APPLICATION OF NON LINEAR MODELS IN THE DETERMINATION OF THE BEHAVIOUR OF INTEREST RATES IN KENYA;

BY

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A RESEARCH PROJECT REPORT SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS OF THE DEGREE OF MASTERS OF BUSINESS ADMINISTRATION, SCHOOL OF BUSINESS, UNIVERSITY OF NAIROBI

NOVEMBER 2012

DECLARATION

This research project report is my original work and has not been presented for a degree in any other university.

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DEDICATION

I dedicate this research report to my dear wife Susan Nyaguthii and our three children Clare Wangu, Mark Muriuki and Austin Karani and finally to my mother Agnes Wangu. To you all thank you for the prayers, encouragement and support over the years of my studies.

ACKNOWLEDGEMENT

I would like to acknowledge the support, advice and tireless efforts of my supervisor Dr. Kisaka Sifunjo in the supervision during my research work and in writing of this project report.

I would also like to acknowledge the assistance provided by the Head of Research Department at the Central Bank of Kenya in securing the time series data on 91 – day Treasury bill rates over the sample period

I also thank the Librarians at the University of Nairobi for allowing me the use of the library facilities.

Regards to my family for providing the much needed moral support and accepting my being away from home throughout the period of study. My regards to my mother for continued supportive prayers.

Finally, I would like to acknowledge the assistance given by the staff and my fellow students at the School of Business, University of Nairobi.

ABSTRACT

Empirical literature shows that stock returns could be non linear. However, studies on the non linear behavior of interest rates in developing economies are limited. This study aims at filling this knowledge gap by comparing linear and non linear models in predicting interest rates.

The study compared the Random Walk Model, Moving averages Models, Autoregressive Models, Autoregressive Moving Average Models, Autoregressive Conditional Heteroskedasticity Models. The main variable for the study was the Treasury bills interest rate series. In Kenya, this is the Central Bank of Kenya three month Treasury bill rate. The study applied the monthly averages of the 91-day Treasury bill rate for the period between August 1991 and December 2011 which were obtained from the Central Bank of Kenya. The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) also called Schwarz-Bayesian information criterion (SBC) were used to select the best fitting model from each type of models.

The results indicate that non linear GARCH (2, 1) performs better than any other models. This is because it has the lowest AIC and BIC values among all the models tested. Therefore this study concluded that non linear models are better than linear models in predicting interest rates in Kenya. Thus interest rates are non linear.

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LIST OF ABBREVIATIONS AND ACRONYMS

AIC	:	Akaike Information Criterion
ARCH	:	Autoregressive Conditional Heteroskedasticity
ARMA	:	Autoregressive Moving Average
ARIMA	:	Autoregressive Integrated Moving Averages
BIC	:	Bayesian Information Criterion
CKLS	:	Chan, Karolyi, Longstaff and Sanders
DAIC	:	Change in Akaike Information Criterion
DBIC	:	Change in Bayesian Information Criterion
GARCH	:	Generalized Autoregressive Conditional Heteroskedastic
SAP	:	Structural Adjustments Programmes
SBC	:	Schwarz-Bayesian information criterion
T-BILL	:	Treasury Bills

CHAPTER ONE

INTRODUCTION

1.1 Background to the study

It is now widely believed that interest rates are affected by multiple factors. Part of this view derives from the fact that the returns on bonds of all maturities are not perfectly correlated. In addition to this simple point, moreover, a number of theoretical studies promote multifactor bond pricing, including Brennan and Schwartz (1979), Schaefer and Schwartz (1984), Heath, Jarrow and Morton (1988), Longsta and Schwartz (1992), and Chen and Scott (1995), among others. Empirical studies of these and related models generally support the existence of multiple factors (see, for example, Dai and Singleton (1997), Litterman and Scheinkman (1991), Longsta. and Schwartz (1992), Stambaugh (1988), Pearson and Sun (1989), and Andersen and Lund (1997)). Despite this volume of evidence, however, surprisingly few stylized facts are known about the stochastic behavior of interest rates in a multi-factor, continuous-time setting.

1.1.1 Theoretical background

Traditional theories define interest rate as the price of savings determined by demand and supply of loanable funds. It is the rate at which savings are equal to investment assuming the existence of a capital market. The loanable fund theory argues that interest rate is determined by non-monetary factors. It assigns no role to quantity of money or level of income on savings, or to institutional factors such as commercial banks and the government. The liquidity theory, on the other hand, looks at the interest rate as the token paid for abstinence and inconveniences experienced for having to part with an asset whose liquidity is very high. It is a price that equilibrates the desire to hold wealth in the form of cash with the available quantity of cash, and not a reward of savings. Interest rate is a function of income. Its primary role is to help mobilize financial resources and ensure the efficient utilization of resources in the promotion of economic growth and development (Ngugi and Kabubo, 1998).

Short-term interest rates are charges levied by the lenders to the borrowers on loans that must be paid within a year such as Treasury bills and credit card loans. The Short Term Interest Rates are important variables in many different areas of the economic and financial theory. They are important in many financial economic models, such as models on the term structure of interest rates, bond pricing models and derivative security pricing models. They are also important in the development of tools for effective risk management and in many empirical studies analyzing term premiums and yield curves where risk free short-term rates are taken as reference rate for other interest rates. Besides, they are also a crucial feature of the monetary transmission mechanism. Monetary transmission mechanism as starts with a monetary authority's actions influencing short-term rates and the exchange rate, which then go on to ultimately affect aggregate demand of inflation. In order to understand the characteristics of the monetary transmission mechanism, it is therefore imperative to have a good model of the behavior of short-term interest rates.

Empirical evidence documents a level effect in the volatility of short term rates of interest (Olan and Sandy, 2005; Turan and Liuren, 2005). That is, volatility is positively correlated with the level of the short term interest rate. Using Monte-Carlo simulations, Olan and Sandy (2005) examined the performance of the Engle-Ng (1993) tests which differentiate the effect of good and bad news on the predictability of future short rate volatility. The short-term interest rates being the US three month Treasury bills rates taken from the Federal Reserve Bank of St. Louis Economic database were sampled at a weekly frequency over the period of 5th January 1965 to 4th November 2003 yielding 2027 observations.

Their results established that the tests exhibit serious size distortions and loss of power in the face of a neglected level effect. The tendency for interest rates to be more volatile as short term rates rise is what is commonly referred to as 'level effects'. The dynamics of short-term treasury interest rates are central to the pricing of all fixed income instruments and their derivatives. Chan, Karolyi, Longstaff and Sanders (1992), hereafter CKLS compared a variety of single factor continuous-time models of the short-term risk-less rate over the period 1964 through 1989. They found that models that allow the volatility of interest changes to be sensitive to the level of the risk-free rate outperform other models. Longstaff and Schwartz (1992) presented a two-factor general equilibrium model, with the level and conditional volatility of short-term rates as factors. They showed that a two-factor model carries additional information about the term structure and leads to better pricing and hedging performance compared to a single factor model, which only uses the level of the short rate.

This lack of evidence is particularly unfortunate as most of our intuition concerning bond and fixed-income derivative pricing comes from stylized facts generated by single factor, continuous-time interest rate models. For example, the finance literature is uniform in its view that interest rate volatility is increasing in interest rate levels, though there is some disagreement about the rate of increase (see, for example, Chan, Karolyi, Longstaff and Sanders (1992), Ait-Sahalia (1996b), Conley, Hansen, Luttmer and Scheinkman (1995), Brenner, Harjes and Kroner (1996) and Stanton (1997)). If interest rates possess multiple factors, such as the level and slope of the term structure (Litterman and Scheinkman (1991)), then this volatility result represents an average over all possible term structure slopes. Conditional on any particular slope, volatility may thus be severely misestimated, with serious consequences especially for fixed-income derivative pricing.

Two issues arise in trying to generate stylized facts about the underlying continuous-time, stochastic process for interest rates. First, how do we specify ex ante the drift and diffusion of the multivariate process for interest rates so that it is consistent with the true process underlying the data? Second, given that we do not have access to continuous-time data, but instead to interest rates/bond prices at discretely sample intervals, how can we consistently infer an underlying continuous-time multivariate process from these data? Recently, in single factor settings, there has been much headway at addressing these issues (see, for example, Ait-Sahalia (1996a), Conley, Hansen, Luttmer and Scheinkman (1995) and Stanton (1997)).

In a single factor world, the instantaneous returns on all interest rate dependent assets must be perfectly correlated.

1.1.2 Interest rates in Kenya

Prior to the implementation of Structural Adjustment Programmes (SAP) in 1983, the financial sector in Kenya suffered from severe repression. Interest rates were maintained below market-clearing levels, and direct control of credit was the primary monetary control instrument of the authorities. Accompanying the SAP, interest rate deregulation took place. In September 1991 the maximum lending rate was increased from 10% to 14 %. The rediscounting rate for crop finance paper was raised to 11.25 %, while the minimum savings deposit rate was raised to 12.5 %. Between 1983 and 1987, the differentials between the interest rates of banks and non-bank financial institutions were narrowed. This improved the competitiveness of commercial banks. One of the first steps towards freeing interest rates was taken in 1989, when the government started selling Treasury Bonds through an auction.

In July 1991, interest rates were completely freed. Since then, interest rates have been following a steep upward ascent, with the gap between loan deposit rates shrinking. After the liberalization period, interest rates were liberalized and indirect monetary policy tools adopted. Steps were taken to establish financial markets, decontrol foreign exchange, liberalize trade and tighten prudential regulations. The role of the Central Bank was strengthened and monetary policy was tightened. From the financial repression theory, a major achievement in the financial liberalization is the decontrol of interest rates. This has a positive impact on economic performance and also in indicating the direction the financial sector takes after the liberalization process (Ngugi and Kabubo, 1998).

High real short-term interest rates have reduced the demand for capital market instruments and crowded-out substantial domestic savings to short-term government securities (Kibuthu, 2005). This situation was particularly evident in 2001 when the Treasury bill (T-bill) rate was 12.6% compared to an inflation rate of 0.8%. However, the situation is being reversed as T-bill rates have fallen to about 8% resulting in increased demand for both equity and debt instruments (World Bank, 2002). Interest rate spreads are high and currently standing at about 13%.

Risk free interest rates play a fundamental role in finance. Theoretical models of interest rates are of interest both for the pricing of interest rate sensitive derivative contracts and for the measurement of interest rate risk arising from holding portfolios of these contracts.

1.2 Statement of the problem

Continuous-time diffusion models have been commonly used in many financial applications, such as in valuing and hedging the huge institutional holdings of fixed income securities and derivatives. Most continuous-time interest rate models involve specifications of a drift function, a diffusion function and a jump function. Economic theory often provides little guidance on specification of these functions, and existing continuous-time interest models usually employ somewhat arbitrary convenient functional forms. In particular, the most commonly used specification of drift, in both univariate (one-factor) and multivariate (multi-factor) modeling setups, is a linear drift (e.g., Vasicek (1977), Cox-Ingersoll-Ross (1985, CIR), Pearson and Sun (1994), Brennan and Schwartz (1979), Black and Karasinski (1991), Chan, Karolyi, Longstaff and Sanders (1992), Duffie and Kan (1996), Andersen and Lund (1997), Duffe, Pan and Singleton (2000)). While the volatility may be estimated relatively accurately using high-frequency observations of the short term interest rate, it is well known that the short rate's high persistence makes the identification of the true shape of the drift function particularly difficult.

Most research in the interest rate literature is more concerned about estimation of continuous-time diffusion models rather than direct testing. They usually estimate a flexible parametric form of drift and check if some parameters associated with a specific nonlinear drift are zero (see, e.g., Chan et al. (1992), Chapman and Pearson (2000), Takamizawa (2008)). This approach essentially considers a specific type of nonlinear drift, and may overlook many important nonlinear drift alternatives.

Ralf and Jana (2010) analyzed the Taylor-type equations for short-term interest rates in the United Kingdom using quarterly data from 1970Q1 to 2006Q2. Starting from strong evidence against a simple linear Taylor rule, they modeled nonlinearities using logistic smooth transition regression (LSTR) models. The LSTR models with time varying parameters consistently track actual interest rate movements better than a linear model with constant parameters. They preferred LSTR model with lagged interest rates as a transition variable and suggests that in times of recessions the Bank of England puts more weight on the output gap and less so on inflation. A reverse pattern was observed in non-recession periods. Parameters of the model did not change after 1992, when an inflation target range was announced. They concluded that for the analysis of historical monetary policy and for interest rate forecasting, the LSTR approach is a viable alternative to linear reaction functions.

Studies conducted in Kenya have focused on the relationship between interest rate and loans, hedging and profitability. Tumbuk (2009) conducted a study on modeling volatility of short term interest rates in Kenya. None of these studies have examined the predictive ability of linear and non linear models in predicting interest rates. Hence the question: Do non linear models predict interest rates better than linear models?

Therefore, this study tries to fill this research gap by investigating the predictability of interest rates by comparing linear and non linear models using data from the Central Bank of Kenya.

1.3 Objective of the study

The objective of this study is to determine the behavior of interest rates in Kenya using non linear models.

1.4 Importance of the study

The policy makers in the ministry of finance, the treasury and the central bank of Kenya will find this study useful. The finding will help them in developing policies related to regulations of interest rates especially of base rates for driving various financial instruments in the Kenya Financial Markets.

The Investment Banks and Financial Advisors will also benefit from this study. The finding of this study will help financial analyst in investment banks, commercial banks and corporate risk managers with the information on how to monitor behavior of interest rates. This will help them to advise the players in the financial sectors on how to mitigate on the risks of possible interest rates fluctuations.

The Investors especially the risk averse investors will find this study helpful in developing optimal hedging strategies which can be very sensitive to changes in the expected interest rate volatility.

This study will finally make a significant contribution to academic literature in the field of behavior of interest rates. Very little is known about interest rates prediction due to few studies in the subject. Academics and researchers will also find the study useful as a basis for further research and discussions on the findings of the study.

CHAPTER TWO

LITERATURE REVIEW

2.1. Introduction

Continuous-time models are important for investigating interest rate term structure and pricing fixed income derivatives. Economic theory often provides little guidance on the choice of the form of continuous-time models, and existing one-factor and multi-factor continuous-time interest rate models often assume a linear drift, among other things. Some studies, based smoothed nonparametric kernel estimation, suggest that the drift of the interest rate process is nonlinear, particularly at high interest rate levels. However, this has been doubted as an artifact of smoothed nonparametric estimation in comparison with highly persistent interest rate data. Whether the drift of the interest rate process is linear or nonlinear remains an unsolved issue in the literature.

This study examines whether interest rates in Kenya are linear or non linear. This is achieved by comparing the predictive power of linear and non linear models. The rest of the paper is organized as follows. In Section 2.2 we discuss why one might want to consider non-linear models. We also introduce linear and non linear models that can be used in predicting interest rates. Section 2.3 discusses the empirical evidence on application of various models and on behavior of interest rates. Section 2.4 highlights empirical evidence on behavior of interest rates in Kenya. Concluding remarks are gathered in Section 2.5.

2.2. Theoretical literature

Most continuous-time interest rate models involve specifications of a drift function, a diffusion function and a jump function. Economic theory often provides little guidance on specification of these functions, and existing continuous-time interest models usually employ somewhat arbitrary convenient functional forms. In particular, the most commonly used specification of drift, in both univariate (one-factor) and multivariate (multi-factor) modeling setups, is a linear drift. There has been an unresolved debate regarding nonlinearity of drift of the interest rate in the literature. Aït-Sahalia (1996) and Stanton (1997) use smoothed nonparametric kernel methods to estimate the drift and diffusion functions of the short rate. They find evidence of nonlinearity in drift.

To study the behavior of interest rates, analysis of long term trends based on monthly observations is necessary. This leads to major model classes basically the linear models and non linear models. The linear models are linear in the parameters which have to be estimated and describe a statistical situation that is explained by one observed variable by several other quantities. In prediction of interest rates it follows that the expected return is explained by several factors such as demand, supply, economic conditions, risk and inflation. The non linear models are based on the fact that an analysis based on linear models assumes linear independence however there is a possibility of non linear independence. Whilst non-linear models are often used for a variety of purposes, one of their prime uses is for forecasting

The seminar work of Box and Jenkins (1970) brought many applications of time series models to the forecasting of business and economics variables. A major use of time series model has been to provide short and medium term forecasts for important macro economic variables, such as consumption, income investment and unemployment, all for which are integrated series. The derived growth rates are found to be somewhat forecast able. Much less forecastable are inflation rates, and returns from speculative markets such as stock bonds, interest rates and exchange rates, Granger (2003).

Engel (2003) while proposing models such as Arch and Garch Models, focused on risk and volatility arguing that the advantage of knowing about risks is that we can change our behavior and that it is really the volatility over a future period that should be considered the risk; hence a forecast of volatility is needed as well as a measure for today.

Further another issue that is important to consider is spurious regression. Ferson, Sarkission and Simin (2003) indicates that when expected returns are persistent, spurious regression bias calls some of the evidence into question because the model results can indicate a significant relation when the variables are really independent. Models predicting interest rates have developed from linear models to non linear models. In each broad group, there are several classes.

Moving average (MA) model is a common approach for modeling univariate time series models. It uses lagged values of the forecast error to improve the current forecast. This moving average model is conceptually a linear model of the current value of the series against previous (unobserved) white noise error terms or random shocks. The random shocks at each point are assumed to come from the same distribution, typically a normal distribution, with location at zero and constant scale. The distinction in this model is that these random shocks are propagated to future values of time series.

An advancement of the autoregressive model and the moving average model is the Autoregressive-moving-average (ARMA) models which are mathematical models of the persistence, or auto correlation, in a time series and are used to predict behavior of a time series from past values alone. The ARMA model is derived from taking the AR model and the MA model.

When data shows non stationarity leading to the changing of the properties of the ARIMA model then the ARIMA models are best suited, these models are generalization of an autoregressive integrated moving average (ARIMA) model and are fitted into time series data, either to better understand the data or to predict future point in the series. They are applied in some cases, where an initial differencing step (corresponding to the "integrated" part of the model) can be applied to remove the non stationarity.

Recently there has been growing interest in the use of non linear time series models in finance and economics (Granger 2003). Many financial series such as returns on stocks and foreign exchange rates, exhibit leptokurtosis and time varying volatility. These two features have been the subject of extensive studies ever since Engle (1982), and Engle and Gonzalez-Rivera (1991) reported them. Random coefficient autoregressive (RCA) models, the autoregressive conditional Heteroskedastic (ARCH) model, Engle (1982), Engle and Gonzalez-Rivera (1991) and its generalization, the GARCH model, Bollerslev (1986) provides a convenient framework for the study of time varying volatility in financial markets. Financial time series models for intra-day trading are a typical example of random coefficient GARCH models.

The ARCH (p) model is based on recent developments in financial econometrics which suggests the use of nonlinear time series structure to model. The ARCH model describes the forecast variance in terms of current observables. Instead of using short or long sampled standard deviations, the ARCH model proposed taking weighted averages of past squared forecast errors and thereby being a simple generalization of sample variance (Engle, 2003).

The GARCH model on the other hand is a generalization of the ARCH model that has parameterization introduced by Bollerslev (1986). This model is also a weighted average of past squared residuals, but it has declining weights that never go completely to zero. In its most general form, it is not a Markovian model, as all past errors contribute to forecast volatility. According to Engle (2003), the GARCH model is the workhorse of financial applications that can be assumed to describe any financial return series.

In practice, a common assumption in applying GARCH models to financial data is that the return series is conditionally normal distributed. This is referred to as the normal GARCH model, which is well known as a part of volatility clustering patterns typically exhibited in financial and economic series. However the kurtosis implied by the normal GARCH model tends to be far less that the sample kurtosis observed for most financial return series. For example Bollerslev (1986) found evidence of conditional leptokurtosis in monthly S&P 500 Composite Index returns and advocates the use of t-distribution. Thus, the non-normal GARCH model is more appropriate for the case of large leptokurtosis typically observed in asset returns.

We argue that the relatively poor forecasting performance of non-linear models calls for substantive further research in this area, given that one might feel uncomfortable asserting that non-linearities are unimportant in describing economic and financial phenomena. The problem may simply be that our non-linear models are not mimicking reality any better than simpler linear approximations

2.3. Empirical literature

Some studies, based smoothed nonparametric kernel estimation, suggest that the drift of the interest rate process is nonlinear, particularly at high interest rate levels. However, this has been doubted as an artifact of smoothed nonparametric estimation in comparison with highly persistent interest rate data.

There has been an unresolved debate regarding nonlinearity of drift of the interest rate in the literature. Aït-Sahalia (1996) and Stanton (1997) use smoothed nonparametric kernel methods to estimate the drift and diffusion functions of the short rate. They find evidence of nonlinearity in drift. Specifically, the estimated drift function is highly nonlinear, especially for large values of the interest rate. Aït-Sahalia (1996a) finds nonlinear mean-reversion of the spot interest rate–around its mean, where the drift is essentially zero, the spot rate behaves like a random walk, reverting toward the mean strongly when far away from the mean (for very high or very low rates). He concludes that "the linearity of the drift imposed in the literature appears to be the main source of misspecification." On the other hand, Stanton (1997) finds little mean reversion for all rates below 15% but the estimated drift drops sharply and becomes negative as the interest rate increases beyond 15%. Similar results are obtained by Conley, Hansen, Luttmer, and Scheinkman (1997), who estimate a drift function that is nonzero only for rates below 3% or above 11%. Jiang and Knight (1997) also find a similar pattern of nonlinear mean reversion for Canadian interest rates.

The simulation study of Chapman and Pearson (2000) indicates that Aït-Sahalia (1996) and Stanton's (1997) results may not be capable of providing convincing evidence of a nonlinear drift, and the smoothed nonparametric methods used there cannot provide a reliable reference for highly persistent interest rate data. In addition the finite sample bias of the truncation of a distribution and the boundary bias problem, the shapes of these nonparametric estimators also depend on the choice of the bandwidth parameter, which is a delicate business – oversmoothed estimates tend to suggest a linear drift, whereas undersmoothed estimates are particularly susceptible to the truncation bias and correlated residual bias, thus resulting in a spurious nonlinear drift.

Jones (2003) also investigates linearity of drift using a Bayesian approach (MCMC) and argued that nonlinearity may be an outcome of special priors. Before looking at the data, a flat prior holder expects to conclude in favor of the existence of nonlinear drift even when it is not a true feature of the data. As in the autoregressive model, the flat prior therefore represents an informative prior belief that the model is stationary, and the flat prior in this case corresponds to a belief that the drift is nonlinear. Thus, the results suggest that the finding of a nonlinear drift highly depends on the choice of the sampling frequency, the type of prior, flat or Jeffreys prior, and the prior belief about whether interest rates are stationary. Durham (2003), using a simulated MLE, also finds that interest rate drift nonlinearity is more associated with noisy interest rate data and a constant drift model is adequate. He suggests that the apparent transitory component not currently captured by the model motivates the adoption of a stochastic mean model of interest rates. Li, Pearson and Poteshman (2004) fail to reject a linear drift model but they argue that this cannot be used as evidence against nonlinearity.

Recently, using panel data, Takamiazawa (2008) and Sam and Jiang (2007) find nonlinearity at high levels of the interest rate but the mean reversion is weaker than that in Stanton (1997) and Jiang (1998). Using interest rate data on the short end of the term structure, Takamiazawa (2008) finds that it is difficult to find strong evidence supporting nonlinear physical drift from a statistical perspective, but nonlinear risk-neutral drift is strongly supported with the time series and cross-sectional dimensions of data. Park (2008), using a novel approach based on martingale regression and time change, supports the hypothesis of linear drift for the short rate.

In conclusion, the literature has not drawn a decisive conclusion regarding the nonlinearity in drift of interest rates yet. Different conclusions are mainly due to the use of different econometric methods as well as the use of different interest rate data. From an econometric perspective, when a test fails to reject linearity in drift, it might be due to low or little power of the test against certain alternatives of nonlinear drift (i.e., Type II error); on the other hand, when a test rejects linearity of drift, it might be due to the over rejection of the test when the null hypothesis of linear drift actually holds (i.e., Type I errors). It is important to use a test that can provide a reliable inference (i.e., does not over reject a correct null hypothesis) in finite samples and has good power against a vast range of nonlinear drift alternatives.

Yongmiao, Yoon and Zhaogang (2009) found out that there exists rather strong evidence of nonlinear drift for the 7-day Eurodollar rate and such evidence is robust to different estimation methods, the presence of level effect, stochastic volatility and jumps. The evidence of nonlinear drift is not likely to be spurious given the reasonable finite sample performance of the generalized spectral derivative test as demonstrated in the empirically realistic simulation study. They also found out that some popular nonlinear drift models substantially improve the goodness of fit over the linear drift model. In particular, AïtSahalia's (1996) nonlinear drift model outperforms both the linear drift model and Ahn and Gao's (1999) quadratic drift model, and it can capture some important features of the drift dynamics, including the asymmetric mean-reverting drift dynamics and interest rate movements at the extreme levels. They concluded that however, the nonlinear drift models are still severely misspecified. The nonlinear drift dynamics of the 7-day Eurodollar rate appears subtle and complicated. There exists room for further improving the modeling of the drift function for the short term interest rate.

2.4. Empirical evidence on behavior of interest rates in Kenya

According to the Central Bank of Kenya (2005), the stability of short term interest rates between 8% and 9%, have been vital to the financial sector stability and overall economic growth. The stability of domestic interest rates in Kenya has contributed to the predictable macroeconomic environment for investors and business people. This in turn has increased the level of confidence in the economy and has led to increased short term capital inflows.

Willem (1995) conducted a comparative empirical study between Ghana, Kenya, Zimbabwe and Nigeria. The sample comprised of four countries, two of the countries with the most advance financial system s in Sub-Saharan Africa (Kenya and Zimbabwe)., and two countries where structural adjustments had been an ongoing process for more than decade (Kenya and Ghana). Willem applied short term (less than 3 months) deposit rates and long term deposit rates (Longer than 12 months) from each of the four countries. The empirical findings from the four sampled countries established that: (i) lending rates initially adjust more slowly than deposit rates, creating initial periods during which the gap between lending and deposit rates narrowed, and even became negative in the case of Zimbabwe, and (ii) the level and volatility of interest rates increased with liberalization.

In Kenya the case study established that interest rates in Kenya have been fairly stable and that a relatively constant gap had been maintained between lending and deposit rates for most of the period. However, it must be borne in mind that, although Kenya was one of the first African countries to implement the SAP, it was only in 1991 that full interest rate liberalization took place. Since then, interest rates have been following a steep upward ascent, with the gap between loan deposit rates shrinking after interest rates liberalization. Willem (1995) further revealed that for the Kenyan case, only changes in contemporaneous short term interest rates seemed to have effect on long term interest rates, but the value of this parameter was smaller than 1 (0.69) which suggested less than a perfect correspondence between short and long rates. Furthermore, the acceptance that lags of short term interest rates were insignificant suggested that long run interest rates do not adjust sluggishly to short term rates

Tumbuk (2008) in his unpublished paper on Modeling Volatility of Short term interest rates in Kenya found that the GARCH Model is better suited for modeling volatility of short term rates in Kenya as opposed to ARCH Models

The GARCH Model is a more general case than the ARCH Model. In their original form, a normal distribution is assumed, with a conditional variance that changes overtime. For the ARCH model, the conditional variance changes over time as a function of past squared deviations from the mean. The GARCH processes variances changes overtime as a function of past squared deviations from the mean and past variances. Overall results demonstrates that although previous research indicates that volatility clustering plays a role in interest rates changes, it is not the primary factor generating these changes. GARCH models with normality assumptions provide a better description of exchange rates dynamics. Frequency distributions show independence still exists in the data after removing the ARCH effects.

Likelihood ratio test indicate the significance of the goodness of fit between the two models as earlier identified by Hanfeng, Jiahua and Kalbfleisch (2000). The study further establishes that the GARCH models are able to capture the very important volatility clustering phenomena that has been documented in many financial time series, including short term interest rates (Bollerslev, Chou, and Kroner, 1992), as well as their leptokurtosis. Note that a GARCH models the volatility is a deterministic function of lagged volatility estimates and lagged squared forecast errors. One problem with GARCH models of the short rate is that the parameter estimates suggest that the volatility process is explosive.

2.5 Summary

The use of linear and non linear models in predicting interest rates especially in a time series context has continued to elicit mixed reaction in financial literature. While there is general recognition of the superior ability of non linear models to describe data, there is less certainty about the ability to forecast data. As such simple linear models often dominate in forecasting exercises due to their simplicity and any loss with respect to non linear models is not economically significant McMillan (2009).

Further there is evidence of non linearity in the stock markets with forecasts of non linearity and earnings exploiting the mean reversion in profitability and Non linearity and with earnings being more predictable when they are further away from their mean. The EMH assumes that prices adjust without delay to the arrival of new information. Since news and events hitting the market arise randomly, the resulting price changes should be unpredictable and follow a random walk however in practice this is not the case and more so investors do not respond at the same rate to new information filtering nor do they have the same accessibility to information.

The application of linear and non linear models in forecasting interest rates in Kenya is of great importance more so in the face of market anomalies, the low level of knowledge of choice of models and the global financial crisis. It is also important to appreciate the use of micro and macro economic factors to predict interest rates and hence create increased knowledge by the use of scientific models Basically the Autoregressive Integrated Moving Average (ARIMA) models and Autoregressive Heteroskedastic Models

(ARCH)/ Generalized Autoregressive Conditional Heteroskedastic Models (GARCH) models.

Though, various researches have been done on interest rates, there is still gap as to whether linear or nonlinear models better suited to predict interest rates and specifically how this is applicable to a developing economy like Kenya. This study contributes towards filling this gap by comparing the predictive ability of linear and non linear model by using data from the Central Bank of Kenya.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the methodology that shall be used to carry out this study. Section 3.2 present research design, section 3.3 discusses the population and sample of the study, next, the data collection method will be discussed in section 3.4; then the conceptual models and analytical models that will be used will be defined in section 3.5.

3.2 Research Design

This is an empirical study designed to compare the predictive ability of linear and non linear models by using Treasury bill rates from the Central Bank of Kenya. It uses the Bayesian information criterion and the archaic information criterion to rank the models. The model with the lowest error ranks high and has high predictive power.

3.3 The Population

The population of interest in this study comprises Central Bank of Kenya 91-days Treasury bill rate for the period between August 1991 and December 2011. This is because the 91-days Treasury bill rate data is readily available from the Central Bank of Kenya.

3.4 Data Collection

The study employs the monthly averages of the 91-days T-Bill rate for the period between August 1991 and December 2011. Prior to 1983, the interest rates used to be controlled by the government until the implementation of Structural Adjustments Programme (SAP) in 1983. In July 1991, the interest rates were fully liberalized. During this period, the factor influencing the interest rates were mainly the market forces. This is therefore the ideal period to study the behavior of interest rates in Kenya.

3.5 Models of Predicting Interest Rates

This section discusses the models used for predicting interest rates. Section 3.5.1 presents conceptual model and section 3.5.2 presents the analytical models. Analytical models in section 3.5.2 will be used to analyse the data.

3.5.1 The conceptual models

Various time series analysis models, which are conceptually linear and non linear regression models, are available for testing the predictability of stock returns. These are presented below.

MA (q) – Moving Average Models

Moving Average (MA) is a common approach for modeling univariate time series models. The notation MR (q) refers to the moving average model of order q:

$$X_t = \mu + \varepsilon_t + \varepsilon_{t-1} + , \dots \dots \dots . + \varepsilon_{t-q} + e_t \quad \dots (1)$$

Where μ is the mean of the series, and the (e_t) are white noise error terms. The value of q is called the order of the MA model.

The moving average model is conceptually linear regression of the current values of the series against previous (unobserved) white noise error terms or random shocks. The random shocks at each point are assumed to come from the same distribution, typically a normal distribution, with location at zero constant scale. The distinction in this model is that these random shocks are propagated to future values of the time series.

However, fitting the MA estimates is more complicated than with autoregressive models because the error terms are not observable. This means that iterative non-linear fitting procedures will be used in place of linear least squares. MA models also have a less obvious interpretation than AR models.

AR (p) – Autoregressive Models

An autoregressive Models (AR) model is a type of random process which is often used to model and predict. The notional AR (p) refers to an autoregressive model of order (p) and it is written as;

$$X_{t=} \sum_{i=1}^{p} X_{t-1} + \varepsilon_t \qquad \text{.. .(2)}$$

Where, ε_t is an error term.

ARMA (p, q) Autoregressive moving Averages Models

Autoregressive-moving-average (ARMA) models are mathematical models of the persistence, or autocorrelation, in a time series which are used to predict behavior of a time series from past values alone. The ARMA model is derived from taking the AR model and the MA model. The notation ARMA (p, q) refers to a model with p autoregressive terms and q moving average terms. This model is written as;

$$X_t = \varepsilon_t + \sum_{i=1}^{p} X_{t-i} + \sum_{i=1}^{q} \varepsilon_{t-i} \quad \text{.......... (3)}$$

The error term ε_t are generally assumed to be independent identically-distributed random variables sampled from a normal distribution with zero mean:

ε_t =N (0,δ^2) where δ^2 is the variance.

However if these assumptions are weakened, the properties of the model will change which will create a fundamental difference giving way to ARIMA models which are better suited in cases where data shows non stationarity.

ARIMA (p, d, q) - Autoregressive Integrated Moving Averages Models

These models is a generalization of an autoregressive moving average (ARMA) model and are fitted into time series data, either to better understand the data or to predict future points in the series. They are applied in some cases where data show evidence of non stationarity, where an initial differencing step (corresponding to the "integrated" part of the model) can be applied to remove the non stationarity. The model is written as;

$$Y_t = Y_{t-1} + \Delta Y_t + e_{t-1} + \varepsilon_t \quad \text{.......... (5)}$$

$$\Delta Y_t = Y_t - Y_{t-1}$$

The model is generally referred to as an ARIMA (*p, d, q*) model where *p ,d ,q* are integers greater than or equal to zero and refer to the order of the autoregressive, integrated and moving average parts of the model respectively.

All these models types are linear, however in practice most prediction factors behave in non linear manner hence giving rise to non linear models such as the ARCH/GARCH models. The ARCH/GARCH specification of errors allows one to estimate models more accurately and to forecast volatility and are best interpreted as measuring the intensity of the news process.

ARCH (p) Autoregressive Heteroskedastic Models

The ARCH (p) is based on recent developments in financial econometrics which suggests the use of non linear time series structures to model the attitude of investors towards risk and expected return. For example, Bera and Higgins (1993, p.315) remarked that " a major contribution of the ARCH literature is the finding that apparent changes in the volatility of economic time series may be predictable and results from a specified type of non linear dependence rather than exogenous structural changes in variables". Engle's (1982) ARCH Model is written as;

$$Y_t = \alpha_0 + \mu + \varepsilon_t$$

$$h^2 = e_{t-1}^2 + , \dots \dots \dots . + e_{t-p}^2 + \varepsilon_t \quad \text{.......} (6)$$

ARCH is a forecasting model in so far as it forecasts the error variance at time t on the basis of information known at time t-1 and, forecasting is conditionally deterministic, that is, the ARCH model does not leave any uncertainty on the exception of the squared error at time t knowing past errors. This must always be true of a forecast, but, of course, the squared error that occurs can deviate widely from this forecast value, leading to a useful generalization of this model – the GARCH model.

GARCH (p, q) – Generalized Autoregressive Conditional Heteroskedastic Models

GARCH model is a generalization of the ARCH model that has parameterization introduced by Bollerslev (1986). This model is a weighted average of past squared residuals, but it has declining rates that never goes completely to zero. In its most general form, it is not a Markovian Model, as all past errors contribute to forecast volatility. A basic GARCH model is written as;

$$Y_t = \alpha_0 + Y_{t-1} + \varepsilon_t$$

$$h^t = \propto + e_{t-1}^2 + e_{t-2}^2 + \ldots\ldots\ldots . e_{t-p}^2 + q_{t-1}^2 + \ldots\ldots q_{t-q}^2 + \varepsilon_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

3.5.2 Analytical Models

The various time series analysis models for stock returns prediction give different results based on the different values of q and p. To determine the most reliable model, the Bayesian information criterion (BIC) and Akaike Information criterion (AIC) will be used to provide the basis for estimation and comparison. The Root Mean Squared Error and the Mean Absolute Error will be used for prediction.

Estimation of MA (q) – Moving Average Models

The basic structure of the MA (1) models takes the form below

$$Y_t = \alpha_0 + \alpha_1 e_{t-1} + \varepsilon_t \quad \text{.............} (8)$$

The first step will be the estimation of the MA (1) model to determine the coefficient α_1. Then the value of q will be varied from 1 to 5 and the estimation repeated. The best MA (q) model will then be selected based on the Bayesian information criterion (BIC) and Akaike Information criterion (AIC). The best model in the MA family, thus selected, will be used for comparison with the best models from other families of models like the ARIMA and GARCH models.

Estimation of AR (P) – Autoregressive Models

The basic form of the AR (p) process is the AR (1) shown below

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \varepsilon_t \quad \text{.............} (9)$$

The AR (1) model will be the estimated to determine the coefficient α_1. Then the value of p will be varied from 1 to 5 and the estimation repeated. The best AR (p) model will then be selected based on the Bayesian information criterion (BIC) and Akaike Information criterion (AIC). The best model in the AR family, thus selected, will be used for comparison with the best models from other families of models.

ARMA (p, q) – Autoregressive moving Averages Models

The basic form of the ARMA (p, q) process is the ARMA (1, 1) shown below

$$X_t = \varepsilon_t + \emptyset_t X_{t-t} + \emptyset_t \varepsilon_{t-t} + \varepsilon_t \quad \text{.......} \quad (10)$$

The ARMA (1, 1) model will be the estimated to determine the coefficient $\emptyset_t$. Following this, the values of *p* and *q* will be varied from 1 to 5 and the estimation repeated. The best ARMA (p, q) model will then be selected based on two goodness of fitting measures - the Bayesian information criterion (BIC) and Akaike Information criterion (AIC). The best model in the ARMA family, thus selected, will be used for comparison with the best models from other families of models like the ARIMA and GARCH models.

Estimation of the ARIMA (p, d, q) – Autoregressive Integrated Moving Averages Models

The basic form of the ARIMA (p, d, q) process is the ARIMA (1, 1, 1) shown below

$$Y_t = \alpha + Y_{t-1} + \Delta Y_t + e_{t-1} + \varepsilon_t \quad \text{.......} \quad (11)$$

The ARIMA (1, 1, 1) model will be the estimated to determine the coefficient α_1. Following this, the values of *p, d* and *q* will be varied from 1 to 5 and the estimation repeated. The best ARIMA (p, d, q) model will then be selected based on two goodness of fitting measures - the Bayesian information criterion (BIC) and Akaike Information criterion (AIC). The best model in the ARIMA models family, thus selected, will be used for comparison with the best models from other families of models like the ARCH/GARCH and ARMA models.

Estimation of the ARCH (p) – Autoregressive Heteroskedasticity Models

The basic form of the ARCH (p,) process is the ARCH (1) shown below

$$Y_t = \alpha_0 + \mu + \varepsilon_t \quad \text{.......} \quad (12)$$

$h^2 = \alpha_0 + e_{t-1}^2 + \varepsilon_t$ .... (13)

The ARCH (1) model will be the estimated to determine the coefficient α_1. Following that the values of p will be varied from 1 to 5 and the estimation repeated. The best ARCH (p) model will then be selected using goodness of fitting measures - the Bayesian information criterion (BIC) and Akaike Information criterion (AIC). The best model in the ARCH models family, thus selected, will be used for comparison with the best models from other families of models like the GARCH and ARMA models.

Estimation of the GARCH (p, q) – Generalized Autoregressive Conditional Heteroskedasticity Models

The basic form of the GARCH (p, q) process is the GARCH (1, 1) shown below

$Y_t = \alpha_0 + Y_{t-1} + \varepsilon_t$ .... (14)

$h^t = \alpha + e_{t-1}^2 + \varepsilon_t$ .... (15)

The GARCH (1, 1) model will be estimated to determine the coefficient α_1. Following that the values of p and q will be varied from 1 to 5 and the estimation repeated. The best GARCH (p, q) model will then be selected using goodness of fitting measures - the Bayesian information criterion (BIC) and Akaike Information criterion (AIC). The best model in the GARCH models family, thus selected, will be used for comparison with the best models from other families of models like the ARCH and ARMA models.

CHAPTER FOUR

DATA ANALYSIS AND INTERPRETATION OF FINDINGS

4.1 Introduction

This chapter presents the results of data analysis and its discussion section 4.2 provides the summary statistics of the return of the returns. Section 4.3 presents the results of the unit root test. Section 4.4 presents the results of estimating the linear models. Section 4.5 presents the results of estimating non linear model. Section 4.6 presents the results of comparing linear and non linear models in predicting stock returns.

4.2 Summary Statistics

This Table 4.1 provides the summary statistics of the data used in this study. The results show that the mean of the returns is positive. The rest of the summary of statistics is also positive. The results also show that returns are slightly positively skewed. This confirms the above assertion that interest rates have been rising. However the interest rates have a high kurtosis 11.39 compared to the normal value of 3. This means that the interest rates experiences extreme changes more often than predicted by the normal distribution. Therefore this suggests that interest rates might not be normally distributed.

Table 4.1 Summary Statistics for 91-days T-Bill rate for the period between August 1991 and December 2011

Statistics	Values
Mean	14.51
Standard Deviation	13.30
Skewness	2.93
Kurtosis	11.39
Minimum	0.83
Maximum	84.67
Range	83.84
Count	238

Source: Authors computations

4.3 Results of Unit Root Analysis

Table 4.2 presents the results of the unit root tests based on the ADF test.

Table 4.2 Unit root test for interest rates

Variable	Levels	Differences
Constant (μ)	0.4828	-0.0150
R(-1)	-0.0342	-0.3925
AIC	4.2886	4.3246
ADF	-3.2485	-8.3663
LAG	2	1
Decision	Reject Ho	Accept Ho

ADF Test critical values: 1% level: -3.4580; 5% level: -2.8736; 10% level: -2.5733.

***Significance at 1% level; **Significance at 5% level

The ADF test was applied on the 91-days T-Bill rate and error terms in level form. The computed t-statistics test is -3.2485. This is higher than the critical value -3.4580. Therefore the null hypothesis of unit root in interest rate levels is non stationary. This calls for the test of stationarity for the difference. The computed t-statistic for differences is -8.3663. This is lower than the critical value -3.4580 for the difference. Therefore the null hypothesis of unit root in interest rate difference is stationary.

4.4 Estimation of the Linear Models

Table 4.3 presents a summary of the results of estimating the Radom walk Model and the moving averages models. In order to select the optimal lag structure for the MA models 6 lags were considered. The preferred model is the one with the minimum AIC and SBC values. Based on Table 3 MA (6) is the optimal model since it has the lowest AIC and SBC values.

Table 4.3 Estimation Results of the Random Walk and MA Models

MODEL	RW	MA(1)	MA(2)	MA(3)	MA(4)	MA(5)	MA(6)
AIC	1222.36	1601.99	1450.27	1334.95	1160.72	1102.67	1087.60
SBC	1233.27	1608.93	1460.68	1348.84	1178.08	1123.50	1111.91
S.E.	3.40	6.90	5.03	3.92	2.72	2.40	2.32
LL	-608.43	-798.99	-722.13	-663.47	-575.36	-545.33	-536.80

Table 4.4 presents a summary of the results of estimating the AR (p) models. The procedure used for estimating MA models was applied to estimate the best fitting model. The results show that AR (5) is the optimal model.

Table 4.4 Estimation Results of the Autoregressive Models

MODEL	AR(1)	AR(2)	AR(3)	AR(4)	AR(4)	AR(5)
AIC	1166.99	1025.95	1023.44	1024.14	1020.42	1022.42
SBC	1176.48	1039.34	1037.33	1041.50	1041.26	1046.72
S.E.	2.78	2.06	2.04	2.04	2.02	2.02
LL	-580.02	-508.98	-507.72	-507.07	-504.21	-504.21

Table 4.5 presents a summary of the results of estimating the ARMA (p, q) models and ARIMA (p, d, q) models. The procedure used for estimating MA models was applied to estimate the best fitting model. The results show that ARMA (2, 1) is the optimal model.

Table 4.5 Estimation Results of the ARMA and ARIMA Models

	ARMA (1,1)	ARMA (1,2)	ARMA (1,3)	ARMA (1,4)	ARMA (1,5)	ARMA (1,6)	ARMA (2,1)	ARMA (2,2)	ARIMA (1,1,4)
AIC	1063.52	1032.72	1025.58	1021.84	1023.67	1025.60	1019.38	1021.27	1026.77
SBC	1073.93	1046.61	1042.94	1042.68	1047.97	1053.38	1033.27	1038.64	1047.58
S.E.	2.23	2.08	2.05	2.03	2.03	2.03	2.02	2.03	2.08
LL	-528.76	-512.36	-507.79	-504.92	-504.83	-504.80	-505.69	-505.64	-507.39

4.5 Estimation of Nonlinear Models

Table 4.6 summarizes the results of estimating the ARCH (p) models. The ARCH (1) model is the optimal based on the lowest AIC value.

Table 4.6 Estimated ARCH (p) Models

	ARCH (1)	ARCH (2)	ARCH (3)	ARCH (4)	ARCH (5)	ARCH (6)
Constant	0.0145 (0.0212)	0.0145 (0.0000)	0.0139 (0.0000)	0.0153 (0.0000)	0.0166 (0.0000)	0.0102 (0.0082)
RESID(-) ^2	1.0270 (0.0000)	1.1009 (0.0000)	1.3191 (0.0000)	1.3170 (0.0000)	1.3587 (0.0000)	1.2267 (0.0000)
RESID(-) ^2		-0.0703 (0.1962)	-0.4750 (0.0002)	-0.3491 (0.0290)	-0.5583 (0.1196)	-0.3068 (0.2272)
RESID(-) ^2			0.1557 (0.0544)	-0.0438 (0.8225)	0.2984 (0.5642)	0.2343 (0.2891)
RESID(-) ^2				0.0713 (0.3775)	-0.2417 (0.6430)	-0.2473 (0.3814)
RESID(-) ^2					0.1035 (0.7090)	0.0744 (0.7932)
RESID(-) ^2						0.0247 (0.8770)
AIC	1.3261	1.3294	1.3056	1.3132	1.3099	1.3628
BIC	1.3698	1.3875	1.3787	1.4005	1.4118	1.4791

P - Values in brackets.

Table 4.7 summarizes the results of estimating the GARCH (p) models. The GARCH (2, 1) model is the optimal based on the lowest AIC value.

Table 4.7 Estimated GARCH (p, q) Models

	GARCH (1, 1)	**GARCH (1, 2)**	**GARCH (1,3)**	**GARCH (2,1)**	**GARCH (2,2)**	**GARCH (2,3)**
Constant	0.0370 (0.0001)	0.0204 (0.0002)	0.0216 (0.0002)	0.0250 (0.0000)	0.1043 (0.0011)	0.0147 (0.7859
RESID(-1)^2	1.3723 (0.0000)	1.4152 (0.0000)	1.4011 (0.0000)	1.3980 (0.0000)	0.4497 (0.0048)	1.4106 (0.0000
RESID(-2)^2				0.2124 (0.2945)	0.3147 (0.6653)	-0.4496 (0.8998
GARCH(-1)	-0.5417 (0.0000)	-0.5168 (0.0000)	-0.4775 (0.0034)	-0.6429 (0.0010)	0.1780 (0.6191)	-0.167 (0.9457
GARCH(-2)		0.0908 (0.2009)	0.0737 (0.4148)		-0.2852 (0.0000)	0.2347 (0.8552
GARCH(-3)			-0.0176 (0.8038)			-0.038 (0.8111
AIC	**1.3063**	**1.8887**	**1.3203**	**1.2929**	**1.5794**	**1.3068**
BIC	**1.4081**	**2.0050**	**1.4512**	**1.3656**	**1.6667**	**1.4087**

P- Values in brackets.

4.6 Comparison of AIC and BIC/SBC Values of the Models

The model with the lowest AIC and BIC/SBC was selected from each type of the models. The results are shown in Table 4.8 below.

Table 4.8: Comparison of Models Based on AIC and BIC/SBC

MODEL	AIC	BIC/SBC
RW	1222.36	1233.27
MA(6)	1087.60	1111.91
AR(5)	1020.42	1041.26
ARMA(2, 1)	1019.38	1033.27
ARIMA(1, 1, 4)	1026.77	1047.58
ARCH (4)	1.3132	1.4005
GARCH (2, 1)	1.2929	1.3656

The ARMA (2, 1) model has the lowest AIC value hence the best in the linear class of models. The GARCH (2, 1) model has the lowest AIC value in the non linear class of models and overall hence it is the best model for predicting interest rates.

4.7 Summary

The summary results of the models The results of testing of linear models on the interest rates based on BIC and AIC indicates that the ARMA (2, 1) model is the best among the linear models and within non linear models the GARCH (2, 1) model is the best. These models were then ranked against each other based on BIC and AIC. Based on these criteria the GARCH (2, 1) performs better with a lower BIC and AIC thus emerging as the best model in predicting interest rates.

CHAPTER FIVE

SUMMARY AND CONCLUSIONS

5.1 Introduction

This chapter presents the summary of the findings in section 5.2; section 5.3 presents study conclusions while section 5.4 focuses on recommendations to investors finally section 5.5 gives suggestion for further research.

5.2 Summary

Empirical literature shows that interest rates could be non linear. However, studies on the non linear behavior of interest rates are limited. This study aims at filling the gaps by comparing linear and non linear models in predicting interest rates using 91 days Treasury bills from Central Bank of Kenya. The study compared the Random Walk Theory, Moving Averages Models, Auto regressive models, ARMA models. Autoregressive Conditional Heteroskedasticity (ARCH) models and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models.

The Central Bank of Kenya 91-days Treasury bill rate was used. The sample period consisted of monthly observations of the 91-days Treasury bill rate for the period between August 1991 and December 2011. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used to select the best fitting model from each type of the models. The results indicated GARCH (2, 1) model performs better than any other models. Therefore this concluded that non linear models are better than linear models in predicting interest rates hence interest rates are non linear.

5.3 Conclusions

From the data analysis in chapter four, this study draws the following conclusions. First ARMA (2, 1) model is the best linear model while GARCH (2, 1) model is the best non linear model. Then comparing the two GARCH (2, 1) model emerges the best. Second, interest rates in Kenya are non linear.

5.4 Limitations of the Study

The study covered a period of only 10 years, from August 1991 and December 2011. This is because prior to 1983, the interest rates used to be controlled by the government until the implementation of Structural Adjustments Programme (SAP) in 1983. In July 1991, the interest rates were fully liberalized. During this period, the factor influencing the interest rates were mainly the market forces. Therefore, a study covering a longer period might have yielded different results.

The study also utilized monthly data on the 91-day Treasury bills rate. A study covering weekly data on 91-day Treasury bill rate might give different results.

5.5 Recommendation to the Policy Makers

The results of this study indicate that interest rates are predictable. Non linear models give the best prediction. Therefore reliance on linear models to predict interest rates in order to make a business decision will lead to sub optimal results.

Therefore it is important for the policy makers in Kenya to note that GARCH-based models are more appropriate for predicting interest rates than ARCH models and linear models. The model will help in development of tools for effective risk management by

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5.6 Suggestions for Further Research

This study recommends that future studies be carried examining longer or different sample period. This will allow comparisons to be made between the evidence adduced here and those relevant sample periods.

This study applied monthly observations, as opposed to daily or weekly observations. Therefore, further research can be done using weekly data on 91-day Treasury bill rate to ascertain if there would be any significant difference from the findings of this study.

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APPENDIX : 91 DAYS TREASURY BILL RATES

No	Issue Date	Average Rate
1	Dec-11	17.898
2	Nov-11	16.136
3	Oct-11	14.796
4	Sep-11	11.932
5	Aug-11	9.227
6	Jul-11	8.986
7	Jun-11	8.954
8	May-11	5.348
9	Apr-11	3.283
10	Mar-11	2.769
11	Feb-11	2.586
12	Jan-11	2.435
13	Dec-10	2.276
14	Nov-10	2.211
15	Oct-10	2.1205
16	Sep-10	2.0345
17	Aug-10	1.831
18	Jul-10	1.598
19	Jun-10	2.982
20	May-10	4.213
21	Apr-10	5.167
22	Mar-10	5.977
23	Feb-10	6.213
24	Jan-10	6.557
25	Dec-09	6.824
26	Nov-09	7.215
27	Oct-09	7.256
28	Sep-09	7.288
29	Aug-09	7.249
30	Jul-09	7.221
31	Jun-09	7.332
32	May-09	7.449
33	Apr-09	7.337
34	Mar-09	7.308
35	Feb-09	7.549
36	Jan-09	8.464

No	Issue Date	Average Rate
37	Dec-08	8.588
38	Nov-08	8.394
39	Oct-08	7.752
40	Sep-08	7.695
41	Aug-08	8.017
42	Jul-08	8.031
43	Jun-08	7.726
44	May-08	7.763
45	Apr-08	7.346
46	Mar-08	6.892
47	Feb-08	7.28
48	Jan-08	6.95
49	Dec-07	6.868
50	Nov-07	7.519
51	Oct-07	7.55
52	Sep-07	7.347
53	Aug-07	7.295
54	Jul-07	6.524
55	Jun-07	6.526
56	May-07	6.774
57	Apr-07	6.646
58	Mar-07	6.316
59	Feb-07	6.224
60	Jan-07	6.031
61	Dec-06	5.728
62	Nov-06	6.413
63	Oct-06	6.826
64	Sep-06	6.453
65	Aug-06	5.955
66	Jul-06	5.895
67	Jun-06	6.596
68	May-06	7.014
69	Apr-06	7.016
70	Mar-06	7.604
71	Feb-06	8.025
72	Jan-06	8.233

No	Issue Date	Average Rate
73	Dec-05	8.07
74	Nov-05	7.843
75	Oct-05	8.188
76	Sep-05	8.577
77	Aug-05	8.655
78	Jul-05	8.587
79	Jun-05	8.502
80	May-05	8.66
81	Apr-05	8.681
82	Mar-05	8.63
83	Feb-05	8.587
84	Jan-05	8.259
85	Dec-04	8.043
86	Nov-04	5.061
87	Oct-04	3.95
88	Sep-04	2.749
89	Aug-04	2.267
90	Jul-04	1.707
91	Jun-04	2.015
92	May-04	2.87
93	Apr-04	2.11
94	Mar-04	1.592
95	Feb-04	1.571
96	Jan-04	1.58
97	Dec-03	1.458
98	Nov-03	1.354
99	Oct-03	1.006
100	Sep-03	0.83
101	Aug-03	1.181
102	Jul-03	1.537
103	Jun-03	2.998
104	May-03	5.843
105	Apr-03	6.254
106	Mar-03	6.239
107	Feb-03	7.774
108	Jan-03	8.384

No	Issue Date	Average Rate
109	Dec-02	8.378
110	Nov-02	8.299
111	Oct-02	8.065
112	Sep-02	7.601
113	Aug-02	8.34
114	Jul-02	8.634
115	Jun-02	7.338
116	May-02	9.04
117	Apr-02	10.01
118	Mar-02	10.144
119	Feb-02	10.611
120	Jan-02	10.855
121	Dec-01	11.012
122	Nov-01	11.498
123	Oct-01	11.629
124	Sep-01	12.393
125	Aug-01	12.839
126	Jul-01	12.873
127	Jun-01	12.07
128	May-01	10.517
129	Apr-01	12.899
130	Mar-01	14.973
131	Feb-01	15.297
132	Jan-01	14.756
133	Dec-00	12.901
134	Nov-00	11.167
135	Oct-00	10.654
136	Sep-00	10.36
137	Aug-00	9.245
138	Jul-00	9.904
139	Jun-00	10.474
140	May-00	11.222
141	Apr-00	12.442
142	Mar-00	11.278
143	Feb-00	14.844
144	Jan-00	20.295

No	Issue Date	Average Rate
145	Dec-99	19.975
146	Nov-99	18.136
147	Oct-99	17.628
148	Sep-99	15.778
149	Aug-99	14.842
150	Jul-99	14.472
151	Jun-99	11.442
152	May-99	9.626
153	Apr-99	9.028
154	Mar-99	8.845
155	Feb-99	8.95
156	Jan-99	10.703
157	Dec-98	11.565
158	Nov-98	17.662
159	Oct-98	20.587
160	Sep-98	22.474
161	Aug-98	23.741
162	Jul-98	24.672
163	Jun-98	25.475
164	May-98	26.381
165	Apr-98	26.981
166	Mar-98	26.736
167	Feb-98	26.326
168	Jan-98	26.282
169	Dec-97	26.369
170	Nov-97	26.782
171	Oct-97	27.147
172	Sep-97	26.195
173	Aug-97	19.695
174	Jul-97	18.45
175	Jun-97	19.442
176	May-97	20.351
177	Apr-97	21.022
178	Mar-97	21.436
179	Feb-97	21.436
180	Jan-97	21.609

No	Issue Date	Average Rate
181	Dec-96	21.525
182	Nov-96	22.093
183	Oct-96	24.08
184	Sep-96	22.638
185	Aug-96	20.528
186	Jul-96	20.642
187	Jun-96	20.685
188	May-96	20.823
189	Apr-96	22.788
190	Mar-96	25.018
191	Feb-96	24.378
192	Jan-96	20.228
193	Dec-95	20.43
194	Nov-95	24.003
195	Oct-95	22.528
196	Sep-95	20.005
197	Aug-95	18.903
198	Jul-95	17.072
199	Jun-95	15.747
200	May-95	14.402
201	Apr-95	14.675
202	Mar-95	16.165
203	Feb-95	16.848
204	Jan-95	17.272
205	Dec-94	17.8
206	Nov-94	15
207	Oct-94	16.1
208	Sep-94	22.1
209	Aug-94	22.3
210	Jul-94	27.8
211	Jun-94	30
212	May-94	29.1
213	Apr-94	27.58
214	Mar-94	25.86
215	Feb-94	22.55
216	Jan-94	31

No	Issue Date	Average Rate
217	Dec-93	39.34
218	Nov-93	48.71
219	Oct-93	60.36
220	Sep-93	63.995
221	Aug-93	66.73
222	Jul-93	70.343
223	Jun-93	70.085
224	May-93	58.416
225	Apr-93	41.187
226	Mar-93	23.575
227	Feb-93	17.114
228	Jan-93	17.121
229	Dec-92	16.641
230	Nov-92	16.527
231	Oct-92	16.953
232	Sep-92	16.887
233	Aug-92	16.324
234	Jul-92	16.245
235	Jun-92	17.162
236	May-92	16.793
237	Apr-92	15.565
238	Mar-92	16.442
239	Feb-92	15.836
240	Jan-92	16.693
241	Dec-91	16.604
242	Nov-91	16.266
243	Oct-91	16.038
244	Sep-91	16.481
245	Aug-91	16.04