analysis. The values in square brackets are *z*-statistics.

Table 12 Results of Estimating GARCH Models of Returns

Variable	GARCH Daily Returns	GARCH Weekly Returns	GARCH Monthly Returns
μ	-0.0003 [-0.4796]	-0.0014 [-1.7573]	-0.0094 [-3.2473]***
D(IDIFF(-1))		-0.0007 [-0.81885]	0.0026 [1.6942]*
HOLIDAY	-0.0022 [-8.5816]***		
MONDAY	-0.0006 [-2.1075] **		
TUESDAY	-0.0002 [-0.4310]		
WEDNESDAY	-0.0005 [-1.6373]		
THURSDAY	-0.0008 [-2.8807] ***		
JANUARY	0.0008 [1.5066]	0.0013 [0.9592]	0.0077 [1.3532]
FEBRUARY	0.0011 [1.4946]	0.0019 [1.1350]	0.0064 [1.2007]
MARCH	0.00046 [0.74587]	0.0004 [0.3323]	0.0140 [4.1939]***
APRIL	-0.0049 [-13.5140] ***	0.0046 [4.4891]***	0.0153 [2.8370]***
MAY	-0.00030 [-0.6011]	0.0022 [1.77731]*	0.0107 [2.0603]**
JUNE	0.0007 [1.3303]	0.0015 [0.7671]	0.0126 [2.1442]**
JULY	0.0009 [1.4710]	0.0004 [0.3354]	0.0149 [2.3786]**
AUGUST	0.0010 [1.4120]	0.0019 [1.3235]	0.0123 [2.2519]**
SEPTEMBER	0.0013 [1.7957] *	0.0010 [0.7437]	0.0116 [1.7553]*
OCTOBER	-0.0042 [-11.6642] ***	0.0008 [0.4669]	0.0079 [1.6273]
NOVEMBER	4.76E-05 [0.0856]	1.85E-05 [0.0153]	0.0017 [0.3411]
R (-1)	0.1975 [7.7161] ***	0.0255 [0.6562]	0.2683 [2.5176]**
R (-2)	-0.0489 [-1.8396] *	0.0318 [0.6193]	
	Variance Equations		
Constant	1.87E-06 7.7330***	4.43E-06	5.63E-06
ARCH (-1)	0.3053 [15.6628] ***	0.1991 [19.8529]***	0.7078 [11.5060]***
ARCH (-2)	-0.1693 [-5.9275] ***		-0.5705 [-5.5238]***
ARCH (-3)	-0.0372 [-1.3151]		
ARCH (-4)	-0.0069 [-0.3116]		
GARCH (-1)	0.6776 [13.7215] ***	0.7608 [65.6292]***	0.8566 [14.6428]***
GARCH (-2)	0.3216 [5.2497]		
GARCH (-3)	0.1897 [4.2987] ***		
GARCH (-4)	-0.3122 [-12.7826] ***		
AIC	-7.70280	-6.6567	-4.8508
ARCH-LM	1.4235	2.6639	2.4528

Note: Critical values for the *z*-test and the indication of significance are 2.576, 1.96 and 1.645 at 1% (***), 5% (**), 10% (*) and 25% (a) levels, respectively. This table summarizes the results of fitting nonlinear models to daily, weekly and monthly returns. R= currency return, R (-1) = lagged R. IDIFF = the interest differential, IDIFF (-1) = lagged IDIFF. D (IDIFF (-1)) = first difference of lagged IDIFF. RESID = residuals, RESID (-1) = lagged residuals. The results shown in this table are those of the best fitting models as indicated by the AIC. The dummies for Friday and December were eliminated to avoid the dummy trap in regression analysis. The values in square brackets are *z*-statistics.

Table 13 Results of Estimating E-GARCH Models of Returns

Variable	E-GARCH – M Daily Returns	E-GARCH – M Weekly Returns	E-GARCH – M Monthly Returns
µ	-0.0023 [-22.8873]***	-0.0046 [-9.5898]***	-0.0101 [-3.5288]***
IDIFF		-0.000693 [-1.057969]	0.0018 [1.5643]
HOLIDAY	0.0008 [5.4191] ***		
MONDAY	-0.0002 [-1.9220] *		
TUESDAY	9.58E-05 [0.8387]		
WEDNESDAY	-0.0020 [-1.5210]		
THURSDAY	-0.0001 [-1.4963]		
JANUARY	0.0026 [17.4231] ***	0.0060 [6.9761] ***	0.0070 [1.1435]**
FEBRUARY	0.0025 [24.6311] ***	0.0059 [4.2301] ***	0.0088 [1.7195]*
MARCH	0.0020 [22.0954] ***	0.0035 [4.3071] ***	0.0150 [3.6331]***
APRIL	-0.0015 [-15.9841] ***	0.0055 [5.8109] ***	0.0187 [3.5802]***
MAY	0.0024 [15.3738 ***	0.0065 [6.4859] ***	0.0129 [2.3592]**
JUNE	0.0070 [20.2136] ***	0.0056 [4.9285] ***	0.0133 [2.0950]**
JULY	0.0026 [12.4625] ***	0.0050 [4.3277] ***	0.0134 [2.2838]**
AUGUST	0.00280 [22.1005] ***	0.0058 [4.3585] ***	0.0131 [2.6622]**
SEPTEMBER	0.0025 [19.5514]***	0.0047 [5.0699] ***	0.0122 [1.84511]*
OCTOBER	-1.51E-06 [-0.0153]	0.0041 [3.6617] ***	0.0127 [2.5237]**
NOVEMBER	0.0025 [21.482]***	0.0046 [6.8322] ***	0.0071 [1.7684]*
R (-1)	0.1423 [7.8606]***	0.0602 [1.1744]	0.1946 [1.4871]
R (-2)	-0.0507 [-2.7344]**	0.0988 [2.7496] ***	
	Variance Equations		
Constant	-0.9646 [-18.1170] ***	-1.6210 [-8.1951] ***	-1.9188 [-10.486]***
C (1)	0.6803 [36.8720] ***	0.7056 [11.2836] ***	1.11224 [3.8362]***
C (2)	0.1534 [0.8867]	-0.1235 [-1.7627] *	-0.1826 [-1.022]
C (3)	0.0145 [0.8867]	0.1247 [3.0219] ***	0.4128 [2.3068]**
C (4)	-0.3380 [-22.2289] ***	0.8703 [46.4076] ***	
C (5)	0.2202 [18.50724] ***		
C (6)	0.4126 [24.11338] ***		
C (7)	0.4677 [38.4432] ***		
C (8)	0.6655 [75.2594] ***		
C (9)	-0.6039 [-33.1156] ***		
AIC	-8.0830	-6.6897	-6.6890
ARCH-LM	0.0015	0.0064	0.0042

Note: Critical values for the *z*-test and the indication of significance are 2.576, 1.96 and 1.645 at 1% (***), 5% (**), 10% (*) and 25% ([a]) levels, respectively. This table summarizes the results of fitting nonlinear models to daily, weekly and monthly returns. R= currency return, R (-1) = lagged R. IDIFF = the interest differential, IDIFF (-1) = lagged IDIFF. D (IDIFF (-1)) = first difference of lagged IDIFF. RESID = residuals, RESID (-1) = lagged residuals. The results shown in this table are those of the best fitting models as indicated by the AIC. The dummies for Friday and December were eliminated to avoid the dummy trap in regression analysis. C (6), C (3), C (2) = coefficients of the asymmetry terms at the daily, weekly and monthly intervals, respectively. The values in square brackets are *z*-statistics.

Table 14 Results of Estimating GARCH-M Models of Returns

Variable	GARCH – M Daily Returns	GARCH – M Weekly Returns	GARCH – M Monthly Returns
μ	-0.0016 [-7.4146]***	-0. [-1.4135]	-6.5655 [-1.4104]
IDIFF		-0.0004 [-0.5630]	-0.0076 [-1.7485]*
HOLIDAY	-0.0015 [-7.9420] ***		
MONDAY	-0.0002 [-1.1347]		
TUESDAY	-7.60E-05 [-0.2984]		
WEDNESDAY	-0.0002 [-1.1138]		
THURSDAY	-0.0004 [-2.3002]**		
JANUARY	0.0018 [5.2508]***	0.0006 [0.4773]	0.0018 [1.4231]
FEBRUARY	0.0017 [3.8399]***	0.0015 [0.9586]	0.0077 [1.3588]
MARCH	0.0015 [5.0752]***	7.17E-05 [0.0627]	0.0079 [1.2574]
APRIL	-0.0040 [-25.0947]***	0.0048 [5.6837]***	0.0138 [2.7433]***
MAY	0.0010 [4.2838]***	0.0019 [1.6486] *	0.0177 [3.2264]***
JUNE	0.0017 [5.9905]***	0.0010 [0.5600]	0.0118 [2.0489]**
JULY	0.0018 [4.318483]***	-4.41E-05 [-0.0355]	0.0104 [1.4221]
AUGUST	0.0020 [5.1310]***	0.0013 [1.0348]	0.0116 [2.3819]
SEPTEMBER	0.0019 [4.1664]***	0.0005 [0.3959]	0.0122 [2.2572]
OCTOBER	-0.0035 [-19.4927]***	-0.0001 [-0.0851]	0.0067 [0.9618]
NOVEMBER	0.0018 [6.0452]***	-0.0003 [-0.3278]	0.0031 [0.4373]
R (-1)	0.1922 [8.6334]***	-0.0267 [-0.5250]	0.0073 [1.884287]*
R (-2)	-0.0453 [-1.9203]*	0.010492 [0.2105]	
GARCH	0.17702 [0.1056]	0.3068 [0.0649]	0.3932 [3.6009]***
Variance Equations			
Constant	1.72E-06 [14.24717] ***	2.82E-06 [6.4677] ***	0.0001 [3.6790]***
ARCH (-1)	0.4068 [16.5760] ***	0.4794 [7.1177] ***	0.8422 [2.8793]***
ARCH (-2)	-0.1878 [-4.2342] ***	-0.2620 [-3.9084] ***	
ARCH (-3)	0.0663 [1.45126		
ARCH (-4)	-0.0203 [-0.7554]		
GARCH (-1)	0.6248 [8.9828] ***	0.8038 [43.4843]***	-0.0809 [-0.7510]
GARCH (-2)	0.1620 [1.8077] *		
GARCH (-3)	0.1588 [3.1100] ***		
GARCH (-4)	-0.1940 [-10.2140] ***		
AIC	-7.8325	-6.6726	-5.3194
ARCH-LM	0.4489	0.0075	0.0068

Note: Critical values for the *z*-test and the indication of significance are 2.576, 1.96 and 1.645 at 1% (***), 5% (**), 10% (*) and 25% (°) levels, respectively. This table summarizes the results of fitting nonlinear models to daily, weekly and monthly returns. R= currency return, R (-1) = lagged R. IDIFF = the interest differential, IDIFF (-1) = lagged IDIFF. D (IDIFF (-1)) = first difference of lagged IDIFF. RESID = residuals, RESID (-1) = lagged residuals. The results shown in this table are those of the best fitting models as indicated by the AIC. The dummies for Friday and December were eliminated to avoid the dummy trap in regression analysis. The values in square brackets are *z*-statistics.

Table 34 Parameter Estimates of the Extremes over Threshold Returns

Threshold	GP Distribution				Point Process Model			
	Number of Exceedances	Scale	Shape	LLR	Location	Scale	Shape	LLR
Panel A: Daily Returns								
0.001	28	0.0100	0.4630	-88.1900	0.2770	0.1320	0.4400	-223.4700
0.003	20	0.0170	0.1880	-57.2200	0.1710	0.0490	0.1880	-147.1200
0.005	19	0.0150	0.2820	-55.4800	0.1920	0.0650	0.2670	-139.9200
0.008	15	0.0170	0.2620	-42.3900	0.2400	0.0960	0.3420	-105.4800
0.010	12	0.0230	0.0890	-32.0600	0.8750	0.6330	0.7100	-79.0100
0.030	3	0.0690	-0.9490	-7.7300	0.0990	0.0030	-0.9140	-15.3700
0.050	3	0.0490	-0.9390	-8.7300	0.0470	0.0160	0.5580	-15.7400
0.080	1	0.0210	-0.9780	-3.7700	1.1310	1.0210	0.9020	-3.5200
0.100	1	0.0020	-0.3350	-5.8900	1.1210	0.9190	0.8200	-3.8600
Panel B: Weekly Returns								
0.001	104	0.0020	0.4380	-487.6400	0.0110	0.0020	0.0700	-906.2600
0.003	48	0.0030	0.5790	-209.9200	1.2790	1.3050	1.0170	-365.1600
0.005	27	0.0020	0.9020	-112.9000	0.0450	0.0140	0.1700	-190.1400
0.008	10	0.0110	0.3920	-31.3300	0.0700	0.0300	0.2840	-52.0800
0.010	8	0.0130	0.3460	-24.0800	0.0750	0.0370	0.3710	-38.9200
0.030	3	0.0480	-0.9320	-8.7600	1.6980	2.9350	1.7270	-8.8800
0.050	1	0.0320	-1.0130	-3.5000	2.1450	5.8600	2.7310	-0.8800
0.080	1	-0.3540	0.0010	-6.0500	2.5690	5.6710	2.2070	-1.0700
0.100	-	-	-	-	-	-	-	-
Panel C: Monthly Returns								
0.001	65	0.0030	0.5450	-272.5900	0.0820	0.0380	0.4300	-575.6800
0.003	41	0.0030	0.7540	-165.8200	0.0790	0.0390	0.4670	-337.4900
0.005	26	0.0030	0.9050	-98.4700	0.7360	0.7420	1.0070	-194.5900
0.008	10	0.0050	1.0140	-45.9600	0.1350	0.0880	0.6440	-89.5600
0.010	9	0.0180	0.2340	-24.9100	0.1180	0.0440	0.2370	-49.1300
0.030	5	0.5000	0.0110	-15.0000	0.1060	0.0420	0.3900	-25.5000
0.050	1	-1.3600	0.0690	-4.2700	1.3360	2.4680	1.8480	-1.7500
0.080	1	0.0210	-0.9570	-3.7400	1.6340	2.4030	1.4690	-2.0600
0.100	1	0.0010	0.1000	-6.3200	1.7940	2.3610	1.3150	-2.1900
Panel D: Quarterly Returns								
0.001	46	0.0050	0.5790	-166.9500	0.1530	0.0750	0.4560	-379.2200
0.003	31	0.0090	0.3990	-103.0100	0.1560	0.0690	0.3930	-233.9400
0.005	24	0.0110	0.3470	-76.2900	2.2700	2.2700	0.9960	-168.3500
0.008	20	0.0080	0.6110	-65.1200	2.0270	1.9020	0.9340	-136.4400
0.010	17	0.0060	0.8540	-55.3100	0.3870	0.2860	0.7370	-116.3800
0.030	4	0.0690	-0.8630	-9.8400	0.1060	0.0030	1.0360	-18.9100
0.050	3	0.0150	0.4350	-8.3800	0.8370	0.7400	0.8840	-12.7800
0.080	1	0.0290	-0.9630	-3.4200	1.1370	1.4870	1.3060	-2.4700
0.100	1	0.0090	-0.9980	-4.7200	1.3300	1.4020	1.0540	-2.6000
Panel E: Semi-Annual Returns								
0.001	42	0.0070	0.4320	-146.9800	0.1600	0.0700	0.3930	-345.4600
0.003	32	0.0080	0.4150	-107.9100	0.0940	0.0200	0.0720	-249.0600
0.005	25	0.0110	0.3150	-80.8800	0.1300	0.0460	0.2860	-186.0500
0.008	17	0.0170	0.0780	-51.0800	0.3590	0.2080	0.5530	-115.2200
0.010	16	0.0140	0.2060	-49.0700	0.3310	0.2030	0.5960	-108.8100
0.030	4	0.0430	-1.0670	-13.1700	0.1060	0.0030	-1.0360	-18.9100
0.050	3	0.0180	-0.9050	-11.2900	0.9410	0.7690	0.8170	13.5900
0.080	-	-	-	-	-	-	-	-
0.100	-	-	-	-	-	-	-	-
Panel F: Annual Returns								
0.001	40	0.0090	0.3200	-134.0000	0.0750	0.0090	-0.1040	-345.4600
0.003	31	0.0120	0.2090	-99.6200	0.1060	0.0250	0.1150	-241.3000
0.005	27	0.0120	0.2410	-86.6300	0.1010	0.0210	0.0700	-206.0800
0.008	22	0.0110	0.2810	-70.2600	0.7340	0.5860	0.7940	-162.5200
0.010	17	0.0160	0.0980	-51.5000	0.3750	0.2270	0.5880	-118.2000
0.030	3	0.0540	-0.9980	-8.7400	0.0810	0.0030	-0.9330	-13.5900
0.050	2	0.0320	-0.9300	-6.5800	0.2460	0.1320	0.5350	-8.6700
0.080	-	-	-	-	1.1210	1.3390	1.1940	-3.4000
0.100	-	-	-	-	-	-	-	-

Table 35 Parameter Estimates of the Extremes Over Threshold Volatility

Threshold	GP Distribution				Point Process Model			
	Number of Exceedances	Scale	Shape	LLR	Location	Scale	Shape	LLR
Panel A: Daily Volatility								
0.001	48	0.0120	0.3880	-146.0500	0.0930	0.0130	-0.0600	-373.3940
0.005	36	0.0130	0.4060	-106.1660	0.2610	0.1140	0.3930	-269.3480
0.008	28	0.0160	0.3310	-78.9000	0.1660	0.0430	0.1470	-198.5420
0.010	22	0.0260	0.0380	-57.8600	1.4680	1.2270	0.8290	-144.6860
0.030	7	0.0660	-0.9260	-18.1800	0.0990	0.0020	-1.0080	-38.6600
0.050	6	0.0370	-0.7330	-16.5700	0.1030	0.0030	-0.7320	-33.4990
0.080	2	0.0200	-0.9550	-7.5700	0.1830	0.0550	0.2940	-8.8720
Panel B: Weekly Volatility								
0.001	160	0.0030	0.6310	-687.3400	0.0320	0.010	0.2190	-1369.8300
0.003	87	0.0030	0.7890	-341.0200	2.5350	2.4050	0.9430	-610.9100
0.005	57	0.0040	0.8190	-207.8600	0.1240	0.0860	0.6880	-396.8700
0.008	33	0.0080	0.6540	-104.8200	0.1370	0.0920	0.6470	-196.3300
0.010	26	0.0110	0.5030	-77.9000	0.1190	0.0660	0.5060	-143.8000
0.030	9	0.0480	-0.7980	-24.7300	0.3270	0.2960	0.9040	-35.3600
0.050	4	0.0370	-0.9240	-12.5000	1.7450	2.9010	1.6620	-9.3200
Panel C: Monthly Volatility								
0.001	121	0.0030	0.6240	-503.0300	0.0860	0.0420	0.4570	-1056.5600
0.003	72	0.0040	0.6540	-276.7300	0.1180	0.0670	0.5460	-569.1800
0.005	47	0.0050	0.7130	-167.9200	1.0920	1.1470	1.0490	-335.2000
0.008	29	0.0060	0.8980	-94.5300	0.2000	0.1440	0.7140	-185.8500
0.010	21	0.0100	0.7110	-61.7700	0.1850	0.1260	0.6610	-121.2700
0.030	8	0.0100	0.8790	-21.6600	0.4770	0.4470	0.9350	-35.1700
0.050	3	0.0490	-0.9470	-8.6500	1.3500	2.1590	1.5990	-7.2800
0.080	3	0.0190	-0.8890	-11.2800	1.4610	1.8210	1.2460	-8.5500
0.100	1	0.0020	-0.4390	-5.9400	1.3500	2.1670	1.6050	-1.1300
Panel D: Quarterly Volatility								
0.001	88	0.0060	0.5640	-313.5800	0.0760	0.0120	-0.0310	-704.7200
0.003	63	0.0080	0.4410	-210.1300	0.1690	0.0780	0.4190	-479.3200
0.005	49	0.0100	0.4020	-156.7400	4.8230	4.3190	0.8890	-327.0600
0.008	39	0.0080	0.6100	-124.3500	0.6320	0.5600	0.8850	-271.8500
0.010	29	0.0140	0.3660	-85.1600	0.1570	0.0570	0.2810	-186.4300
0.030	9	0.0470	-0.5160	-23.1100	0.1050	0.0100	-0.4210	-44.0300
0.050	6	0.0350	-0.4820	-16.9600	0.5610	0.4210	0.7490	-26.1500
0.080	1	0.0290	-0.9920	-3.5200	0.3250	0.3590	1.1040	-1.9600
Panel E: Semi-Annual Volatility								
0.001	78	0.0080	0.4580	-266.2200	0.0650	0.0080	-0.1140	-623.2700
0.003	59	0.0100	0.3850	-191.6900	0.0990	0.0220	0.0840	-452.3500
0.005	48	0.0110	0.3540	-151.5600	0.1190	0.0300	0.1270	-354.2000
0.008	33	0.0190	0.0420	-96.2100	0.7340	0.5690	0.7660	-221.0400
0.010	31	0.0170	0.1390	-91.7400	0.1600	0.0560	0.2770	-209.4800
0.030	8	0.0430	-0.8710	-23.3700	0.0790	0.0030	-0.7810	-42.6000
0.050	6	0.0210	-0.6960	-19.4500	0.2240	0.1040	0.4630	-29.6000
0.080	0	-	-	-	-	-	-	-
Panel F: Annual Volatility								
0.001	68	0.0110	0.2820	-219.0800	0.0910	0.0120	-0.0810	-538.7590
0.003	57	0.0110	0.3030	-181.0420	0.1150	0.0280	0.1270	-442.0320
0.005	48	0.0120	0.2740	-149.6600	0.1310	0.0350	0.1660	-361.4210
0.008	34	0.0200	-0.0180	-99.2130	1.6120	1.3660	0.8410	-232.9380
0.010	31	0.0200	-0.0150	-90.6410	0.1770	0.0640	0.2910	-213.2860
0.030	10	0.0450	-0.8480	-29.2080	0.3850	0.2470	0.6410	-55.3940
0.050	4	0.0290	-0.8990	-13.1940	0.9940	0.9320	0.9370	-16.6800
0.080	1	0.0020	-0.4470	-16.6800	0.1250	0.0300	0.2370	-4.3080
0.100	0	-	-	-	-	-	-	-