AN ASSESSMENT OF ALTERNATIVE MODELS OF INTEREST RATE VOLATILITY IN THE BOND MARKET IN KENYA

BY

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DECLARATION

This project report is my original work and it has not been submitted for any degree at any other university

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This project report has been submitted with my approval as the university supervisor.

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DR. SIFUNJO KISAKA

DEDICATION

I dedicate this research work to my parents Mr. Zablon Manani and Mrs. Wilkister Mokeira Manani, all my siblings and friends . I sincerely thank you all for the prayers, encouragement and support you gave me throughout my study period. Thank you again.

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ABSTRACT

This research project focuses on estimating volatility in interest rates in the bond market in Kenya. It assesses the linear and non linear models of estimating volatility. Data comprising of redemption yields for all bonds issued since January 1995 was obtained from NSE. In the analysis six different models were assessed in estimating volatility. These six models were the random walk, moving average (MA), autoregressive (AR), autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), autoregressive conditional heteroskedasticity (ARCH) and generalised autoregressive conditional heteroskedasticity (GARCH). The Akaike Information Criterion (AIC) were used to rank the models. This study found out that the bond market in Kenya mainly comprised of treasury bonds and twelve listed corporate bonds. It was also observed from the data that the number of participants and trading frequency still remain low as compared to other developed bond markets. The non-linear models ie ARCH and GARCH models scored the lowest AIC values. From the findings of this study it was concluded that non-linear models better estimate volatility as compared to linear models.

TABLE OF CONTENTS

LIST OF TABLES

ABBREVIATIONS

AIC	Akaike Information Criterion
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroskedasticity
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
BIC	Bayesian Information Criterion
CRRA	Constant Relative Risk Aversion
EGARCH	Exponential Generalised Autoregressive Conditional Heteroskedasticity
EMH	Efficient Market Hypothesis
EWMA	Exponentially Weighted Moving Average
GARCH	Generalised Autoregressive Conditional Heteroskedasticity
MA	Moving Average
NSE	Nairobi Securities Exchange
SV	Stochastic Volatility
TARCH	Threshold Autoregressive Conditional Heteroskedasticity
VaR	Value at Risk

CHAPTER ONE

INTRODUCTION

1.1 BACKGROUND OF THE STUDY

Torben et al (1998) states that volatility permeates finance. The variation in economy-wide risk factor is important for the pricing of financial securities, and return volatility is key input to option pricing and portfolio allocation problems. They argue that accurate measures and good forecasts of volatility are critical for the implementation and evaluation of asset and derivative pricing theories as well as trading and hedging strategies. They recognized the fact that dating back to Mandelbolt (1963) and Fama (1965) that financial returns display pronounced volatility clustering.

The estimation of the variance of return on an asset is crucial issue in modern applied finance. Volatility was first introduced into the financial world in Markowitz's (1952) mean variance model of portfolio selection. It was later demonstrated to play a crucial role in option pricing in the Black & Scholes (1973) model. However the most significant role for volatility forecasts in modern financial markets is in the estimation of Value at Risk (VaR).

According to Grossman (1995) markets have an allocational role; even in the absence of news about payoffs, prices change to facilitate trade and allocate resources to their best use. Allocational price changes create noise in the signal extraction process, and markets where such trading is important are markets in which we may expect to find a failure of informational efficiency. An important source of allocational trading is the use of dynamic trading strategies caused by the incomplete equitization of risks. Incomplete equitization causes trade. Trade implies the inefficiency of passive strategies, thus requiring investors to determine whether price changes are informational or allocational. Samuelson (1991) considered a case of a two-state Markov process in which the portfolio share is reset to a precommitted constant value at the start of each time period within the decision interval. He found that with log utility and either no serial correlation or negative serial correlation, the length of the decision interval has no effect on the risky share; he also found that with a more risk averse CRRA utility function, the decision interval still has no effect in the absence of serial correlation, but with negative serial correlation a longer decision interval leads to a higher value for the optimal risky share. Samuelson speculated that this result would be reversed by assuming either positive serial correlation or a utility function less risk averse than log utility. Finally, Balvers and Mitchell (2000) considered precommitted paths of the risky asset holding when a not necessarily constant sequence of risky holdings is precommitted to at the decision time. They found that under negative serial correlation, and possibly under positive serial correlation as well, the precommitted risky holding can be lower the farther into the future the precommitment is for.

Allowing for possibility of serial correlation of risky asset returns, as do Fischer and Pennacchi (1985), Samuelson (1991), and Balvers and Mitchell (2000), can substantially complicate the theoretical analysis of portfolios. But serial correlation is an important consideration due especially to recent empirical work. Poterba and Summers (1988) and Fama and French (1988) found negative autocorrelation in annual stock returns, although Kim et al. (1991) suggested that this result is mostly attributable to the inclusion of pre-World War II data. Lo and MacKinlay (1988), on the other hand, found that weekly returns exhibit positive serial correlation. Thus it is important to know whether and how the presence of positive or negative serial correlation influences the effect of the decision interval on the risky asset share.

The power of mean reversion tests has long been a tacit issue of the market efficiency literature. Early tests of market efficiency, as summarized in Fama (1970) found no economically significant evidence of serial correlation in stock returns. However, Summers (1986) later suggested that this was because these tests lacked power: Summers suggested a model of AfadsB in which stock prices take long swings away from their fundamental values, and showed that even if fads component such as this accounted for a large fraction of the variance of returns, the fads behavior might be difficult to detect by looking at short horizon autocorrelations of returns as these early tests had done.

The intuition behind Summers' reasoning was that if stock prices took large jumps away from their fundamental or full-information values, and then only reverted back towards the fundamental price over a period of years, the autocorrelations of monthly or daily returns would capture only a small fraction of this mean reversion.

1.1.1 Contextual Background: Bond market in Kenya

Ngugi and Agoti (2009) in her study showed that the bonds market in Kenya has weak microstructure characteristics. Although treasury bonds were introduced into the Kenyan market in the early 1980s, the market faced various challenges that constrained its development. Until 2001 when the government took a deliberate effort to shift domestic debt to long term instruments, government bonds maturities were short. Corporate bonds were introduced in mid-1990s, but the growth momentum was not maintained. Ten years after the first bond was listed, there are less than ten corporate bonds listed in the market. Further, the demand to diversify the bonds with mortgage-backed bonds among the banking institutions and infrastructure bonds has not been successful.

Ngugi and Agoti (2009) found out that treasury bonds market is more liquid with higher traded value and more traded days as compared to corporate bonds market. The corporate bonds are found to be less volatile. She established that treasury bonds returns have a higher volatility for the longer for the longer tenors than for the shorter tenors.

Ngugi and Agoti explained that while the 1990s saw a wave of capital market reform, a lot of emphasis was on the stock market with very minimal effort put on the bonds market. This saw substancial development of stock markets with new stock exchanges being established, regulatory systems getting strengthened and trading systems rejuvenated. However, in most cases this has not attracted a significant number of listings. In most cases, bonds are traded in the stock exchange with a dominance of the government bonds. Corporate bonds are almost non-existent. For a bond market to contribute significantly to the development process, it requires that the market caters for a diverse risk preference, is liquid, efficient and has minimal volatility.

There are several good reasons for developing bond market. The most fundamental reason is to make financial and capital market more complete by generating market interest rates that reflect the opportunity cost of funds at each maturity. This is essential for efficient investment and financing decisions. Moreover the existence of tradable instruments helps risk management. Further the use of financial guarantees and other types of underwriting is becoming increasingly common in corporate debt market as financing deals become more complex. If borrowers have available to them only a narrow range of instruments (e.g. in terms of maturity, currency etc) then they can be exposed to significant mismatches between their assets and their liabilities.

The risks entailed by such mismatches have to be managed and the ability to do so will often depend on whether certain exposures can be adequately hedged. Liquid markets help capital market participants to hedge their exposures. If bond market is not well developed for instance firms may have to finance the acquisition of long-term assets by incurring short-term debts. As a result their investment policies may be biased in favour of short-term projects and away from entrepreneurial ventures. The relationship between intermediation through banks and disintermediation through capital markets is controversial. Even in developed economies this two rather distinct systems have grown up one where capital markets are very important and one where banks dominate. A question that arises concerns the role commercial banks can play in developing our bond markets.

1.2 STATEMENT OF THE PROBLEM

Torben et al (2007) state that daily standardized returns are not normally distributed. Although GARCH and other dynamic volatility models do remove some of the non-normality in the unconditional returns, conditional returns still exhibit non-normal features. However these features vary systematically from market to market. They argue that the forex exchange market returns are generally strongly conditionally kurtotic, but approximately symmetric. Meanwhile, most aggregate index equity returns appear to both conditionally skewed and fat tailed. Heston and Nandi (2000) suggest a specific affine GARCH –normal model, which may work well for certain portfolios, and which, combined with the methods of Albanese, Jackson, and Wiberg (2004) allows for relatively easy calculation of the term structure of VaRs.

The conditional non-normality of daily returns has been a key stylized fact in market risk management. Finding a volatility measure that can generate standardized returns that are close to normal is therefore noteworthy. Most studies carried in the Nairobi Securities Exchange in risk management have focused mainly on the models i.e Gichana (2009) Comparison of linear and nonlinear models in predicting stock models; Kipngetich (2011) The relationship between interest rates and financial performance of commercial banks in Kenya; Kinyeki (2011) A test of relationship between stock market price volatility and unit trusts returns; Mudi (2011) The assessment of risk in the four markets of the NSE; Ngunjiri Moses (2010) The relationship between dividend payment policies and stock price volatility companies; Mutonga (2009) Credit risk management Models by commercial banks in Kenya; Tumbuk (2008) Modeling volatility of short-term interest rates in Kenya.

There is no study which has been carried out to determine how the bond interest rates in the Kenyan market behave and the most appropriate model to manage their risk. Risk management requires fully specified conditional density models, not just conditional covariance models. Resampling returns standardized by the conditional covariance matrix presents an attractive strategy for accommodating conditionally non-normal returns.

This paper seeks to asses risk management models to determine the appropriate risk model to apply in the Kenyan bond market. How are bond interest rates distributed in Kenya?

The distribution of bond interest rates are not normally distributed

1.3 OBJECTIVE OF THE STUDY

To assess the models best suited in estimating volatility in the bond market in Kenya

1.4 IMPORTANCE OF THE STUDY

To assist policy makers have a deeper understanding when designing policy and guidelines to govern the bond market.

To enable managers identify the best and most optimal tool and model to use in risk management. In the financial services industry, various value-at-risk and stress-testing approaches have long been the preferred risk management tools. Though some of these core methods are well known, poor model design and choices can— and have—resulted in major, unexpected, and potentially preventable losses.

For non-financial companies whose assets are primarily intangible, measuring the value and the associated risks of these assets has long been a problem. In addition to the same dangers of poor model design and choice faced by financial services firms, these companies do not even have a best practices approach to management of risk. There are some non-financial companies using our f-irm (financially integrated risk model) to better measure and manage cash-flow-at-risk. Second, senior managers are challenged to keep abreast of best practices as they evolve; a small percentage of risk experts play a vital role in keeping clients informed of new developments. They have assisted various industry bodies, such as the Group of Thirty, the International Swaps and Derivatives Association, the Committee of Chief Risk Officers, and the Treasury Management Association in developing risk management principles and evaluating best practices.

CHAPTER TWO

LITERATURE REVIEW

2.1 INTRODUCTION

Financial markets volatility has received significant attention from researchers, policy makers and professionals in the last two decades. Volatility being a major component in measuring risk in both asset and portfolio management participants in the financial markets need it for pricing, modeling and forecasting. The constant question among researchers is the accuracy of volatility measurement and the precision in predicting future trends in financial markets. These has led to the development of many financial models to analyze interest rates in the stock and bond markets with the objective of achieving accuracy in measuring volatility.

Engle (1982) proposed a way of measuring volatility in data series through a new class of stochastic processes called Autoregressive Conditional Heteroskedastic (ARCH) processes, which take into account that the level of uncertainty in an asset price changes with time. The ARCH processes also recognized that two types of variances exist for the error term in a time series: the unconditional variance and the conditional variance. The unconditional variance is a constant computed at a single point in time, without referring to the values of past variances. The conditional variance, on the other hand, is an estimate based on past variances, which means it will vary over time, depending on the range of historical variances included. This phenomenon of a time-varying variance is termed *heteroskedasticity*.

Cox (1990) underscores the importance of models that guide the course of what many researchers seek to find from large volumes of data in the financial markets. This paper seeks to examine different models which have been applied to measure volatility. In the first section it examines the linear models, the second section, non linear models, third section, empirical evidence on predictability of interest rates subsequently then lastly the summary.

2.2 LINEAR MODELS OF INTEREST RATES

Cowles (1933, 1944), Kendall (1953), and Roberts (1959) in their studies showed evidence of the lack of correlations in stock prices of US markets. Fama (1970) concluded these previous studies on the unpredictability of returns theory empirically, and placed them within the framework of the Efficient Market Hypothesis (EMH). The Efficient Market Hypothesis states that market prices adjust instantaneously to the arrival of new information, and current prices will reflect all available and relevant information. Because information arrives randomly, changes in interest rates will also be random and unpredictable.

Tests on the validity of the EMH theory have provided mixed evidence, with some authors finding evidence for efficiency and other finding evidence against it. Tests of the semi-strong form of efficiency have been the most divergent, and have led to the identification of anomalies, such as the January anomaly. Reilly and Brown (2003) provide a discussion of various market anomalies. The existence of these anomalies has led to the development of new theory to explain why a relationship exists between prices and publicly-available information such as price-earnings ratios and the size of the firm.

Proponents of behavioural theory; DeBondt and Thaler (1985), Kahneman and Tversky (1979), and Mullainathan and Thaler (2001) suggest that investors tend to make investment decisions based on cognitive biases, which are deviations from rational behaviour.

The EMH and behavioural theorists disagree on the behaviour of investors, and the existence of arbitrage opportunities. According to the EMH, all investors behave rationally, with the objective of making profits. Because of this rational behaviour, any arbitrage opportunities in a market are quickly neutralized, thus the market prices assets accurately. Behavioural theorists on the other hand, argue that investors may act irrationally at times and base investment decisions on objectives other than profit. This behaviour leads to the creation of arbitrage opportunities.

Malkiel (2003) provides a treatment of the criticisms that have been levelled at the three classes of the EMH by opposing theories. These criticisms present instances in which one of the three forms of the EMH theory fails to be observed. Consequently, they provide evidence against the validity of the EMH theory. Of particular interest to this study is Malkiel's discussion on the evidence of short-run predictability presented in opposing literature.

Malkiel uses Lo, Mamaysky et al. (2000) and Shiller (2000) as examples of authors who find evidence of some momentum in short-run stock prices and suggest that technical analysis may allow traders to obtain superior returns. To counter these findings, Malkiel argues that the magnitude of these correlations found between present and past prices may be statistically significant, but are not sufficient enough to provide a return over and above the transaction costs that would be involved in an effort to make superior returns from them. Similar arguments are found in Cowles (1960). Further, Malkiel argues that whatever deviations from the EMH may exist in a market, they are not systematic or regular, and can therefore not offer investors a dependable source of returns. Any evidence of predictable patterns also seems to disappear after they are published in the finance literature or in the public domain. Using these arguments, he concludes that the EMH is still valid, and the market is still weak-form efficient despite correlations found.

2.3 NON-LINEAR MODELS OF INTEREST RATES

Estimating and forecasting volatility in financial markets has received significant attention from researchers around the world because of the increasing potential for financial loss in recent years. The focus of this review of literature is on the methods that employ past data on interest rates and prices to provide volatility estimates.

Time series models produce a type of volatility known as *historical* (*actual or realized*) *volatility* because it is dependent on past observations. This form of volatility was identified in Black and Scholes (1973). According to Poon and Granger, time series models can be further divided into the following: 1) Models that predict volatility based on past standard deviations, 2) Autoregressive Conditional Heteroskedasticity (ARCH) Models, and 3) Stochastic Volatility Models. This classification is expanded in the following discussion, by adding another class of volatility estimation methods – the un-weighted volatility estimators - that have been proposed in literature, which were proposed as improvements on the classic method of standard deviation.

Traditionally, the standard deviation was the generally accepted estimator of volatility in asset returns. However, Patev and Kanaryan (2004) argue against standard deviation as a measure of volatility since it weighs equally the deviations of the average return, while most investors determine the risk on the basis of small or negative returns. The implication of this is that high positive returns, which the investor may not regard as risk, are treated in the same manner as low returns or negative returns, which the investor does consider as manifestation of risk.

The un-weighted methods were proposed with the intent of improving upon the classic method of standard deviation. Parkinson (1980) developed the High Low Range Volatility method, also known as the Parkinson number, which suggested the use of the variance of extreme values (the high and low prices) provides a far superior estimate compared to the variance of closing prices. This method estimates the volatility of returns for a random walk using the high and low price in any particular period. Prices are observed on a fixed time interval, say t = 10 days or 30 days or 180 days. The high-low return is then calculated as the natural logarithm of the ratio of a high stock's price to low stock's price. The Parkinson number, which is the measure of volatility, is obtained as:

$$\mathrm{HL\_HV}_{\mathrm{daily}} = \sqrt{\frac{\sum_{t=1}^{n} \frac{1}{4 * ln\, 2} * \left(x_t^{HL}\right)^2}{\mathrm{n}}}$$

where x_t^{HL} is the difference between the high and low price.

According to Parkinson, this method of using extreme values is superior to the standard deviation as a measure of volatility, as it is much more sensitive to variations of dispersion. Other authors that have improved upon Parkinson’s original method include Garman and Klass (1980) and Brunetti & Lildholdt (2002).

The traditional methods have one constraint: they assume that the error component in a time series, which constitutes the volatility of the series, varies constantly through time. The works of Mandelbrot (1963) and Fama (1965) suggested that the variance of stock market returns is not constant over time. It was therefore necessary to obtain a model that could capture the time-varying nature of the error variances, by making current estimates of volatility functions of past volatility.

The first of the conditional methods of estimating volatility is the Exponentially Weighted Moving Average (EWMA). This approach expands on the simple standard deviation by computing today's value of volatility as a weighted average of the previous day's standard deviation and the return on the previous day.

The seminal work of Engle (1982) proposed an alternative measure of volatility in data series through a new class of stochastic processes called Autoregressive Conditional Heteroskedastic (ARCH) processes, which take into account that the level of uncertainty in an asset price changes with time. This phenomenon of a time-varying variance is termed *heteroskedasticity*.

The major contribution of the ARCH processes is they proposed to measure volatility using the conditional variance of a price series, as opposed to the simplistic standard deviation applied in traditional econometric models. The ARCH model thus produced a volatility estimate that is a weighted average of past volatility, where recent volatility evidence is allotted a high weight and volatility in the distant past given small weights. Engle (2004) argues that the standard deviation is logically inconsistent, as it assumes that volatility is constant over time. However, a measure of volatility for one year ending today would rationally be different from a measure of one year volatility ending the previous day. While the ARCH model captured the time-varying nature of series volatility, it also had a complex lag structure that required estimation of too many parameters. This in turn led to violation of the non-negativity constraints imposed by the model itself, such that the volatility estimate produced by the model was a negative value (Bollerslev, 1986; Nelson, 1991).

Bollerslev (1986) extended the arguments of the Engle's ARCH process and constructed the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model with the aim of addressing the shortcomings of the ARCH model. The GARCH model improves on the ARCH model by incorporating adaptive or learning behaviour. Another advantage of the GARCH (p, q) model is parsimony: it requires estimation of fewer variables, and thus reduces the probability of errors in the estimation process. Consider a time series R_t , which represents the return from an financial asset over time. The GARCH model presented in Bollerslev (1986) models R_t as a dependent variable, explained by a vector of explanatory variables, $X_t^{'}$ and a vector b of unknown parameters, i.e.

$$R_t = X_t^{'}\, b + \varepsilon_t$$

where ε_t is the residual term representing random innovations in the asset returns.

The error term ε_t has the following properties: i)The expected value of ε_t is zero, $E(\varepsilon_t) = 0$ and ii) The variance of ε_t is given as $Var(\varepsilon_t) = \sigma_t^2$

The objective is to estimate the process by which ε_t changes or varies, given that it is a conditionally heteroskedastic process, i.e., it has a time-varying variance, which is dependent on past values. This can be presented in mathematical notation as:

$$\sigma_t^2 = \mathrm{Var}(\varepsilon_t \mid \varepsilon_{t-1},\ \varepsilon_{t-2}, \varepsilon_{t-3}, \ldots)$$

The GARCH (p, q) regression model then estimates the conditional variance of the error term ε_t as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i\, \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i\, \sigma_{t-1}^2 \qquad \alpha_i \geq 0; \quad \beta_i \geq 0 \qquad (2.1)$$

According to Nicholls and Tonuri (1995), the use of such a GARCH models in the study of stock market returns makes allowances for the features of serial correlation in the returns and in the squares of the returns. This model has also been found to encompass characteristics such as skewness and leptokurtosis commonly found in financial prices.

One shortcoming of the ARCH/GARCH models is that they ignore the direction of returns, either positive or negative, and only consider the magnitude of returns (Engle, 2001). Black (1976) noted that the direction of returns affects the level of volatility; therefore, market declines will cause higher volatility compared to market increases. The argument for this behaviour, known as the *asymmetric volatility effect*, is that a drop in the value of the stock (negative return) increases financial leverage, which makes the stock riskier and increases its volatility. The inability of ARCH/GARCH models to capture asymmetric volatility led to the development of asymmetric or non-linear GARCH models, which sought to capture additional characteristics of financial time series. Specifically, they were aimed at modelling the tendency of financial time series to be negatively skewed, in addition to the other characteristics already captured by ARCH/GARCH.

One of the more popular variants of the ARCH/GARCH models is the Exponential GARCH (EGARCH) model of Nelson (1991). This model was aimed at improving the GARCH model. The EGARCH model focussed on making the conditional variance dependent on both the magnitude and sign (positive or negative) of returns and by eliminating the non-negativity constraints on the parameters to be estimated. Nelson and Cao (1992) support this, by arguing that the non-negativity constraints in the linear GARCH model are too restrictive.

Another variant of the ARCH/GARCH models is the GJR-GARCH model, first used by Glosten, Jagannathan and Runkle (1993). This model allows for seasonal patterns in volatility and asymmetric volatility, such that positive and negative innovations on returns will have different effects on conditional volatility. The Threshold GARCH (TARCH) model by Zakoian (1994) is similar to GJR-GARCH; the only difference is that the TARCH model uses the conditional standard deviation instead of conditional variance.

The stochastic volatility (SV) models share a lot of properties with the GARCH models. These two classes of volatility models both consider the time-varying nature of volatility. The major difference between the two approaches is that, while GARCH models treat the volatility as a deterministic function of past returns, the stochastic models assume the volatility is an unobserved variable, whose logarithm is modelled as a stochastic process (Moix, 2001). The seminal work of Wiggins (1987) and Hull and White (1987) led to the development of stochastic volatility models, by seeking to generalize the Black-Scholes model of option pricing. Because of their dynamic nature, the SV models are primarily used to measure volatility in high-frequency data, and provide an *instantaneous* estimate of volatility. They are most suited to application on tick-by-tick data in high-volume markets, to provide volatility estimates for option pricing. Ghysels, Harvey and Renault (1996) provide a survey of stochastic volatility works; however, empirical research in this field evolves rapidly.

2.4 EMPIRICAL EVIDENCE ON PREDICTABILITY OF INTEREST RATES

The study of weak-form efficiency in markets seeks to verify the proposition that prices and returns cannot be predicted from past security market information. According to Reilly and Brown (2003, p. 179), there are two ways of testing for independence of returns: 1) an autocorrelation test, which measures whether the return on day *t* correlates with the return on day *t-1, t-2, t-3,* and so on. Autocorrelation, or serial correlation, is therefore a measure of the relationship between the value of a random variable today and its value some days in the past; and 2) a runs test, which assigns a plus sign (+) if there is a price increase, or a minus sign (-) in the event of a price decrease. Two or more consecutive changes of the same sign constitute a run; the run is broken when there is a change in the opposite direction. The total number of runs in a price series is compared to an expected value to determine whether the series contains predictability.

The evidence on the unpredictability of index returns is divergent; while some studies find evidence of return predictability, others find no such evidence. Engle (2004) studies daily levels of the Standard and Poor’s 500 Composite index from 1963 through late November 2003, and finds that return autocorrelations are almost all insignificant at a 5 percent confidence level, and are therefore uncorrelated and unpredictable.

Dickinson and Muragu (1994) test the validity of the weak-form efficiency theory for stock prices of 30 companies in the Nairobi Stock Exchange from 1979 to 1989. They use three sets of prices: the transaction price, the bid price and ask price of a stock, in an effort to bring out market microstructure effects. Their hypothesis is that stock price returns are independent, that is, no correlations exist between past returns and present ones. Various techniques are used to prove independence: the autocorrelation test, the binomial test, the Ljung-Box Q-statistic, and a runs test. All tests return the same result: there is no evidence of interdependence in stock returns for the period. While the results do not provide categorical evidence that the market is weak-form efficient, they do not contradict the weak-form of the EMH theory. They propose the need for extensive tests to prove the existence of a weak-form efficient market.

Conflicting viewpoints on return predictability have been presented in other literature. Harvey (1995) examines empirically the differences in behaviour of 20 emerging market returns and 3 developed markets, using a long-term data sample (1900–2001) from the United States, Japan, the United Kingdom, Germany, and France as well as a shorter-term data sample (1970–2000) for 15 countries. He reports higher serial correlation of monthly returns in emerging markets, compared to developed markets. 12 of the 20 emerging markets studied have serial correlation coefficients greater than 10 percent and 8 of the markets have coefficients above 20 percent, indicating significant predictability of returns. In contrast, he finds that all three developed markets have first-order serial correlations less than 1 percent.

Mandelbrot (1963), large price variations in asset returns tend to be followed by large price variations, of either sign, and small price variations tend to be followed by small price variations. This trend is known as volatility clustering, and is evidenced by the presence of serial correlation in squared asset returns. While asset returns are unpredictable in most cases, squared returns are found to be serially correlated, and therefore predictable.

While studies of correlations in returns have found differing evidence, most empirical studies are in agreement that the squares of the returns exhibit significant serial correlation. Engle's (2004) analysis of the S & P 500 index finds autocorrelation in the squared returns. Gokcan's (2000) examination of the indexes of seven emerging markets (Argentina, Brazil, Colombia, Malaysia, Mexico, Philippines, Taiwan) finds evidence of autocorrelations in the squared returns for all markets except Brazil and Philippines.

Chortareas, McDermott and Ritsatos (2000) examine the statistical behaviour of the Athens Stock Exchange (ASE) Index to observe the effects of liberalization measures instituted in the late 1980s and early 1990s. They find evidence of serial correlation in both the squared daily returns and squared weekly returns for the Athens Stock Exchange Index for the period. Further, they split the sample into two periods. The two periods, 1987 to 1991 and 1991 to 1997, exhibit significant changes in the time series properties of the ASE index. Specifically, autocorrelations in returns decrease in the second period. The conclusion is that the time series properties of an emerging market may be expected to change over time with market maturation.

Nicholls and Tonuri (1995) find strong autocorrelations in the squared return series for the Fifty Leaders Index in Australia for the period 1988 to 1991. Patev and Kanaryan (2004) also find autocorrelation evidence for the squared returns of the Bulgarian stock index SOFIX for the period 2000 to 2004. The presence of autocorrelations in the squared returns is proof of a non-constant conditional variance (Engle, 2004).

In contrast to the findings of Bachelier (1900), Mandelbrot (1963) found that: 1) price changes are erratic and fluctuate irregularly; some periods have large changes in prices, while others have small ones. He suggested that the variances of prices often behave as if they were infinite. 2) He found that probability distributions of stock returns are leptokurtic, that is, they have positive kurtosis, and longer and fatter tails than the normal distribution.

This departure from the properties of the normal distribution – which has a finite variance and a kurtosis level of 3 – prompted Mandelbrot to discount Bachelier's postulation that the normal distribution was suitable in modelling stock prices. He proposed instead the *stable Paretian* class of probability distributions, whose variances are infinite, as a more suitable basis. Mandelbrot's Stable Paretian Hypothesis has formed the basis of the study of kurtosis and skewness in financial time series. Other than kurtosis and skewness measures, proof of non-normality in the index return distribution is usually supported by an extremely high value of for the Jarque-Bera test for normality. For normal distributions, the Jarque-Bera (1987) test returns a value of zero. The presence of the two properties in financial time series has been confirmed in various literature (Mandelbrot, 1963; Fama, 1965; Baillie and de Gennaro, 1990; Bollerslev, Chou and Kroner, 1992; Cont, 2001; Premaratne and Bera, 2001).

2.5 SUMMARY

Malmsten and Terasvirta (2004) identify several ways in which volatility estimation models can be compared, including comparison of likelihood values, Akaike's (1974) Information Criterion (AIC), Schwarz's (1978) Bayesian Information Criterion (BIC) and misspecification tests. Nicholls and Tonuri (1995) states that the suitability of a statistical model to a particular time series is determined by its ability to capture and explain the stylized facts most common in that series. The model to be applied in a particular study is therefore dependent upon what the researcher wishes to investigate.

Many scholars have put arguments for and against each of the models. While stochastic volatility models are more sophisticated than the GARCH models, and are more representative of the dynamic behaviour of returns in financial markets, they are also more difficult to estimate, and are therefore not as widely applied in industry.The GARCH (1,1) specification, in particular, has many supporters and is pegged as a good starting point to describe the volatility dynamics of almost any financial time series. Engle (2004) proposes the use of the GARCH (1,1) model as it is widely applicable in any scenario, regardless of the rules governing a particular stock market.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 INTRODUCTION

This chapter presents the methodology that shall be used to carry out this study. Section 3.2 presents research design, Section 3.3 discusses the population and sample of the study, Section 3.4 outline the data collection method that will be used; the conceptual models and analytical models that will be used will be defined in section 3.5 and then lastly in section 3.6 looks at the data volatility and reliability.

3.2 RESEARCH AND DESIGN

This empirical study designed to compare the predictive ability of linear and non linear models by using bond interest rates at the Kenyan bond market. It uses The Bayesian Information Criterion and the 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 will comprise of all the twelve companies quoted on the Nairobi Securities Exchange that have issued bonds since 1990. However the number of companies participating in the Kenyan bond market has been low over the years.

3.4 DATA AND DATA COLLECTION

The study will use secondary data for the period starting January 2000 to December 2011.The data will comprise bond interest rates (yield to maturity) of all bonds of between one to four years issued since 1995. All the data will be obtained from the NSE.

3.5 MODELS OF PREDICTING BOND VOLATILTY

This section discusses the models used for predicting bond volatility. Section 3.5.1 presents conceptual models while Section 3.5.2 presents the analytical models.

3.5.1 CONCEPTUAL MODELS

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

MA (q) –Moving Average Models

Moving average (ma) model is common approach for modeling univariate time series models.

The notation MA (*q*) refers to the moving average model of order *q* :

$X_t = \mu + \varepsilon_t + \varepsilon_{t-1} + \ldots\ldots\ldots\ldots \varepsilon_{t-q} + e_t$

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 is conceptually a linear regression of the current value of the series against previous (unobserved) white noise error terms or random shocks. However, fitting the MA estimates is more complicated 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)-Auto regressive Models

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

$X_t = \sum_{i=l}^{p} X_{t-i} + \varepsilon_t$

Where ε_t is an error of term.

ARMA (p,q) –Autoregressive moving average 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 the 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,

$$X_t=\mathcal{E}_t+\sum_{i=l}^{p} X_{t-i}+\sum_{i=l}^{q} \mathcal{E}_{t-i}$$

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 $N(0,6^2)$ where 6^2 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 betters suited in cases where data shows non stationarity.

ARIMA (p,d.q) –Autoregressive Integrated Moving Average Model

This model is a generalization of autoregressive moving average model (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 shows evidence of non-stationarity, where an initial differencing step (corresponding to the “integrated” part of the model) can be applied to remove the non-statinarity. The model is written as

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

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

All these model types are linear, however in practice most prediction factors behave in a 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 Conditional Heteroskedastic Models

The ARCH (p) Model is based on recent developments in financial econometrics which suggests the use of nonlinear time series structures to model the attitude of investors toward risk and expected return . Engle’s (1982) ARCH Model is written as

$$Y=\alpha_0+ \mu +\varepsilon_t$$

$$h^2=e^2{}_{t-1}\ldots\ldots\ldots\ldots\ldots\ldots+e^2{}_{t-p} +\varepsilon_t$$

ARCH is a forecasting model insofar as it forecasts the error variance at the 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 expectation 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 also a weighted average of past squared residuals, but it has declining weights that never go completely to zero. A basic GARCH model is written as

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

$$h^t = \alpha +e^2{}_{t-1} + e^2{}_{t-2}+\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ e^2{}_{t-p}+ q^2{}_{t-1} +\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots+q^2{}_{t-q} + \varepsilon_t$$

3.5.2 EMPIRICAL MODELS

The various time series analysis models for bond 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 provides the basis for estimation and comparison. The best model thus selected, will be used for comparison with the best models from other families of models. The Root Mean Squared Error and the Mean Absolute Error will be used for prediction.

Estimation of MA (q) –Moving Average Model

The basic structure of the MA (I) model takes the form below

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

The first step will be the estimation of the MA (I) model to determine the coefficient $\acute{\alpha}_1$, 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 BIC and AIC.

Estimation of the AR(p) –Autoregressive Models

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

$Y_t= \alpha_0 + \alpha_1 Y_{t-1} + \varepsilon_t$……………………………………..(2)

The AR (I) model will be estimated to determine the coefficient $\acute{\alpha}_1$, 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 BIC and AIC.

ARMA (p,q)-Autoregressive moving Average Models

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

$X=\varepsilon_t \text{Ø}_1 X_{t-1}+\text{Ø}_i \ \varepsilon_{t-1}$………………………………………(3)

The ARMA (1,1) model will be estimated to determine the coefficient $Ø_{1.}$ 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 BIC and AIC.

Estimation of the ARIMA (p,d,q) –Autoregressive Intergrated Moving Average Models

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

$Y_t = \alpha + Y_{t-1} + \Delta Y_t + e_{t-1} + \varepsilon_t$...(4)

The ARMA (1,1,1) model will be estimated to determine the coefficient α_1 .Following that, 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 using the goodness of fitness measures- BIC and AIC.

Estimation of the ARCH (p) –Autoregressive Conditional Heteroskedastic Models

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

$Y_t = \alpha_0 + \mu + \varepsilon_t$..(5)

$h^2 = \alpha_0 + e^2_{t-1} + \varepsilon_t$...(6)

Values

The ARCH (I) model will be 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 the goodness of fitness measures- BIC and AIC.

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

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

$Y_t = \alpha + Y_{t-1} + \varepsilon_t$ ....(7)

$h^t = \alpha + e^2_{t-1} + \varepsilon_t$..(8)

The GARCH (1 ,1) model will be 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 GARCH (*p*,*q*) model will then be selected using the goodness of fitness measures- BIC and AIC.

3.6 DATA VOLATILITY AND RELIABILITY

The suitability of a statistical model to a particular time series is determined by its ability 2to capture and explain the stylized facts most common in that series. The model to be applied in a particular study is therefore dependent upon what the researcher wants to observe. There are several ways in which volatility estimation models can be compared. This study will focus on determining how the bond interest rates are distributed then suggest suitable models for estimating volatility. Data will be obtained from NSE and checked for all the dates. If there will be any missing values then they will be obtained and inserted as required.

CHAPTER FOUR

DATA ANALYSIS AND INTERPRETATION OF FINDINGS

4.1 Introduction

This chapter presents the data analysis and discuses the findings. Graphs and tables have been used to present the analysis and findings of data. Section 4.2 will look at the summary of statistics, section 4.3 will look at the estimation of the models, section 4.4 discussion and 4.5 summarises this chapter.

4.2 Summary Statistics

All data on the bonds which have been issued since 1995 and their redemption yield were obtained from NSE. Data for bonds with 1-4 years durations were analysed.

Table 4.1 provides basic information on a variety of descriptive statistics of interest rates data set for 1-4 yrs bonds, from 1995 to 2011.

Table 4.1: Descriptive statistics of the bond interest rate

	1- 4yrs bonds
Observations	262
Mean	11.58139
Std. Dev.	4.51846
Variance	20.41648
Min	1.526
Max	26.404
Skewness	0.171557
Kurtosis	3.652193

Looking at the statistics the bond interest rates have standard deviation of 4.51846. This shows that there have been variations in the rates over the years. The mean has a value of 11.58139 which gives an impression that the more rates falls around this value. The results show that the rates are slightly positively skewed. This is evidence that bond interest rates would be increasing. The results also indicate a kurtosis value of 3.652193 which gives an impression that the rates could be normally distributed.

Graphical observation of volatility in bond interest rates

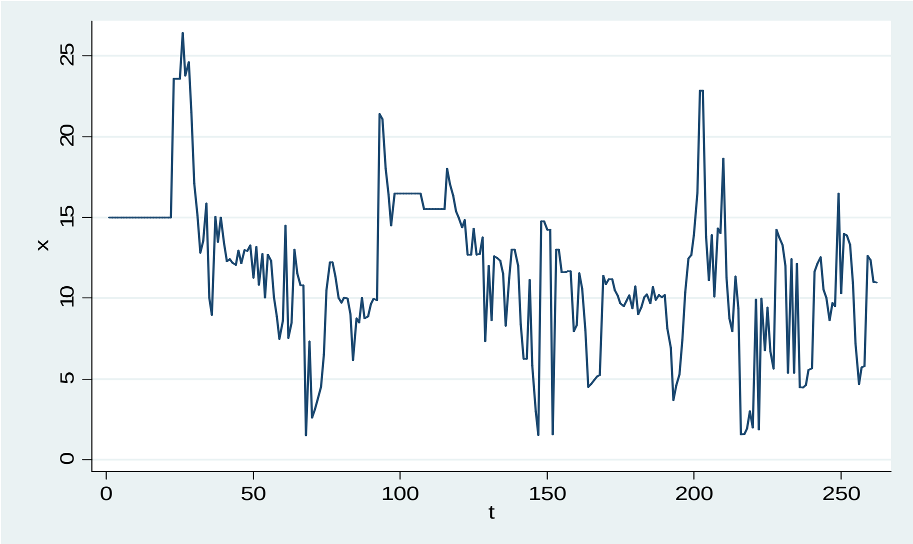

Figure 4.1(a): A line graph showing volatility of 1-4 years duration bonds between 1995 and 2011

Figure 4.1 (a), show the graphical distribution of the bond interest rate volatility over time. From this, it is possible to make one observations that the series has a non-constant variance because the amplitude of the rates varies over time, that is, ARCH effects are present.

4.3 Estimated Results of the Models

Table 4.2: Moving Average (MA) models

Variable	**MA(1)**	**MA(2)**	**MA(3)**	**MA(4)**	**MA(5)**	**MA(6)**
Standard error	3.6247	3.1585	3.0529	3.0368	2.9749	2.9399
Log likelih-ood	-708.3235	-671.9909	-662.5777	-660.6913	-654.8526	-651.2927
AIC	1420.6472	1349.9819	1333.1556	1331.3828	1321.7052	1316.5855
SBC	1427.7838	1360.6869	1347.429	1349.2245	1343.1153	1341.564

Table 4.2 above shows results from the data of bond interest rates for (MA) models. Using AIC and SBC values one would see the values decreases as the number of lags in-

creases. MA (6) would be selected to estimate volatility from this family of models because it has the lowest AIC value.

Table 4.3: Estimated Results for Autoregressive Models

Variable	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)	AR(6)
Standard error	2.9737	2.9175	2.9190	2.9187	2.9069	2.9021
Log likelihood	-656.70794	-651.24721	-650.88403	-650.36905	-648.83015	-647.9127
AIC	1317.4159	1308.4944	1309.7681	1310.7381	1309.6603	1309.8256
SBC	1324.5526	1319.1994	1324.0414	1328.5798	1331.0704	1334.804

Table 4.3 gives a summary of results for the AR family models. From the table of AR models, while applying the AIC to select the optimal model, AR (2) would be selected since it has the lowest AIC value.

Table 4.4: Estimated Results for ARMA (p, q) Models

Variable	ARMA(1, 1)	ARMA(1, 2)	ARMA(1, 3)	ARMA(1, 4)	ARMA(1, 5)	ARMA(1, 6)	ARMA(2, 1)	ARMA(2, 2)	ARMA(2, 3)
Standard error	2.9254	2.9259	2.9034	2.9087	2.8986	2.9016	2.9180	2.9234	2.9387
Log likelihood	-651.954	-651.4994	-649.0174	-648.9956	-647.6101	-647.3859	-650.7996	-650.7733	-649.607
AIC	1309.909	1310.9989	1308.0349	1309.9913	1309.2203	1310.7718	1309.5993	1311.5466	1309.214
SBC	1320.614	1325.2723	1325.8767	1331.4013	1334.1987	1339.3186	1323.8726	1329.3883	1327.0366

Table 4.6 presents a summary of results for ARMA family models. Using AIC values to compare the models, ARMA (1, 3) has the lowest value. This will therefore, imply that ARMA (1, 3) model would be used to estimate volatility in the ARMA models.

Table 4.5: Estimated results for ARCH (p) Models

Variable	**ARCH(1)**	**ARCH(2)**	**ARCH(3)**	**ARCH(4)**	**ARCH(5)**	**ARCH(6)**
Adjusted R-squared	-6.6239	-6.6534	-6.6830	-6.7129	-6.7431	-6.7734
Standard error	12.4761	12.5002	12.5244	12.5487	12.5732	12.5979
Log likelihood	-1014.017	-1013.283	-1013.160	-1012.921	-1012.840	-1012.706
AIC	7.7558	7.7578	7.7645	7.7703	7.7774	7.7840
SBC	7.7830	7.7987	7.8190	7.8384	7.8591	7.8793

Table 4.5 above presents a summary of ARCH results of the bonds data. Comparing the AIC and SBC values for all the ARCH models, ARCH (1) has the lowest values. This therefore indicates that ARCH (1) would better estimate volatility while using models in the ARCH family.

Table 4.6: Estimated results for GARCH (p, q) Models

Variable	**GARCH(1,1)**	**GARCH(1,2)**	**GARCH(1,3)**	**GARCH(2,1)**	**GARCH(2,2)**	**GARCH(2,3)**
Adjusted R-squared	-6.6534	-6.6830	-6.7129	-6.6830	-6.7129	-6.7431
Standard error	12.5002	12.5244	12.5487	12.5244	12.5487	12.5732
Log likelihood	-1013.398	-1013.335	-1012.703	-1012.951	-1012.856	-1012.090
AIC	7.7587	7.7659	7.7687	7.7629	7.7698	7.7716
SBC	7.7996	7.8203	7.8368	7.8174	7.8379	7.8533

Table 4.6 presents a summary of the GARCH results. The GARCH (1, 1) with a log likelihood value of -1013.398 be selected to estimate volatility. This is because it has the lowest AIC and SBC values as compared to other GARCH models.

Table 4.7: Summary of comparisons of the models using AIC values

Model	AIC value
MA (6)	1316.5855
AR (2)	1308.4944
ARMA (1, 3)	1308.0349
ARCH (1)	7.7558
GARCH (1, 1)	7.7587

Table 4.7 presents a summary of comparisons using AIC values for the selected models from each family as discussed early. The linear models ie MA, AR and ARMA have high AIC values as can be observed. The non-linear models have lower AIC values giving enough evidence to suggest that non-linear would be better estimates of volatility in the bond market in Kenya.

4.4 Discussion

Tables 4.1, 4.2, 4.3, 4.4, 4.5, 4.6 and 4.7 show the results for the models under consideration in this study. Data for bonds with duration ranging between one to four years were analysed and their results summarised as in tables 4.1 to 4.7. AIC and SBC values for all the models were generated. In general AIC values remained consistently low hence selecting it as a criterion to us to compare and rank the models. From each family of the models the best was selected using AIC values.

Comparing the selected models from each family using the AIC values in the summary tables above ARCH/GARCH models had relatively lower values of 7.75 than all the other models. This suggests that ARCH/GARCH models are more appropriate in estimating bond interest rate volatility in Kenya.

4.5 Summary

The long-run average variance has the least weight as daily data is applied in the estimation. For bonds with longer duration, it would have a more significant effect (Engle, 2004). The previous period's variance has the greatest weight and therefore has the most impact on today's volatility. The time-varying nature of volatility can be observed. From the above analysis there is evidence that non-linear models would better estimate volatility as compared to linear models.

CHAPTER FIVE

SUMMARY AND CONCLUSIONS

5.1 Introduction

This chapter concludes this study. Section 5.2 gives a summary of the study and findings, section 5.3 concludes the study, 5.4 states the limitations of the study and finally section 5.5 gives recommendations for further research in this area.

5.2 Summary of the Study

This study provides the first insight into the alternative models for interest rates volatility structure in the bond market in Kenya. We find evidence of autocorrelation in the bond interest rates. In addition, we find that differences exist in these statistical properties with the different bond durations. Using ARCH/GARCH model of volatility that takes into account this non-constant variance inherent in the volatility, it is established that bonds with different durations exhibits occurrences of high volatility followed by low volatility, that this volatility is better estimated using the non-linear models.

We have found that in all the models considered in this study ARCH/GARCH models have the lowest values of AIC. There is evidence that the bond market in Kenya in not well developed and therefore the number of bond transaction is not large as compared to other well developed financial markets. Whereas MA, AR and ARIMA require a large amount of transactions, GARCH models is more appropriate in estimating volatility since it requires low transaction numbers.

High volatility in a market indicates to investors that there is uncertainty and fear in the market. It then becomes very difficult for investors, especially one who has a long-term investment horizon, to make decisions on appropriate investments. However, this volatility is not necessarily a bad thing. Sophisticated investors can use it to make profits in a sharply fluctuating market.

5.3 Conclusions

From the data analysis in chapter four there is enough evidence that ARCH/GARCH models best estimates bonds volatility. Applying AIC values while ranking the models ARCH/GARCH models have the lowest value of the error term hence they better estimate volatility. This enables this study to conclude that non-linear models emerge as better estimators of volatility than linear models.

5.4 Limitations of the study

The redemption bond yields for bonds issued were used in the study as opposed to the interest rates values of bonds over time. Bonds with durations ranging between one and four years only were considered.

5.5 Recommendations for further Research

Among the factors to consider while estimating volatility is the fact that non-linear models better estimate volatility as compared to linear models according to this study. While evidence for varying rate of volatility found is not enough to conclude that GARCH models are best suitable for estimating volatility. The autocorrelation values presented here are a first step toward the investigation of the structure of the bond market, not conclusive evidence. There is need for more extensive research comparing a wider category of more financial models in bond interest rate volatility.

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Appendix

Issue No.	Tenure (Years)	Issue/Reopen date	Redemption Yield (%)	Issue No.	Tenure (Years)	Issue/Reopen date	Redemption Yield (%)
FXT1/1995/1	1	15-Jan-95	15.000	FR 7/2000/1	1	30-Oct-00	12.918
FXT2/1995/1	1	14-Feb-95	15.000	FR 8/2000/1	1	4-Dec-00	13.253
FXT3/1995/1	1	15-Mar-95	15.000	S7/2000/1	1	4-Dec-00	11.281
FXT4/1995/1	1	18-Apr-95	15.000	FR 1/2001/1	1	22-Jan-01	13.192
FXT5/1995/1	1	15-May-95	15.000	S8/2001/1	1	22-Jan-01	10.836
FXT6/1995/1	1	15-Jun-95	15.000	FR 2/2001/1	1	26-Feb-01	12.742
FXT8/1995/1	1	15-Aug-95	15.000	S9/2001/1	1	26-Mar-01	10.045
FXT9/1995/1	1	15-Sep-95	15.000	FR 3/2001/1	1	26-Mar-01	12.701
FXT10/1995/1	1	15-Oct-95	15.000	FR 4/2001/1	1	16-Apr-01	12.311
FXT11/1995/1	1	15-Nov-95	15.000	S3/2001/1	1	16-Apr-01	10.078
FXT12/1995/1	1	15-Dec-95	15.000	S4/2001/1	1	21-May-01	8.868
FXT1/1996/1	1	15-Feb-96	15.000	S5/2001/1	1	25-Jun-01	7.498
FXT2/1996/1	1	15-Mar-96	15.000	S6/2001/1	1	30-Jul-01	8.611
FXT3/1996/1	1	15-Apr-96	15.000	FXT1/2001/1	1	27-Aug-01	14.500
FXT4/1996/1	1	15-May-96	15.000	S7/2001/1	1	8-Oct-01	7.535
FXT5/1996/1	1	15-Jun-96	15.000	S1/2002/1	1	7-Jan-02	8.478
FXT7/1996/1	1	15-Jul-96	15.000	FXT1/2002/1	1	21-Jan-02	13.000
FXT8/1996/1	1	15-Aug-96	15.000	D1/2002/1	1	29-Jul-02	11.513
FXT9/1996/1	1	16-Sep-96	15.000	D2/2002/1	1	25-Nov-02	10.806
FXT10/1996/1	1	15-Oct-96	15.000	FXD2/2002/1	1	25-Nov-02	10.806
FXT11/1996/1	1	15-Nov-96	15.000	S3/2002/1	1	9-Dec-02	1.526
FXT12/1996/1	1	16-Dec-96	15.000	ZC1/2003/1	1	24-Mar-03	7.320
FR 1/1997/1	1	15-Jan-97	23.580	ZC2/2003/1	1	29-Sep-03	2.593
FR 2/1997/1	1	30-Jan-97	23.580	ZC3/2003/1	1	29-Dec-03	3.109
FR 3/1997/1	1	4-Mar-97	23.580	D1/2004/1	1	21-Jun-04	3.688
FR 4/1997/1	1	30-Jun-97	26.404	FXT1/2004/1	1	27-Sep-04	4.500
FR 5/1997/1	1	29-Sep-97	23.781	ZC1/2004/1	1	25-Oct-04	6.500
FR 1/1998/1	1	26-Jan-98	24.627	ZC2/2004/1	1	29-Nov-04	10.494
FR 2/1998/1	1	30-Mar-98	21.521	ZC3/2004/1	1	27-Dec-04	12.224
FR 3/1998/1	1	29-Jun-98	17.105	ZC1/2005/1	1	17-Jan-05	12.227
FR 4/1998/1	1	28-Sep-98	15.147	ZC2/2005/1	1	21-Feb-05	11.346
FR 1/1999/1	1	25-Jan-99	12.828	ZC3/2005/1	1	21-Mar-05	10.016

Issue No.	Tenure (Years)	Issue/Reopen date	Redemption Yield (%)	Issue No.	Tenure (Years)	Issue/Reopen date	Redemption Yield (%)
FR 2/1999/1	1	29-Mar-99	13.543	ZC4/2005/1	1	25-Apr-05	9.730
FR 3/1999/1	1	28-Jun-99	15.878	ZC5/2005/1	1	23-May-05	10.045
S1/1999/1	1	30-Jun-99	10.005	ZC6/2005/1	1	20-Jun-05	9.970
S2/1999/1	1	16-Aug-99	8.960	SFX1/2006/1	1	30-Jun-06	9.000
FR 4/1999/1	1	27-Sep-99	15.028	ZC1/2006/1	1	31-Jul-06	6.163
S3/1999/1	1	27-Dec-99	13.474	ZC2/2006/1	1	25-Dec-06	8.739
S4/2000/1	1	24-Jan-00	14.987	ZC1/2007/1	1	27-Aug-07	8.499
FR 1/2000/1	1	24-Jan-00	13.408	SFX1/2007/1	1	3-Dec-07	10.000
FR 2/2000/1	1	27-Mar-00	12.277	SFX2/2007/1	1	18-Dec-07	8.750
S5/2000/1	1	26-Jun-00	12.433	ZC1/2008/1	1	25-Feb-08	8.864
FR 3/2000/1	1	26-Jun-00	12.187	ZC2/2008/1	1	28-Jul-08	9.653
FR 4/2000/1	1	31-Jul-00	12.063	ZC3/2008/1	1	24-Nov-08	9.943
S6/2000/1	1	31-Jul-00	12.944	ZC1/2009/1	1	26-Jan-09	9.860
FR 5/2000/1	1	4-Sep-00	12.175	FXD1/2011/1	1	26-Dec-11	21.408
FR 6/2000/1	1	25-Sep-00	12.978	FXD1/2012/1	1	30-Jan-12	21.082
FXD3/2012/1	1	26-Mar-12	16.432	FXD2/2012/1	1	27-Feb-12	18.030
FXT1/2001/1.5	1.5	24-Sep-01	14.500	1/2001/2	2	29-Oct-01	14.750
FXT1/1995/2	2	15-Jan-95	16.500	FXT1/2001/2	2	29-Oct-01	14.750
FXT2/1995/2	2	15-Feb-95	16.500	2/2001/2	2	31-Dec-01	14.250
FXT3/1995/2	2	15-Mar-95	16.500	FXT2/2001/2	2	31-Dec-01	14.250
FXT4/1995/2	2	18-Apr-95	16.500	S 1/2002/2	2	7-Jan-02	1.580
FXT5/1995/2	2	15-May-95	16.500	D1/2002/2	2	25-Feb-02	13.000
FXT6/1995/2	2	15-Jun-95	16.500	2/2002/2	2	29-Apr-02	13.000
FXT7/1995/2	2	17-Jul-95	16.500	D1/2002/2	2	26-Aug-02	11.621
FXT8/1995/2	2	15-Aug-95	16.500	FXD1/2002/2	2	26-Aug-02	11.621
FXT9/1995/2	2	15-Sep-95	16.500	D2/2002/2	2	28-Oct-02	11.677
FXT10/1995/2	2	15-Oct-95	16.500	FXD2/2002/2	2	28-Oct-02	11.677
FXT11/1995/2	2	15-Nov-95	15.500	S 2/2002/2	2	4-Nov-02	7.949
FXT1/1996/2	2	15-Jan-96	15.500	S 3/2002/2	2	9-Dec-02	8.317
FXT2/1996/2	2	15-Feb-96	15.500	D3/2002/2	2	23-Dec-02	11.564
FXT4/1996/2	2	15-Apr-96	15.500	D1/2003/2	2	24-Feb-03	10.565
FXT6/1996/2	2	15-Jun-96	15.500	ZC1/2003/2	2	28-Apr-03	8.027
FXT9/1996/2	2	16-Sep-96	15.500	D1/2004/2	2	23-Feb-04	4.522

Issue No.	Tenure (Years)	Issue/Reopen date	Redemption Yield (%)	Issue No.	Tenure (Years)	Issue/Reopen date	Redemption Yield (%)
FXT11/1996/2	2	15-Nov-96	15.500	D2/2004/2	2	22-Mar-04	4.673
FXT12/1996/2	2	16-Dec-96	15.500	D3/2004/2	2	24-May-04	4.945
FR 1/1998/2	2	3-Aug-98	17.997	D4/2004/2	2	23-Aug-04	5.168
FR 2/1998/2	2	7-Sep-98	17.045	FXT1/2004/2	2	27-Sep-04	5.250
FR 3/1998/2	2	28-Sep-98	16.348	ZC1/2005/2	2	21-Mar-05	11.388
FR 4/1998/2	2	2-Nov-98	15.356	D1/2005/2	2	25-Apr-05	10.878
FR 5/1998/2	2	7-Dec-98	14.992	D2/2005/2	2	29-Aug-05	11.158
FR 1/1999/2	2	25-Jan-99	14.380	FXD2/2005/2	2	29-Aug-05	11.158
FR 2/1999/2	2	28-Jun-99	14.838	D3/2005/2	2	26-Sep-05	10.475
S 1/1999/2	2	30-Jun-99	12.706	D1/2006/2	2	30-Jan-06	10.144
S 2/1999/2	2	16-Aug-99	12.706	D2/2006/2	2	27-Mar-06	9.682
FR 3/1999/2	2	13-Dec-99	14.289	SFX1/2006/2	2	30-Jun-06	9.500
S 3/1999/2	2	27-Dec-99	12.706	FXD3/2006/2	2	27-Oct-06	9.825
S 4/2000/2	2	24-Jan-00	12.720	FXD1/2007/2	2	29-Jan-07	10.177
FR 1/2000/2	2	27-Mar-00	13.753	FXD2/2007/2	2	26-Mar-07	9.354
S 5/2000/2	2	26-Jun-00	7.338	SFX1/2007/2	2	3-Dec-07	10.750
FR 2/2000/2	2	26-Jun-00	11.993	SFX2/2007/2	2	18-Dec-07	9.000
S 6/2000/2	2	21-Jul-00	8.634	FXD3/2007/2	2	24-Dec-07	9.442
FR 3/2000/2	2	31-Jul-00	12.599	FXD1/2008/2	2	28-Apr-08	10.069
FR 4/2000/2	2	4-Sep-00	12.493	FXD2/2008/2	2	26-May-08	10.235
FR 5/2000/2	2	25-Sep-00	12.298	FXD3/2008/2	2	25-Aug-08	9.668
FR 6/2000/2	2	30-Oct-00	11.482	FXD4/2008/2	2	29-Dec-08	10.670
S 7/2000/2	2	4-Dec-00	8.299	FXD1/2009/2	2	23-Mar-09	9.886
FR 7/2000/2	2	4-Dec-00	11.241	FXD2/2009/2	2	25-May-09	10.193
FXT1/2002/2	2	4-Dec-00	13.000	FXD2/2009/2(R1)	2	29-Jun-09	10.064
FXT2/2002/2	2	4-Dec-00	13.000	FXD3/2009/2	2	21-Sep-09	10.196
FXD1/2002/2	2	4-Dec-00	12.000	FXD1/2010/2	2	1-Feb-10	8.127
S8/2001/2	2	22-Jan-01	8.384	FXD2/2010/2	2	29-Mar-10	6.936
S9/2001/2	2	26-Mar-01	6.239	FXD3/2010/2	2	27-Sep-10	3.698
S3/2001/2	2	16-Apr-01	6.254	FXD4/2010/2	2	27-Dec-10	4.586
FR 2/2001/2	2	16-Apr-01	11.144	FXD1/2011/2	2	28-Feb-11	5.284
S4/2001/2	2	21-May-01	5.843	FXD2/2011/2	2	25-Apr-11	7.439
S5/2001/2	2	25-Jun-01	2.998	FXD2/2011/2(R1)	2	30-May-11	10.387

Issue No.	Tenure (Years)	Issue/Reopen date	Redemption Yield (%)	Issue No.	Tenure (Years)	Issue/Reopen date	Redemption Yield (%)
S6/2001/2	2	30-Jul-01	1.537	FXD2/2011/2(R2)	2	27-Jun-11	12.442
FXD2/2011/2(R3)	2	25-Jul-11	12.684	FXD4/2011/2 (TAP)	2	28-Nov-11	22.844
FXD3/2011/2	2	26-Sep-11	13.897	FXD1/2012/2	2	30-Apr-12	13.826
FXD3/2011/2(R1)	2	31-Oct-11	16.526	FXD2/2012/2	2	27-Aug-12	11.114
FXD4/2011/2	2	28-Nov-11	22.844	S 4/2000/3	3	24-Jan-00	11.260
FR 1/1999/3	3	1-Mar-99	13.898	S 5/2000/3	3	26-Jun-00	8.752
S 1/1999/3	3	30-Jun-99	10.087	S 6/2000/3	3	31-Jul-00	7.972
FR 2/1999/3	3	2-Aug-99	14.321	FR 1/2000/3	3	4-Sep-00	11.367
S 2/1999/3	3	16-Aug-99	14.008	S 7/2000/3	3	4-Dec-00	9.367
S 3/1999/3	3	27-Dec-99	18.642	S8/2001/3	3	22-Jan-01	1.580
S5/2001/3	3	25-Jun-01	1.978	S9/2001/3	3	26-Mar-01	1.592
FR 1/2001/3	3	25-Jun-01	9.920	S3/2001/3	3	16-Apr-01	1.927
S6/2001/3	3	30-Jul-01	1.876	S4/2001/3	3	21-May-01	2.992
FR 2/2001/3	3	24-Sep-01	9.977	S 2/2002/3	3	4-Nov-02	5.393
FR 2/2001/3	3	24-Sep-01	6.752	FXT3/2002/3	3	25-Nov-02	12.419
FR 3/2001/3	3	3-Dec-01	9.414	S 3/2002/3	3	9-Dec-02	5.393
FR 3/2001/3	3	3-Dec-01	6.701	D1/2003/3	3	20-Jan-03	12.148
S 1/2002/3	3	7-Jan-02	5.629	D2/2003/3	3	28-Jul-03	4.473
1/2002/3	3	21-Jan-02	14.250	D3/2003/3	3	24-Nov-03	4.450
2/2002/3	3	25-Mar-02	13.750	D4/2003/3	3	29-Dec-03	4.629
D1/2002/3	3	27-May-02	13.293	D1/2004/3	3	26-Apr-04	5.553
D2/2002/3	3	30-Sep-02	12.006	D2/2004/3	3	26-Jul-04	5.661
D1/2006/3	3	27-Feb-06	10.542	D1/2005/3	3	25-Apr-05	11.633
SFX1/2006/3	3	30-Jun-06	10.000	D2/2005/3	3	23-May-05	12.149
FXD2/2006/3	3	28-Aug-06	8.632	D3/2005/3	3	25-Jul-05	12.530
FXD3/2006/3	3	25-Sep-06	9.696	SFX1/2007/3	3	1-Jun-07	9.500
FXD1/2004/4	4	26-Jan-04	5.710	FXT1/1996/4	4	5-Nov-96	16.500
D2/2004/4	4	21-Jun-04	5.790	FR 1/2001/4	4	30-Jul-01	10.290
D1/2005/4	4	23-May-05	12.611	FXT1/2002/4	4	29-Apr-02	14.000
FXD3/2005/4	4	26-Oct-05	12.353	D1/2002/4	4	29-Jul-02	13.884
FXD1/2006/4	4	24-Apr-06	11.023	D2/2002/4	4	23-Dec-02	13.320
FXD1/2007/4	4	26-Feb-07	10.968	D1/2003/4	4	24-Mar-03	10.917
D3/2003/4	4	27-Oct-03	4.672	D2/2003/4	4	23-Jun-03	7.183