A COMPARISON OF LINEAR AND NONLINEAR MODELS IN PREDICTING STOCK RETURNS AT THE NAIROBI STOCK EXCHANGE

BY

GICHANA, ISAIAH MBOTO
REG NO: D61/P/8201/2003

A RESEARCH PROJECT REPORT SUBMITTED IN PARTIAL FULFILLMENT OF REQUIREMENTS OF THE DEGREE OF MASTER OF BUSINESS ADMINISTRATION

UNIVERSITY OF NAIROBI

OCTOBER 2009

DECLARATION

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

Signature: .... Date:

ISAIAH MBOTO GICHANA

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

Signature: .... Date: 6/n / Optf

MR. KISAKA SIFUNJO

LECTURER

DEPARTMENT OF FINANCE AND ACCOUNTING

UNIVERSITY OF NAIROBI

DEDICATION

I dedicate this research report to my parents Mr. Solomon Gichana and Mrs Jemima Gichana, my dear wife Devinah Nyaboke and our three children Deborah Moraa, Joshua Mboto and Moses Gichana and finally to my siblings. To you all thank you for the prayers, encouragement and support over the years in my studies.

ACKNOWLEDGEMENT

I would like to acknowledge the invaluable advice, support and professional fire of my supervisor Mr. Kisaka Sifunjo in the supervision during my research work and in the writing of this project report.

I would also like to acknowledge staff at NSE for assistance providing data.

I also would like the support provided by Mr. Michael Karue (Finance Officer - University of Nairobi), for creating an excellent environment and funding opening. Further I would like to appreciate the support of fellow MBA colleagues and staff at the University of Nairobi Library.

Finally, I would like to acknowledge the assistance given by the staff at the school of business, and former workmates in the finance Department University of Nairobi

ABSTRACT

Empirical literature shows that stock returns could be nonlinear. However, studies on the nonlinear behavior of stock returns in emerging markets are limited. This study aims at filling this knowledge gap by comparing linear and nonlinear models in predicting stock returns at the NSE. The study compared the Random Walk Model, Moving Average Models, Autoregressive model ARMA models, Autoregressive conditional Heteroskedasticity (ARCH) models.

The Nairobi stock Exchange index was used as a proxy for stock prices and hence changes in the NSE index represented stock returns. The sample period consisted of daily observations of the NSE index. The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were used to select the best fitting model from each type of models. Then the best fitting model from each type of models were used to predict returns over the sample period of three months. The mean absolute error (MAE) and the Root mean square error (RMSE) were used to select the best model. The results indicate that (ARCH (1) performs better than the other models. Therefore this study concluded that nonlinear models are better than linear models in predicting stock returns on the NSE. Thus stock returns are nonlinear.

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LIST OF ABBREVIATIONS AND ACRONYMS

ADF	:	Augmented Dickey-Fuller
AIC	:	Akaike Information Criterion
BIC	:	Bayesian Information Criterion
DAIC	:	Change in Akaike Information Criterion
DBIC	:	Change in Bayesian Information Criterion
EMH	:	Efficient Markets Hypothesis
NSE	:	Nairobi Stock Exchange

CHAPTER ONE

INTRODUCTION

1.1 Background to Study

For many decades, an important area of research in both theoretical and empirical finance has been in the area of predictability in stock returns. Several models have been advanced to explain predictable patterns and, although the extent to which returns are predictable is subject to considerable debate, some evidence supporting predictability has been obtained. For example, theoretical models consistent with time-varying required returns or risk premia are supported by empirical evidence of mean reversion in long-horizon returns (periods from 7years - 20 years) and by autocorrelation patterns in short-horizon returns (Periods from one month to one year).The existence of predictability does not, however, necessarily imply market inefficiency and the ability to earn risk-adjusted economic profits or abnormal returns. Predictability may be consistent with market efficiency if it was to arise from time-varying risk premia or auto correlated patterns in economic variables. The lack of agreement regarding the extent and nature of predictability in asset returns does not imply that an examination of alternative investment strategies is unwarranted, since, as argued by Grossman (1995), the very existence of trade suggests that passive strategies are sub-optimal.

The existence of predictability in stock returns has important implications for several areas of finance. If predictability is the result of time-variation in risk premia rather than a violation of weak form efficiency, then research on performance analysis must account for this time-variation in risk. This has been indicated by several studies. For example, in the pricing of options, Lo and Wang (1995) have shown that predictability may affect estimates of the diffusion coefficient (that is the gradual diffusion of information across asset markets leads to cross-asset return predictability) used in the Black-Scholes model. In the area of portfolio theory, Samuelson (1991) has shown that, if returns are mean reverting, optimal portfolio weights may differ from those where returns follow a random walk. Balvers and Mitchell (2000) confirm that common advice concerning changes in the weights invested in risky assets in relation to the investment horizon (7 years -20 years) is optimal given negatively correlated risky asset returns.

Two basic approaches to investigating long-horizon predictability or mean reversion in market returns have been employed. The first approach, which involves the estimation of univariate models and is used by Summers (1986), finds that market returns are negatively autocorrelated at long horizons. A second methodology employs price-based variables such as the dividend yield (Fama and French, 1988, 1992), earnings to price ratio and book to market ratio (Kothari and Shanken, 1997) to predict market returns. Although a large number of studies have investigated mean reversion, there is no general agreement as to the implications of the evidence and there are at least three competing views concerning this form of predictability. One view holds that long-horizon predictability, at least when measured by univariate models, is much weaker than generally thought. Problems of statistical inference associated with long-horizon returns can be formidable and evidence of predictability from univariate models when long-horizon historical returns are used may be the result of measurement error. For any fixed-length data series, the longer the return horizon, the smaller the sample. Thus, a significant problem with evidence of long-horizon return predictability is the small sample size. When Richardson and Stock (1989) correct for small sample bias, the Fama and French (1988a) and Poterba and Summers (1988) findings are weakened considerably.

The most generalized class of Linear Models used in time series analysis for forecasting stock returns are the Arima models through the seminal paper of Box and Jenkins (1970).A nonseasonal ARIMA model is classified as an "ARIMA(p,d,q)" model. **ARIMA (p,d,q):** ARIMA models are, in theory, the most general class of models for forecasting a time series which can be stationarized by transformations such as differencing.

On the other hand the Arch /Garch models by Engle (2003) aim to forecast and analyze the size of the errors of the model. In this case, the questions are about volatility, and the standard tools have become the ARCH/GARCH models. The basic version of the least squares model assumes that the expected value of all error terms, when squared, is the same at any given point. This assumption is called homoskedasticity, and it is this assumption that is the focus of ARCH/GARCH models.

The most widely used specification is the GARCH (1,1) model introduced by Bollerslev (1986) as a generalization of Engle (1982). The (1,1) in parentheses is a standard notation in which the first number refers to how many autoregressive lags appear in the equation, while the second number refers to how many lags are included in the moving average component of a variable.

1.1.1 Predictability of Stock Returns

A large number of studies have examined the predictability and relationship between abnormal or excess returns and firm characteristics. It has been found that a number of firm variables, such as size, book value divided by market value, and earnings divided by price, are related to excess return. The size effect was the first of the firm variables to be shown to be related to excess returns. One of the earliest of firm size effect studies, and the most often cited empirical study of the firm size effect, is that by Banz (1981) who obtained evidence that, over the 1936-1977 periods, the differential returns from purchasing the stocks of very small firms relative to those of very large firms were about 19.8 per cent per year. Importantly, subsequent studies have found that a substantial portion of the size effect occurs in January. For example, a strong relationship exists between the size and the January effects, with the difference in returns in January due to size being about half of the annual difference.

Comparing stock returns appears to be a troublesome anomaly for rational expectations, because according to conventional wisdom, measuring stock returns hinges upon future economic conditions and must be riskier than assets in place. In addition growth opportunities are usually the source of high betas, because measuring growth options tend to be most valuable in good times and have implicit leverage, which tends to increase beta, they contain a great deal of systematic risk. Further, growth options are always riskier than assets in place, as these options are leveraged on existing assets. Growth stocks, which derive market values more from stock return options, must therefore be riskier than value stocks, which derive market values more from assets in place.

Previous studies have discussed several factors related to expected stock returns. For instance, Banz (1981) examined the empirical relationship between returns and the market values of common stocks. According to that study, smaller firms have higher average returns than larger firms do. Moreover, this size effect has existed for at least four decades. Fama and French (1992) investigated the same issue, indicating that two variables were consistently related to stock returns:

Academics have long stated that competition among traders eliminates asset mispricing. As a result, every stock is always correctly priced and efforts to outperform simple random selection of stocks are destined to fail.

1.2 Statement of the Problem

Markets are known to be characterized by complex dynamics, and according to Mattarocci (2006) the studies proposed in literature to analyse and predict stock price dynamics assume that, by looking at the past, one may collect useful information. To further understand the price formation mechanism; the so-called technical analyses, assume that the price dynamics could be approximated with linear trends and could be analysed using a standard mathematical or graphical approach.

However the high number of factors that are likely to influence the stock market dynamics makes the linear trend assumption incorrect and calls for the definition of more complex approaches that may succeed in studying these multiple relationships. For this purpose the nonlinear models are a heterogeneous set of econometric approaches that allow higher predictability levels, but not all the approaches may be easily applied to real data.

Further, according to the EMH, prices adjust without delay to the arrival of new information. Since news or events hitting the market arise randomly, the resulting price changes should be unpredictable and follow a random walk. There are instances where investors do not respond instantaneously to information as predicted by the EMH. Hinich and Serletis (2007) conjectured that when unexpected shock hits the market, it takes longer time for investors to work out the full impact of the news before settling at a new equilibrium level.

Finally a lot of studies have been conducted on the predictability of stock returns in developed countries. According to Rashid and Ahmad(2008), in the empirical finance literature , generally the existing evidences concerning the forecasting of stock returns volatility are related to well-developed stock markets. Rashid and Ahmad (2008) contribute to the growing literature by examining the relative ability of variouslinear and nonlinear models to forecast daily stock price index volatility in relatively immature markets namely the Karachi stock exchange. Chahudhuri and Wu (2001) have focused on investigating whether stock-indexes of seventeen emerging markets can be characterized random walk or mean reversion.

Studies conducted at the NSE have focused on the holiday effect on stock returns (Rasugu (2005) while Mokua (2003) has conducted studies on the weekend effect and Cherutioi (2006) investigated the foreign exchange risk exposure by commercial banks.

None of these studies have examined the predictive ability of linear and non linear models in predicting stock returns. In Kenya, for instance, a lot of studies have been performed on NSE but none of them has investigated this phenomenon at the NSE. Hence the question; Do linear models predict stock returns better than non-linear models?

Therefore, this study tries to fill this research gap by investigating the predictability of stock returns comparing linear and nonlinear models using data from the NSE.

1.3 Objectives of the study

The objective of this study is to compare linear and nonlinear models in predicting stock returns at the Nairobi stock exchange.

1.4 Importance of the study

This study will be of importance to the following parties:

The policy makers will find the study useful as a basis of formulating policies, which can be effectively implemented for better and easier regulation of public companies. This is intended to lead to increased investor confidence as well as encourage growth in the Nairobi stock exchange while leading to a better environment for cross listing.

The government could use the study so as to come up with clear criteria of promoting public companies in Kenya based on the analysis of both the micro and macro factors active in prediction of stock returns and the efficient application of both the linear and non linear models relating to securities returns

The researchers and academic community could use this study as a stepping stone for further studies on public companies in the area of returns, factors that can be used to predict returns and the applicable models

The management of the public companies will find the study invaluable in making decisions regarding measuring stock returns. This will prove invaluable in devising both investment and financing strategies aimed at attracting capital and remaining competitive.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

The expansion of time series analysis as a discipline permits one to analyze stock market prices in ways not previously explored. In particular, "what is the predictability of the error term" and "is there predictability in daily stock market returns". Peculiar problems arise when daily patterns are present in stock price data. Kato (1990a) indicates very important aspects associated with variation of stock returns and closing prices associated with the day of the week. This study along with Moorkejee and Yu (1999) suggested that patterns exist in the time series of stock exchanges in Japan, Shanghai and Shenzhen. These studies were unique in that they investigated returns for individual firms and not for indexes of stock exchange behavior.

Other studies indicating the predictability of stock exchange behavior in Asia include Kubota and Takahara (2003). They investigated whether the activity of financial firms creates value and/or risk to the economy within the asset pricing framework. They used stock return data from non-financial firms listed in the first section of the Tokyo stock exchange. Their value-weighted index which was solely composed of non-financial firms was augmented with the index of the firms from the financial sector. In turn, they estimated the multivariate asset pricing model with these two indices. Their procedure can simultaneously take into account the cross-holding phenomena among Japanese firms, especially between the financial sector and the non-financial sector.

In conclusion, their financial sector model helps explain the return and risk structure of Japanese firms during the so-called "double-bubble" period indicating some predictability in closing prices of Japanese securities. Lastly, Jarrett and Kyper (2006) studied the predictability of daily returns on more than 50 firms listed on exchanges in the USA and concluded that daily variation exists and the time series contain predictable properties. This study examines whether stock returns in the NSE are linear or non linear. This is achieved by comparing the predictive power of linear and non linear models.

2.2 EMH and Stock Returns Predictability

Based on the random walk model, the best forecast of today's return volatility is yesterday's observed volatility and according to the EMH, prices adjust without delay to the arrival of new information. Since news or events hitting the market arise randomly, the resulting price changes should be unpredictable and follow a random walk. However, there are instances where investors do not respond instantaneously to information as predicted by the EMH. Hinich and Serletis (2007) conjectured that when unexpected shock hits the market, it takes longer time for investors to work out the full impact of the news before settling at a new equilibrium level. Moreover, the EMH assumes that the market is composed of homogenous participants, which is unreasonable in real financial markets. Instead, under the heterogeneous markets hypothesis introduced by Dacorogna *et al.* (2001), financial markets are populated with heterogeneous agents and the same information can be interpreted in different ways by traders. This differential interpretation will not lead to a uniform market reaction but rather sequences of secondary reactions triggered by the initial event would slowly unfold over a period of time.

Further, Antoniou *et al.* (1997) argued that uninformed traders may delay their responses to see how informed market participants behave because they do not have the resources to fully analyze the information or the information is not reliable. Such gradual market adjustment process will generate a pattern of nonlinear price movements relative to previous movements, hence forming nonlinear serial dependencies in returns series. The above explanation demonstrates that evidence of nonlinearity not only challenges the unpredictable criterion of EMH, but also questions the implicit assumption of rapid information incorporation into stock prices.

For several decades, researchers have been attempting to search for a parsimonious theory or model that can explain the cross-section of expected stock returns. Of special interest to the academics is to determine whether stock returns follow a linear or non linear process.).

Rationality-based asset-pricing theories assert that the cross-section of expected stock returns can be explained by betas or factor loadings on a set of common factors that are related to the state of the economy (Merton, 1973). Merton»(1973) and Cochrane (2001) also point out that any sensible economic-based asset-pricing theory would link the "pricing" with some factors, state variables, or sources of priced risk. The sequence of studies by Fama and French (1993) and

Davis *et al.* (2000) represent this line of research that attempts to explain stock returns in a rational multifactor framework. Specifically, Fama and French (1993) argue that size and BM capture certain distressed factors. This view has gained several empirical supports over the past decade.

Enormous recent behavioral evidence suggests, however, that systematic bias in investor behavior may cause asset prices to deviate from their fundamental values. Daniel *et al.* (2001) propose a characteristics-based model that refutes the factor-based explanation of asset-pricing anomalies, and argue that it is the firm characteristics, firm size and book to market value, that account for the cross-section of expected returns. Using Japanese data, Daniel *et al.* (2001) also reject Fama and French's factor specification, and suggest that the documented anomalies are unrelated to risk, but due to mispricing or other behavioral reasons.

Despite the focus of the debates between the rational and behavioral theories, stock markets cannot persistently function in isolation from the macroeconomic conditions. Conceptually, as the return on a security is measured as the sum of its future dividend flows, discounted by a proper discount factor, variables that affect future dividend flows and the discount factor would also affect the stock return. Thus, macroeconomic variables that reflect the state of the economy serve as the natural candidates for the common factors. Chen, Roll, and Ross (1986) identify four macroeconomic factors as the "fundamental" forces: changes in industrial production; changes in expected and unexpected inflation; changes in risk premium; changes in term structure. They demonstrate that the macroeconomic factors significantly explain the cross-section of stock returns. Flannery and Protopapadakis (2002) find that stock returns are correlated with inflation and money growth.

To better understand the nature of the size and Book to Market effects, He and Ng (1994) investigate whether size and Book to Market proxy for macroeconomic risks found in Chen, Roll, and Ross (1986). They find that the factors cannot explain either effects, and that size and Book to Market are related to relative distress. However, while relative distress can explain the size effect, it only partially explains the*Book to Market effect. Brennan *et al.* (1998) find that the size and Book to Market effects persist even when returns are risk-adjusted using either the Fama-French three-factor model or the APT models based on asymptotic principal components.

Thus, the vast empirical evidence suggests that rational theories alone cannot fully explain the size and value puzzles in the cross-section of monthly stock returns, and suggests a role for behavioral factors. Indeed, Daniel *el al.* (2001) show that security returns are jointly determined by both risk and misevaluation when some investors are overconfident. Hirshleifer (2001) further suggests that in the future "the purely rational paradigm will be subsumed by a broader psychological paradigm that includes the full rationality as a significant special case".

2.3 Linear and Non Linear models of stock returns

To study the relationship between economic activity represented by macroeconomic factors and the behavior of prices in the stock market, analysis of long term trends based on monthly observations is necessary. This leads to major model classes basically the linear models and the 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 stock returns it follows that the expected return is explained by several factors such like stock price index, interest rates 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.

Since the seminal work of Box and Jenkins (1970), there have been many applications of time series models to the forecasting of business and economic variables, these use a single integrated series. Granger (2003) indicates that this misses an important feature and it turns out that the difference between a pair of integrated series can be stationery and this property is known as cointegration.

A major use of time series models has been to provide short and medium term forecasts for important macro variables, such as consumption, income investment and unemployment, all of which are integrated series. The derived growth rates are found to be somewhat forecastable. Much less forecastable are inflation rates and returns from speculative markets, such as stocks, bonds and exchange rates, Granger (20003).

Engle (2003) while proposing models such as the 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. Fereson, Sarkissam and Simin (2003) indicate 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 stock returns have developed from linear models to non linear models and within each broad group, there are several classes, and as Rashid and Ahmad (2008) point out these models start with the random walk model which is based on the premise that the best of today's stock return volatility is yesterday observed volatility. An advancement of this model is the autoregressive (AR) model which 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.

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. The 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 the 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 autocorrelation, in a time series and are used to predict behaviour of a time series from past values alone. The ARMA model is derived from taking the AR model and the MA

When data shows non stationarity leading to the changing of the properties of the ARMA model then the ARIMA models are best suited, these models are a generalisation 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 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 suggest the use of nonlinear time series structures to model the attitude of investors toward risk and expected return. The ARCH model described the forecast variance in terms of current observables. Instead of using short or long sample 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 used to describe almost any financial return series. This applies not only to US stocks but also to stocks traded in most developed markets and to most stocks traded in emerging markets.

In practice, a common assumption in applying GARCH models to financial data is that the return series is conditionally normally distributed. This is referred to as the normal GARCH model, which is well known as part of the volatility clustering patterns typically exhibited in financial and economic time series. However, the kurtosis implied by the normal GARCH model tends to be far less than 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 the t-distribution. Thus, the non-normal GARCH model is more appropriate for the case of large leptokurtosis typically observed in asset returns

2.4 Evidence of Nonlinearity in the stock Market

Fama and French (2000) used the ratio of earnings before interest but after taxes over assets as a measure of nonlinearity. They forecasted nonlinearity with year-by-year cross-section regressions, and they used the average slopes and their time-series standard errors to draw inferences. The results of Fama and French (2000) are consistent with the mean reversion assumption of nonlinearity. With a simple partial adjustment model in their study, they show that the rate of mean reversion is about 38 per cent per year. They note that the mean reversion of profitability is highly nonlinear. Mean reversion is faster when profitability is below its mean and when it is further from its mean in either direction. There is an important practical implication of this result, according to Fama and French (2000), forecasts of nonlinearity and earnings by analysts should exploit the mean reversion in profitability. Nonlinearity and earnings are more predictable when they are further away from their mean.

Fama and French (2000) did not test their results extensively for industry effects. They excluded financial firms and utilities from their sample since they were highly regulated during the period under examination and could produce unusual behavior of nonlinearity.

2.5 Empirical evidence oil Predictability of stock returns

Several studies have been conducted on the predictability of stock returns in developed countries. According to Rashid and Ahmad(2008), in the empirical finance literature , generally the existing evidences concerning the forecasting of stock returns volatility are related to well-developed stock markets: the USA(Porteba and Summer(1986), Akgiray, 1989 and Najand(1991, 2002)), the UK (Dimson and Marsh, 1990 and McMillan, Speight and Gwilym, 2000, Japan(Tse,1991), Singapore (Tse and Tung, 1992) Australia(Brailsford and Faff, 1996), Switzerland(Adjoute, Bruand and Gibson-Asner,1998), the Netherlands, Germany, Spain and Italy and an extensive review of these models and their applications is available from Bollerslev et al.(1992, Frances and Ghijsels, 1999 and in Turkey(Balaban, 1998)

Rashid and Ahmad (2008) contribute to the growing literature by examining the relative ability of various linear and nonlinear models to forecast daily stock price index volatility in relatively immature markets namely the Karachi stock exchange. Chahudhuri and Wu (2001) have focused on investigating whether stock-indexes of seventeen emerging markets can be characterized random walk or mean reversion.

In the NSE, Rasugu (2005) focused on the presence of holiday effects on stock returns however the study found no holiday effect and concluded that technical trading rules can not be applied to earn higher than average returns. Mokua (2003) investigated whether the NSE exhibits the week-end effect variations on shares traded at the market, argued that given that there was no significant difference on returns at the NSE, there was no weekend effect detected. Finally Cherutoi (2006) looked at the extent of foreign risk and its impact on commercial banks returns, the study concluded that there is minimal exposure to foreign exchange risk by commercial banks.

2.6 Summary

The use of linear and non linear models in predicting stock returns especially in a time series context has continued to elicit mixed reactions in financial literature. While there is general recognition of the superior ability of non linear models to describe data, there is less certainty about their 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 D.G. (2009)

Further there is evidence of nonlinearity in the stock markets with forecasts of non linearity and earnings exploiting the mean reversion in profitability and Nonlinearity 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 or 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.

While looking at studies done at the NSE, focus has been on the holiday effect, weekend effect and foreign exchange as means predicting stock returns and hence driving speculation however this is limited because the NSE is not fully integrated to the global financial markets.

The application of linear and non linear models at the Nairobi stock exchange is of great importance more so in the face of market anomalies, the low level of investor confidence and the global financial crisis and as a test of the efficient markets theory at the stock exchange. It is also important to appreciate the use both micro and macro economic factors to predict returns and how to build stock portfolios and hence create increased investor activity 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 at the stock exchange, there is still a gap as to whether linear or non linear models are better suited to predict stock returns at the stock exchange and specifically how this is applicable to developing economy stock exchanges like the NSE. This study contributes towards filling this gap by comparing the predictive ability of linear and non linear models by using data from the NSE.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the methodology that shall be used to carry out this study. Section3.2 presents 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.

3.2 Research Design

This is an empirical study designed to compare the predictive ability of linear and non linear models by using share prices at the Nairobi stock exchange. 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 of all companies quoted on the Nairobi stock exchange. They are forty eight in total as at 2008.However the number has been fluctuating over the years.

3.4 Data collection

The study employs the NSE 20-share Index for the period starting January 2004 to December 2008.The data was obtained. This consisted of daily observations of the NSE Index.

3.5 Models of Predicting Stock Returns

This section discusses the models used for predicting stock returns. Section 3.5.1 presents conceptual models while Section3.5.2 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 stock returns. 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*\

$$X_t = \quad e\ t+£\ t\text{-}i + \ldots\ldots\ldots\ldots + 8t\text{-}q + e_t$$

where 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 a linear regression 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 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 (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

$$X_t = X \sum_{i=1}^{P} X t\text{-}i + e_t$$

Where e_t is an error 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 behaviour 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,

$$X_t = 6, + \sum_{i=1}^{P} X_{,.i} + \sum_{i=1}^{q} E_{t},$$

The error terms s_t are generally assumed to be independent identically-distributed random variables sampled from a normal distribution with zero mean: $£_t$ n N (0, S^2) where 5^2 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 Average Models

These models is a generalisation 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 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-stationarity. The model is written as

$$Y_t = Y_{t-i} + A Y_t + e_{t-i} + e_t$$

$$A Y_t = Y_t - Y_{t-i}$$

The model is generally referred to as an ARIMA *(p, d, q)* model where *p, d,* and *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 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 Heteroskedastic Models

The ARCH (p) model is based on recent developments in financial econometrics which suggest the use of nonlinear time series structures to model the attitude of investors toward 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 result from a specific type of nonlinear dependence rather than exogenous structural changes in variables." . Engle's (1982) ARCH Model is written as

$$Y_t = a_0 + |i + £_t$$

$$h^2_n = e^2_n{}_{t-i} + \ldots\ldots\ldots + e^2_n{}_{t-p} + £t$$

ARCH is a forecasting model insofar as it forecasts the error variance at time *t* on the basis of information known at time / - land, 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. 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

$$Y_t = a + y_{t-i} + e_t$$

$$h^t = a + e^2{}_{t-i} + e^2{}_{t-2} + \ldots\ldots\ldots + e^2{}_{t-p} + q^2{}_{t-i} + \ldots\ldots + q^2{}_{t-q} + £t$$

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 provides 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 Model

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

$$Y_t = a_0 + a_1 e_{t-1} + e_t \qquad (1)$$

The first step will be the estimation of the MA (1) model to determine the coefficient ai 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 the 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 the AR (p) - Autoregressive Models

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

$$Y_t = a_0 + a_1 y_{t-1} + \varepsilon_t \qquad (2)$$

The AR (1) model will be estimated to determine the coefficient ai 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 the 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 Average Models

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

$$X_t = \delta_t + \theta_1 X_{t-1} + \theta_1 \varepsilon_{t-1} + \varepsilon_t \qquad (3)$$

The ARMA (1, 1) model will be estimated to determine the coefficient 0j 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 fitness measures- the Bayesian information criterion (BIC) and the 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 ARCH/GARCH and ARIMA models.

Estimation of the ARIMA (p, d, q) - Autoregressive Integrated Moving Average Models

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

$$Y_t = a + Y_{t-i} + A Y_t + e_{t-i} + £_t \quad \ldots\ldots (4)$$

The ARIMA (1, 1, 1) model will estimated to determine the coefficient ai. Following that, the values of *p, d* and *q* will be varied from 1 to 5 and the estimation repeated. The best ARIMA (p, p,q) model will then be selected using goodness of fitness measures- the Bayesian information criterion (BIC) and the 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 Heteroskedastic Models

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

$$Y_t = a_0 + \backslash i + s_t \quad \ldots\ldots (5)$$

$$h^2_n = ao + e^2_{t-i} + £\, t \quad \ldots\ldots (6)$$

The ARCH (1) model will estimated to determine the coefficient ai 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 fitness measures- the Bayesian information criterion (BIC) and the 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 Heteroskedastic Models

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

$$\mathbf{Y_t = a + y_M + e_t} \text{...} (7)$$

$$h^l = a + e^2{}_{t}\text{-}i + St \text{...} (8)$$

The GARCH (1, 1) model will be estimated to determine the coefficient ai. 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 fitness measures- the Bayesian information criterion (BIC) and the 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.

CHAPTER FOUR

DATA ANALYSIS AND INTERPRETATION OF FINDINGS

4.1 Introduction

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

4.2 Summary Statistics of Returns

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. This implies that on average stock prices have been rising and investors have reaped from investing in stocks at the Nairobi Stock Exchange (NSE). The rest of the summary statistics are positive except the minimum return. The results also show that returns are slightly positively skewed. This confirms the above assertion that returns on the NSE have been rising. However, the returns have a high kurtosis (153.6878) compared to the normal value of 3. This means that the NSE experiences extreme changes in returns more often than predicted by the normal distribution. Therefore, this suggests that returns might not be normally distributed as indicated by some studies.

Table 4.1 Summary Statistics for Returns on the NSE 2004 - 2008

Statistic	Value
Mean	0.000196
Standard Error	0.000488
Median	0.000184
Mode	0.000000
Standard Deviation	0.017300
Sample Variance	0.000299
Kurtosis	153.6878
Skewness	0.237320
Range	0.605989
Minimum	-0.300141
Maximum	0.305848
Sum	0.245984
Count	1258.000

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 stock returns

Variable	Rerturn	Error
Constant (n)	0.000233 (0.4853)	0.000233 (0.4853)
R(-l)	-1.1833 (-42.6278)***	
e(-l)		-1.1833 (-42.6278)**
AIC	-5.3072	-5.3072
ADF	-42.6278***	-42.6278**
LAG	22	22

Note: Critical for the ADF are -3.4353 , -2.8636 and -2.5679 at 1 %(***), 5% (**) and 10%(*) levels respectively

The ADF test was applied on the NSE price index returns and error terms in level form. The computed t-statistics are -42.6278 for both variables. These values are greater in absolute value compared to the critical value -3.4354 at 1 percent significance level. Therefore, the null hypothesis of unit root in both returns and errors of the constant returns model are stationary.

4.4 Estimation of Linear Models

Table 4.3 presents a summary of the results of estimating the Random Walk model and the Moving Average models. In order to select the optimal lag structure for the MA models 8 lags were considered. Using the AIC and the BIC did not provide clear cut results. Therefore, changes in each statistic (DAIC and DBIC, respectively) were computed and plotted against the respective lag length as show in Figure 4.1. The optimal lag corresponds to the lag that marks the beginning of the plateau in the variations of the AIC and the BIC. The optimal lag for each model is indicated by an asterisk in Table 4.3. Based on graph of changes in BIC and AIC against the lag length MA (2) is the optimal model at which returns estimation stabilizes and then slopes gently as more lags are added. At'other points the movement is sporadic and hence difficult to predict.

Table 4.3 Estimation Results of the Random Walk Model and the Moving Average Models

Variable	RW	MA(1)	MA(2)	MA(3)	MA(4)	MA(5)	MA(6)	MA(7)	MA(8)
Constant(n)	**0.00019 (0.4008)**	**0.00020 (0.41086)**	**0.0002 (0.4140)**	**0.00019 (- 0.4023)**	**0.00018 (0.3857)**	**0.00018 (0.3763)**	**0.00018 (0.3791)**	**0.00018 (0.3736)**	**0.00018 (0.3666)**
Lag		1	2*	3	4	5	6	7	8
e(-l)		0.07810 (2.7720)							
e(-2)			0.04031 (1.4065)						
e(-3)				-0.0079 (- 0.2762)					
e(-4)					0.01460 (0.6117)				
e(-5)						-0.0310 (- 1.0777)			
e(-6)							-0.0244 (- 0.8494)		
e(-7)								-0.0431 (-1.4969)	
e(-8)									0.01709 (0.5926)
AIC	-52754	-5.2784	-5.2776	-5.2753	-5.2734	-5.2719	-5.2701	-5.2695	-5.2675
BIC	-5.2713	-5.2702	-5.2729	-5.259	-5.2529	-5.2474	-5.2414	-5.2367	-5.2305

Note: 2* is the optimal lag

Figure 4.1: Graph for the Selection of the Optimal Lag of MA (q) Based on Change in AIC and BIC

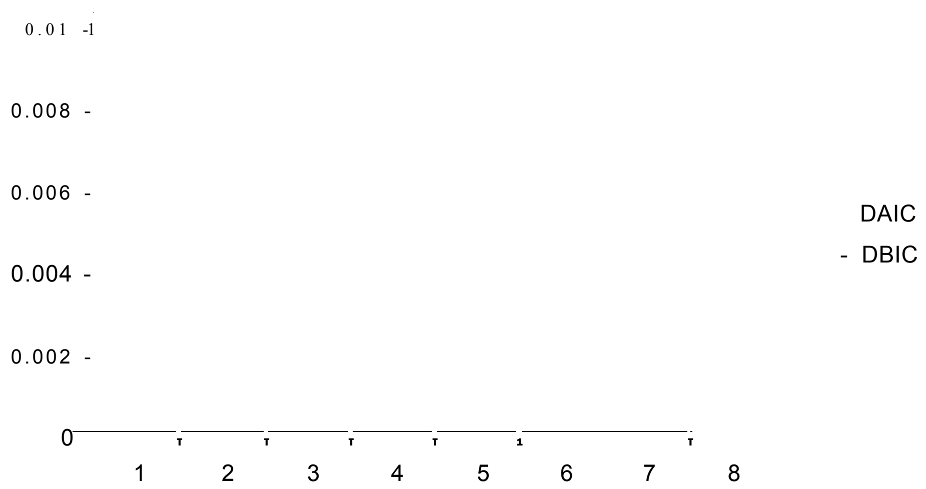


Table 4.4 presents a summary of the results of estimating the AR (p) models. The procedure used for estimating MA models was applied to estimate the best fitting AR model. The results show that AR (4) is the optimal model.

Table 4.4 Results of Estimating the Autoregressive Models

Variable	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)	AR(6)	AR(7)	AR(8)
Lag	1	2	3	4*	5	6	7	8
Constant^	0.00023 (0.4853)	0.00022 (0.4640)	0.00021 (0.4453)	0.00020 (0.4336)	0.0002 (0.4212)	0.00020 (0.4233)	0.00021 (0.4377)	0.00021 (0.4553)
R(-l)	-0.1833 (6.6045)							
R(-2)		0.0458 (1.6240)						
R(-3)			0.0484 (1.7127)					
R(-4)				0.0006 (0.0235)				
R{-5)					-0.01454 (0.5133)			
R(-6)						-0.0336 (1.1874)		
R(-7)							-0.3054 - 1.0764)	
R(-8)								-0.04859 (- 1.7125)
AIC	-5.3072	-5.3069	-5.3069	-5.3046	-5.3027	-5.3015	-5.3001	-5.3000

Note: 4* is the optimal lag

Figure 4.2 Optimal Lag of AR (p) Based on Changes in AIC and BIC

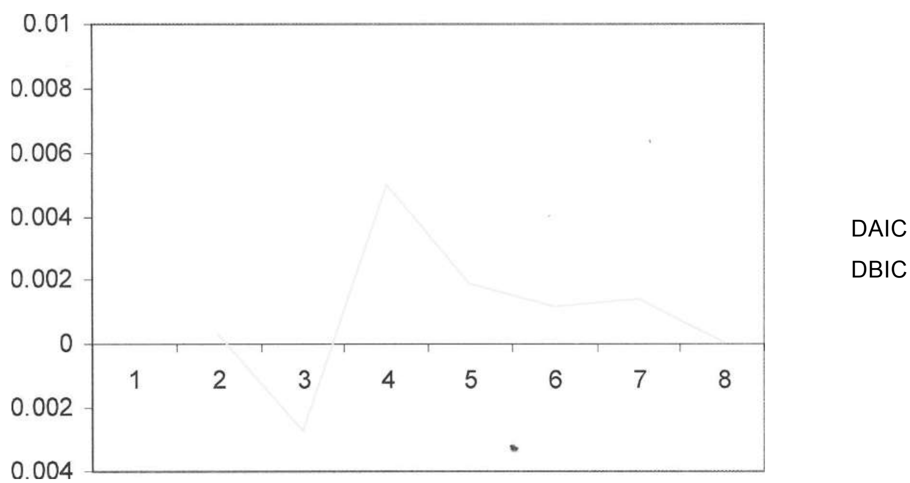
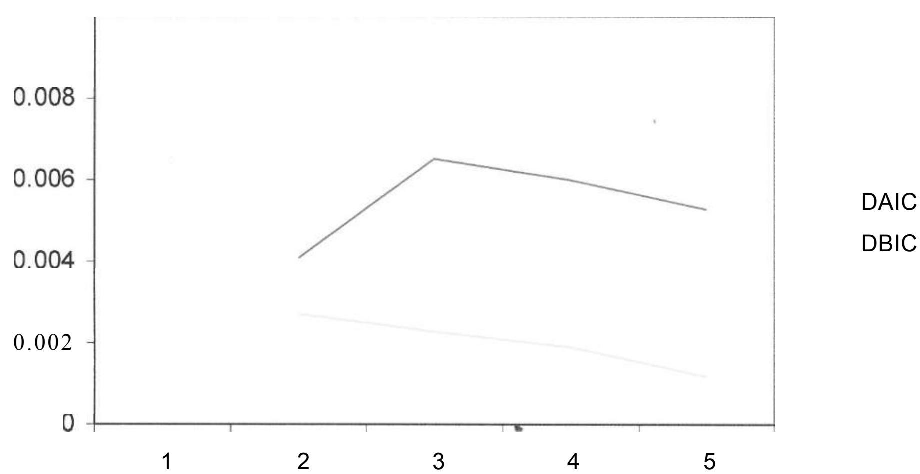


Table 4.5 summarizes the results of estimating ARMA (p, q) models. The ARMA (1, 3) is the optimal model based on the same procedure employed above. This is because it uses fewer variables than other family models and it parsimonious.

Table 4.5 Results of Estimating the ARMA(p, q) Models

Variable	ARMA(1,1)	ARMA(1,2)	ARMA(1,3)	ARMA(1,4)	ARMA(1,5)	ARMA(2,1)	ARMA(2,2)	ARMA(2,3)	ARMA(2,4)	ARM/
Constant(n)	0.000232 (0.4827)	**0.000234** **(0.4872)**	**0.000229** **(0.4758)**	**0.000220** **(0.4571)**	**0.00021** **(0.4444)**					
R(-l)	-0.1748 (-6.1932)	-0.1770 (-6.2673)	-0.1771 (-6.2562)	-0.1773 (6.2590)	-0.1779 (6.2800)					
R(-2)						1.1855 (0.4827)	1.1964 (0.4872)	1.1699 (0.4758)	1.1249 (0.4571)	1.0944 (0.444
e(-l)	0.0458 (1.6240)					-1.1396 (-0.4640)				
e(-2)		0.0484 (1.7127)					0.0484 (1.7127)			
e(-3)			0.000667 (0.0235)					0.000667 (0.02354)		
e(-4)				-0.01454 (-0.5133)					-0.01454 (-0.5133)	
e(-5)					-0.03366 (-1.1874)					-0.033 (-1.18"
AIC	-5.3069	-5.3069	-5.3046	-5.3027	-5.3015	-5.3069	-5.3069	-5.3046	-5.3027	-5.301
BIC	-5.2947	-5.2905	-5.2841	-5.2781	-5.2728	-5.2947	-5.2905	-5.2841	-5.2781	-5.272

Figure 4.3 Graph for the Selection of the Optimal Lag of ARMA (p, q) Based on Change in AIC and BIC



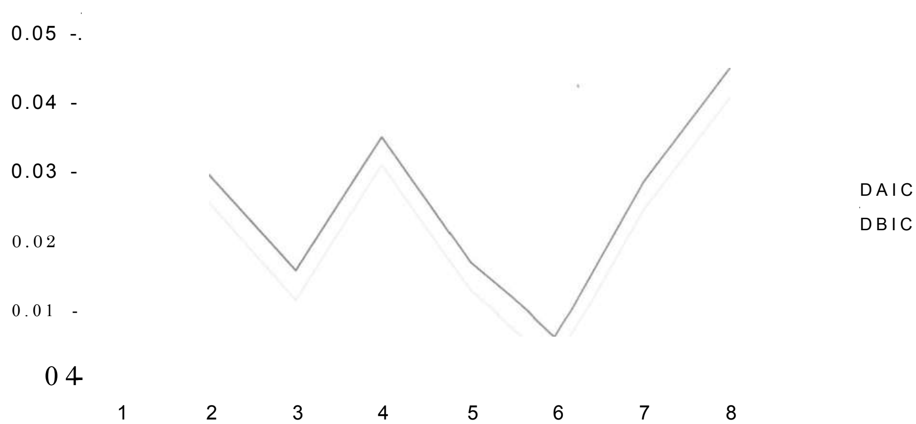
4.5 Estimation of Nonlinear Models

Table 4.6 summarizes the results of estimating the ARCH (p) models. The ARCH (1) model is the most optimal based on the probability value of 0.0000. This is because the BIC and AIC values show no stability as displayed in Table 4.6 and Figure 4.4 creating the need to use the p-values.

Table 4.6 Results of Estimating the ARCH (p) Models

Variable	ARCH(I)	ARCH(2)	ARCH(3)	ARCH(4)	ARCH(5)	ARCH(6)	ARCH(7)	ARCH(8)
Constant(n)	0.00155 (152.2956)	**3.83E-05 (0.0621)**	-0.0001 **(0.1529)**	**0.0021 (38.7284)**	**-0.00098 (-1.4174)**	**-0.001211 (- 1.7196)**	**-0.00083 (1.1325)**	**-0.000868 (- 1.1677)**
RESID(-1)^2	0.3711 (8.4913)							
RESID(-2)^2		-0.01619 (-1.3731)						
RESID(-3)^2			-0.00409 (-0.2548)					
RESID(-4)^2				0.06507 (2.3197)				
RESID(-5)^2					0.06772 (1.3245)			
RESID(-6)^2						-0.0003764 (-0.3343)		
RESID(-7)^2							-0.002685 (-0.7322)	
RESID(-8)^2								-0.0010 (-0.1119)
AIC	-5.7678	-5.7423	-5.7308	-5.6998	-5.6870	-5.6845	-5.6600	-5.6192
BIC	-5.7391	-5.7095	-5.6939	-5.6588	-5.6419	-5.6354	-5.6068	-5.5619

Figure 4.4 Optimal Lag of ARCH (p) Based on Change in AIC and BIC



The results of estimating the GARCH (p, q) models are shown in Table 4.7. The z-statistic and p-values were use to select the best model. The results indicate that the GARCH (1, 1) is the best fitting model. However, the GARCH (-1) element is only marginally significant with a p-value of 0.1909.

Table 4.7 Results of Estimating the GARCH (p, q) Models

Variable	GARCH(1,1)	GARCH(1,2)
Z Score	0.000229 (-23.126)	**0.00028 (6.2336)**
RESID(-1)^2	0.3259 (6.6820)	0.2507 (5.2968)
VAR{-1)	-0.05527 (1.3080)	
VAR (-2)		-0.0214 (-0.6671)
AIC	-5.7254	-5.6026
BIC	(-5.6927)	-5.5659

4.6 Prediction of Returns using Linear and Nonlinear Models

The predictive power of the models was measured by the Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). The models were ranked on the basis of the RMSE and MAE, the smaller the error the better the model. . The results are shown in Table 4.8.

Table 4.8: Comparison of Models Based on RMSE and MAE

Variable	MA(2)	AR(4)	ARMA(1,3)	ARCH(l)
RMSE	0.0173	0.0173	0.0173	0.0173
MAE	0.00751	0.00760	0.00753	0.0075

The MA(2) model has a Root Mean Squared Error of 0.0173 which is the same as the ARMA(1,3) at 0.0173 and ARCH(l) at 0.0173. The Mean Absolute Error shows the ARCH (1) model at 0.00751 followed by the MA (2) model at 0.00751. Based on the MAE the ARCH (1) model is the best in predicting stock returns.

4.7 Summary

The results of testing of linear models on the stock index based on B1C and A1C indicates that the MA (2) model is the best among linear models and within the nonlinear models the ARCH (1) model is the best. These models were then ranked against each other based on the Root Mean Squared Error and the Mean Absolute Error. Based on these criteria the ARCH (1) performs better with a lower Mean Absolute Error thus emerging as the best model in predicting stock returns.

CHAPTER FIVE

SUMMARY AND CONCLUSIONS

5.1 Introduction

This chapter presents the summary of the study 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 suggestions for further research.

5.2 Summary

Empirical literature shows that stock returns could be nonlinear. However, studies on the nonlinear behavior of stock returns in emerging markets are limited. This study aimed at filling this knowledge gap by comparing linear and nonlinear models in predicting stock returns at the NSE. The study compared the Random Walk Model, Moving Average Models, Autoregressive model ARMA models, Autoregressive conditional Heteroskedasticity (ARCH) models.

The Nairobi stock Exchange index was used as a proxy for stock prices and hence changes in the NSE index represented stock returns. The sample period consisted of daily observations of the NSE index. The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were used to select the best fitting model from each type of models. Then the best fitting model from each type of models were used to predict returns over the sample period of three months. The mean absolute error (MAE) and the Root mean square error (RMSE) were used to select the best model. The results indicate that (ARCH (1) performs better than the other models. Therefore this concluded that nonlinear models are better than linear models in predicting stock returns on the NSE hence stock returns are nonlinear.

5.3 Conclusions

From the data analysis in chapter four, this study draws the following conclusions. First MA(2) model is the best linear model while the ARCH(l) model is the best nonlinear model, then based on the Mean Absolute Error (MAE) and the Root Mean Squared error(RMSE) the ARCH(l) model emerges as the best. Second, returns at the NSE are nonlinear.

5.3 Limitations

The study covered a period covered only five years, from January 2004 to December 2008. Therefore, a study covering a longer period may give different results.

5.4 Recommendations to Investors

The results of this study indicate that returns are predictable. Non linear models give the best prediction. Therefore reliance on linear models to make investment decisions will lead to sub optimal results.

5.5 Suggestions for Further Research

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

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Appendix

	2004		*2005*		2006		2007		2008
DATE	**INDICES**	**DATE**	**INDICES**	**DATE**	**INDICES**	**DATE**	**INDEX**	DATE	INDEX
2-Jan-04	2753.33	3-Jan-05	2955.99	3-Jan-06	3991.18	2-Jan-07	5679.57	2-Jan-08	5167.18
5-Jan-04	2739.46	4-Jan-05	2980.48	4-Jan-06	4011.80	3-Jan-07	5714.18	3-Jan-08	5133.48
6-Jan-04	2745.73	5-Jan-05	2991.32	5-Jan-06	4014.89	4-Jan-07	5811.58	4-Jan-08	5015.50
7-Jan-04	2743.87	6-Jan-05	2981.10	6-Jan-06	4030.97	5-Jan-07	5895.68	7-Jan-08	5180.14
8-Jan-04	2762.47	7-Jan-05	3007.94	9-Jan-06	4074.71	8-Jan-07	5962.46	8-Jan-08	5419.93
9-Jan-04	2788.98	10-Jan-05	3018.55	10-3an-06	4072.46	9-Jan-07	6026.51	9-Jan-08	5338.77
12-Jan-04	2802.82	II-Jan-05	3049.92	II-Jan-06	4101.76	10-Jan-07	6085.59	10-Jan-08	5341.82
13-Jan-04	2797.77	12-Jan-05	3065.05	12-Jan-06	4125.40	11-Jan-07	6117.35	11-Jan-08	5335.23
14-Jan-04	2803.74	13-Jan-05	3082.52	13-Jan-06	4140 66	12-Jan-07	6161.46	14-Jan-08	5207.16
15-Jan-04	2818.29	14-Jan-05	3102.16	16-Jan-06	4177 24	15-Jan-07	6125.28	15-Jan-08	5124.45
16-Jan-04	2834.60	17-Jan-OS	3092.89	17-Jan-06	4205.72	16-Jan-07	6066 66	16-Jan-08	5206.15
19-Jan-04	2873.43	18-Jan-05	3083.38	18-Jan-06	4217.37	17-Jan-07	6041.42	17-Jan-08	5111.74
20-Jan-04	2877.93	19-Jan-05	3073.82	19-Jan-06	4204.68	18-Jan-07	603083	18-Jan-08	5098.48
20-Jan-04	2877.93	20-Jan-05	3085.56	20-Jan-06	4198.31	19-Jan-07	6025.41	22-Jan-08	5063.44
21-Jan-04	2857.59	21-Jan-05	3078.93	23-Jan-06	4194.02	22-Jan-07	6027.17	23-Jan-08	4942.30
22-Jan-04	2860.23	24-Jan-05	3091.35	24-Jan-06	4183 91	23-Jan-07	6060.21	24-Jan-08	4912.25
23-Jan-04	2893.12	25-Jan-05	3091.19	25-Jan-06	4196.48	24-Jan-07	601647	25-Jan-08	4967.88
26-Jan-04	2957.45	26-Jan-05	3092.82	26-Jan-06	4159.16	25-Jan-07	6010.17	26-Jan-08	4811.79
27-3an-04	3040.33	27-Jan-05	3098.74	27-Jan~06	4173.50	26-Jan-07	5961.61	29-Jan-08	4576.31
28-Jan-04	3159.28	28-Jan-05	3092.24	30-3an-06	4169.99	29-Jan-07	5949.71	30-Jan-08	4690.72
29-Jan-04	3183.10	31-Jan-05	3094.38	31-Jan-06	4171 80	30-Jan-07	5870.68	31-Jan-08	4712.71
30-Jan-04	3157.88					31-Jan-07	5774.27		
								1-Feb-08	4795.96
2-Feb-04	3136.14	I-Feb-05	3128.60	I-Feb-06	4167.14			4-Feb-08	4724.57
3-Feb-04	3107.34	2-Feb-05	3132.43	2-Feb-06	4159.17	1-Feb-07	573905	5-Feb-08	4677.47
4-Feb-04	3090.29	3-Feb-05	3137.04	3-Feb-06	4163.64	2-Feb-07	5663.65	6-Feb-08	4637.45
5-Feb-04	3100.67	4-Feb-05	3167.79	6-Feb-06	4156.36	5-Feb-07	5633.61	7-Feb-08	4651.94
6-Feb-04	3138.37	7-Feb-05	3181.29	7-Feb-06	4137 82	6-Feb-07	5628.88	8-Feb-08	4657.60
9-Feb-04	3145.82	8-Feb-05	3194.21	8-Feb-06	4131.78	7-Feb-07	5649.99	11-Feb-08	4784.00
10-Feb-04	3149.03	9-Feb-05	3184.99	9-Feb-06	4119.25	8-Feb-07	5710.21	12-Feb-08	4857.64
II-Feb-04	3166.09	10-Feb-05	3198.23	10-Feb-06	4100.22	9-Feb-07	5817.04	13-Feb-08	4957.54
12-Feb-04	3144.65	II-Feb-05	3198.06	13-Feb-06	4101.26	12-Feb-07	5895.18	14-Feb-08	4996.08
13-Feb-04	3175.80	14-Feb-05	3211.76	14-Feb-06	4089 44	13-Feb-07	5884.26	15-Feb-08	4986.06
16-Feb-04	3177.83	15-Feb-05	3209.01	15-Feb-06	4088.26	14-Feb-07	5867.03	18-Feb-08	4958.80
17-Feb-04	3153.42	16-Feb-05	3210.45	16-Feb-06	4092,07	14-Feb-07	5266.54	19-Feb-08	4932.52
18-Feb-04	3162.81	17-Feb-05	3203.19	17-Feb-06	4071.00	14-Feb-07	5867.03	20-Feb-08	4951.86
19-Feb-04	3131.70	18-Feb-05	3191.78	20-Feb-06	4093.45	14-Feb-07	5867,03	21-Feb-08	4929.78
20-Feb-04	3125.57	21-Feb-05	3187.01	21-Feb-06	4068.81	14-Feb-07	5867.03	22-Feb-08	4924.35
23-Feb-04	3161.81	22-Feb-05	3207.73	22-Feb-06	4068.29	15-Feb-07	5773.29	25-Feb-08	4933.08
24-Feb-04	3157.10	23-Feb-05	3203.34 §j	23-Feb-06	4069.16	16-Feb-07	5798 73	26-Feb-08	4909.76
25-Feb-04	3157.64	24-Feb-05	3213.28	24-Feb-06	4062.56	19-Feb-07	5766.46	27-Feb-08	4858.47
26-Feb-04	3152.06	25-Feb-05	3219.37	27-Feb-06	4050 14	20-Feb-07	5771.39	28-Feb-08	4843.75
27-Feb-04	3175.36	28-Feb-05	3212.81	28-Feb-06	4056.63	21-Feb-07	5816 77	29-Feb-08	5072.41
						22-Feb-07	5763.85		
						23-Feb-07	5732.67	3-Mar-08	5142.27
I-Mar-04	3173.90	I-Mar-05	3209.70	I-Mar-06	4045.13	26-Feb-07	5665 79	4-Mar-08	5268.04
2-Mar-04	3178.82	2-Mar-05	3185.68	2-Mar-06	4043.92	27-Feb-07	5534.20	5-Mar-08	5377.60
2-Mar-04	3102.65	3-Mar-05	3204.64	3-Mar-06	4055.78	28-Feb-07	5387.28	6-Mar-08	5405.38
4-Mar-04	3129.18	4-Mar-05	3208.66	6-Mar-06	4023.34			7-Mar-08	5354.68
5-Mar-04	3155.45	7-Mar-05	3186.81	7-Mar-06	3989.76			10-Mar-08	5317.34
8-Mar-04	3183.95	8-Mar-05	3187.83	8-Mar-06	3916.55	1-Mar-07	5237.68	11-Mar-08	5205.38
9-Mar-04	3153.47	9-Mar-05	3206.67	9-Mar-06	3878.88	2-Mar-07	5245.62	12-Mar-08	5159.32
10-Mar-04	3134.90	10-Mar-05	3224.00	10-Mar-06	3872.21	5-Mar-07	5292.14	13-Mar-08	5111.01
1I-Mar-04	3089.89	II-Mar-05	3212.65	13-Mar-06	3863.74	6-Mar-07	5252.46	14-Mar-08	4959.44
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16-Mar-04	2987.05	16-Mar-05	3179.20	15-Mar-06	3916.25	9-Mar-07	5268.99	19-Mar-08	4809.26
17-Mar-04	2982.90	17-Mar-05	3168.10	16-Mar-06	3924.75	12-Mar-07I	5239.01	20-Mar-08	4907.29
18-Mar-04	2944.21	18-Mar-05	3170.25	17-Mar-06	3955.42	13-Mar-07	5250 04	25-Mar-08	4905.77
19-Mar-04	2939.31	2I-Mar-05	3154.25	20-Mar-06	3973.11	14-Mar-07	5241.25	26-Mar-08	4851.29
22-Mar-04	2937.16	22-Mar-05	3149.34	21-Mar-06	3973.75	15-Mar-07	5200.75	27-Mar-08	4835.26
23-Mar-04	2923.34	23-Mar-05	3148.87	22-Marjpe	4005.35	16-Mar-07	5171.13	28-Mar-08	4855.36
24-Mar-04	2887.58	24-Mar-05	3155.01	23-Mar-06	4038.55	19-Mar-07	5103.83	31-Mar-08	4843.17
25-Mar-04	2865.81	29-Mar-05	3137.85	24-Mar-06	4067.41	20-Mar-07!	4961 89		
26-Mar-04	2849.55	30-Mar-05	3128.40	27-Mar-06	4085.61	21-Mar-07	4809.72	1-Apr-08	4839.14
29-Mar-04	2820.05	3I-Mar-05	3126.07	28-Mar-06	4102.61	22-Mar-07	4637 31	2-Apr-08	4837.08
30-Mar-04	2793.20			29-Mar-06	4115.90	23-Mar-07	4465.09	3-Apr-08	4892.25

	2004		2005		2006		2007		2008
DATE	INDICES	DATE	INDICES	DATE	INDICES	DATE	INDEX	DATE	INDEX
31-Mar-04	2770.60			30-Mar-06	4115.30	26-Mar-07	4489.76	4-Apr-08	4951.73
		I-Apr-05	3139.54	31-Mar-06	4101.64	27-Mar-07l	4614.40	7-Apr-08	4996.14
		4-Apr-05	3148.50			28-Mar-07	4791.22	8-Apr-08	5015.29
I-Apr-04	2721.33	5-Apr-05	3141.19			29-Mar-07	4978.93	9-Apr-08	5010.42
2-Apr-04	2673.84	6-Apr-05	3150.81	3-Apr-06	4092.48	30-Mar-07j	5133 67	10-Apr-08	5035.08
5-Apr-04	2664.30	7-Apr-05	3163.26	4-Apr-06	4086.27			11-Apr-08	5021.82
6-Apr-04	2600.26	8-Apr-05	3163.95	5-Apr-06	4056.65			14-Apr-08	5070.81
7-Apr-04	2576.23	1I-Apr-05^	3159.03	6-Apr-06	4048.36	2-Apr-07j	5154.76	15-Apr-08	5109.94
8-Apr-04	2581.46	12-Apr-05	3137.24	7-Apr-06	4025.30	3-Apr-07	5183.11	16-Apr-08	5107.23
13-Apr-04	2595.04	13-Apr-05	3145.80	10-Apr-06i	4000.41	4-Apr-07	5216.68	17-Apr-08	5141.29
14-Apr-04	2668.22	14-Apr-05	3138.64	II-Apr-06	3984.82	5-Apr-07	5215.20	18-Apr-08	5141.62
15-Apr-04	2693.88	15-Apr-05	3138.17	12-Apr-06	3976,32	10-Apr-07	5227.81	21-Apr-08	5126.15
18-Apr-04	2727.73	18-Apr-05	3137.01	13-Apr-06	3973.79	11-Apr-07.	5218.64	22 Apr-08	5126.26
19-Apr-04	2734.68	19-Apr-05	3138.94	18-Apr-06	3995.83	12-Apr-07	5228,75	23-Apr-08	5156.53
20-Apr-04	2742.33	20-Apr-05	3145.29	19-Apr-06	3974 64	13-Apr-07j	5242.88	24-Apr-08	5184.06
21-Apr-04	2758.22	21-Apr-05	3164.35	20-Apr-06	3960.19	16-Apr-0*T	5228.88	25-Apr-08	5207.23
22-Apr-04	2755.23	24-Apr-05	3165.19	24-Apr-06	3968.63	17-Apr-07	5185,67	28-Apr-08	5240.39
23-Apr-04	2747.52	26-Apr-05	3204.47	25-Apr-06	3986 74	18-Apr-07	5085.89	29-Apr-08	5255.42
26-Apr-04	2735.18	27-Apr-05	3206.43	26-Apr-06	3991.26	19-Apr-07	5092.07	30-Apr-08	5336.03
27-Apr-04	2725.34	28-Apr-05	3217.01	27-Apr-06	4004,48	20-Apr-07	5099.00		
28-Apr-04	2720.76	29-Apr-05	3227.59	28-Apr-06	4025.21	23-Apr-07	5105.41	2-May-08	5364.72
29-Apr-04	2704.81					24-Apr-07	5178 07	5-May-08	5355.02
30-Apr-04	2707.60					25-Apr-07	5173.33	6-May-08	5356.24
		3-May-05	3228.14	2-May-06	4040.05	26-Apr-07	5211.27	7-May-08	5385.14
		4-May-05	3233.70	3-May-06	4076.97	27-Apr-07	5148.07	8-May-08	5324.55
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6-May-04	2650.67	10-May-05	3258.08	9-May-06	4220.52	2-May-07	5151.46	14-May-08	5199.38
7-May-04	2626.12	II-May-05	3266.55	10-May-06	4278.55	3-May-07	5169.53	15-May-08	5169.22
10-May-04	2629.89	12-May-OS	3271.01	II-May-06	4292.36	4-May-07	5116,02	16-May-08	5170.55
II-May-04	2674.23	13-May-05	3292.75	12-May-06	4316.72	7-May-07	5091.12	19-May-08	5153.13
12-May-04	2679.62	16-May-05	3245.72	15-May-06	4393.17	8-May-07	5101,43	20-May-08	5163.87
13-May-04	2666.10	16-May-05	3291.93	16-May-06	4451.41	9-May-07	5067.74	21-May-08	5132.85
14-May-04	2644.80	17-May-05	3314.17	17-May-06	4447.99	10-May-07	5071.33	22-May-08	5159.42
17-May-04	2637.69	18-May-05	3320.71	18-May-06	4441.54	11-May-07	5114.17	23-May-08	5149.96
18-May-04	2638.86	19-May-05	3322.99	19-May-06	4411.81	14-May-07	5181.77	26-May-08	5119.15
19-May-04	2621.22	20-May-05	3353.51	22-May-06	4389.69	15-May-07	5169.28	27-May-08	5094,21
20-May-04	2593.99	23-May-05	3346.64	23-May-06	4383.83	16-May-07	5179.21	28-May-08	5101.04
21-May-04	2567.69	24-May-05	3383.76	24-May-06	4363,97	17-May-07	5175.11	30-May-08	5175.83
24-May-04	2585.98	24-May-05	3341.67	25-May-06	4322.91	18-May-07	5167.34		
25-May-04	2586.29	25-May-05	3418.16	26-May-06	4338.42	21-May-07	'5191.53	3-Jun-08	5253.53
26-May-04	2607.80	26-May-05	3460.17	29-May-06	4358.75	22-May-07	5154 41	4-Jun-08	5341.41
27-May-04	2667.73	27-May-05	3492.58	30-May-06	4365 90	23-May-07	5108.69	5-Jun-08	5401.76
28-May-04	2680.75	30-May-05	3492.96	31-May-06	4349.75	24-May-07	5132.74	6-Jun-08	5477.70
31 May-04	2689.14	31-May-05	3505.39			25-May-07	5134,54	9-Jun-08	5445.67
						28-May-07	5118.39	10-Jun-08	5334.50
				2-Jun-06	4339.47	29-May-07	5048.23	11-Jun-08	5309.08
2-Jun-04	2689.12	2-Jun-05	3500.04	5-Jun-06	4294.44	30-May-07	5051.21	12-Jun-08	5328.13
3-Jun-04	2681.15	3-Jun-05	3506.05	6-Jun-06	4280.96	31-May-07	5001.77	13-Jun-08	5320.28
4-Jun-04	2662.49	6-Jun-05	3532.14	7-Jun-06	4221.57			16-Jun-08	5321.69
7-Jun-04	2647.13	7-Jun-05	3544.68	8-Jun-06	4204,34			17-Jun-08	5307.71
8-Jun-04	2653.02	8-Jun-05	3612.02	9-Jun-06	4189.66	4-Jun-07	5043.35	18-Jun-08	5311.82
9-Jun-04	2649.06	9-Jun-05	3657.94	12-Jun-06	4194.59	5-Jun-07i	5063.98	19-Jun-08	5284.08
I(K)un-04	2648.76	10-Jun-05	3716.90	13-Jun-06	4214.38	6-Jun-07	'5065.62	20-Jun-08	5271.90
II-Jun-04	2639.83	13-Jun-05	3731.45	14-Jun-06	4216,79	7-Jun-07	5054 35	23-Jun-08	5251.72
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15-Jun-04	2688.83	15-Jun-05	3751.18	16-Jun-06	4272.43	11-Jun-07	5064.57	25-Jun-08	5180.67
16-Jun-04	2693.18	160un-05	3759.72	19-Jun-06	4288.31	12-Jun-07	5074.08	26-Jun-08	5159.81
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21-Jun-04	2693.71	21-Jun-05	3828.90	2iMun-06	4286.30	15-Jun-07	5137.45		
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23-Jun-04	2676.91	23-Jun-05	3858.11	26-Jun-06	4227.16	19-Jun-07	5141.52	2-Jul-08	5169.19
24-Jun-04	2667.40	24-Jun-05	3860.83	27-Jun-06	4218.10	20-Jun-07,	5147.85	3-Jul-08	5158.81
25-Jun-04	2669.34	27-Jun-05	3881.94	28-Jun-06	4250.20	21-Jun-or	5144.93	4-Jul-08	5129.73
28-Jun-04	2647.27	28-Jun-05	3911.20	29-Jun-06	4239.96	22-Jun-07	5124.14	7-JUI-08	5112.16

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S-Jul-04	2632.14	5-JUI-05	4071.66	6-Jul-06	4246 38			16-Jul-08	5057.96
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14-Jul-04	2689.32	14-Jul-05	4246.36	17-JUl-06	4271.37	10-JUI-07	5120.40	25-JUI-08	4963.46
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20-JUI-04	2655.60	20-Jul-05	4068.23	21-Jul-06	4244 16	16-JUI-07	5121.08	31-Jul-08	4868.27
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15-Sep-04	2652.05	16-Sep-05	3801.87	20-Sep-06	4876.13	10-Sep-07,	5582.38	2-Oct-08	4180.34
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21-Sep-04	2648.11	23-Sep-05	3791.57	28-Sep-06	4881.10	18-Sep-07	5490.99	13-Oct-08	3815.64
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27-Sep-04	2652.27			4-Qct-06	4937.20	26-Sep-07	5282.77	22-Oct-08	3563.87
28-Sep-04	2642.68			5-OcM)6	4946.12	27-Sep-07	5176.88	23-Oct-08	3459.33
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28-Oct-04	2834.62	8-NOV-05	3915 42	13-NOV-06	560825	31-0ct-07	4971 04		
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		15-Dec-05	3944.50	14-D&C-06	5582.42	29-NOV-07	5215.36		
		16-Dec-05	3963.26	15-Dec-06	5589.64	30-NOV-07	5234.54		
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3-Dec-04	2954.09	21-Dec-05	3957.08	20-Dec-06	5525 40	3-Dec-07|	5205.06		

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8-Dec-04	2984.60	27-Dec-05	3968.97	27-Dec-06	5522.81	6-Dec-07	5266.78		
9-Dec-04	2986.98	28-Dec-05	3979.61	28-Dec-06	5560.44	7-DBC-07	5265.15		
10-Dec-04	2999.54	29-Dec-05	3969.40	29-Dec-06	5640.91	10-Dec-07	5269.08		
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21-Dec-04	2944.48					14-Dec-07	5339.80		
22-Dec-04	2942.06					17-Dec-07	5278.73		
23-Dec-04	2920.79					18-Dec-07	5291.69		
24-Dec-04	2923.86					20-Dec-07	5287.93		
28-Dec-04	2923.81					21-Dec-07	5339.75		
29-Dec-04	2907.45					24-Dec-07	5444.83		
30-Dec-04	2928.35								
31-Dec-04	2945.58								