Predictive Models for Nairobi Stock Exchange share prices

A

Dissertation

Submitted to the board of Postgraduate studies

Egerton University

in partial fullfilment of the requirement for the degree

of

Master of Science in Statistics

by

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APRIL

1998

DECLARATION

This dissertation is my original work and has NEVER been presented in any institution for award of ANY degree.

Signature.. Date..............3/4/1998..............

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APPROVAL PAGE

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ACKNOWLEDGEMENT

I thank the almightly God for giving me patience, sound mind and good health which has enable me to achieve this goal.

I owe my supervisor Dr. Dankit K. Nassiuma sincere gratitude, for his cooperation and material support particularly for availing his computer which I used for analysing the stock data. His criticisms and suggestions have been the guilding beacons in building the stock models.

I am also indebted to my lecturers Dr. Nassiuma D.K., Dr. Ali S.I and Dr. F. Onyango for their endless words of wisdom, advice and challenge which made me develop interest in statistics. I am also grateful to my colleagues Obwoge, Owili and Mwangi for their cooperation and willingness to share and exchange ideas.

Thanks to the board graduate school for securing funds for me throughout the entire programme, without which completing the programme could have been a nightmare.

I extend my sincere gratitude to my parents, family members and friends for their support, encouragement and challenge. In particular I was inspired by the academic achievement of my brothers; Musembi Bsc.(Nairobi) and Muthui Bsc (Egerton) which I yearned to emulate.

Lastly my special thanks and acknowledgement go to my wife Jane for her understanding, encouragement and comfort throughout the entire course and to Lorraine my daughter whose sight was a constant source of inspiration.

ABSTRACT

The Nairobi Stock Exchange (NSE) founded in 1954, as a voluntary organisation of the stockbrokers is now one of the most active capital markets in African where investors buy and sell shares and other securities. The share prices in the stock market usually vary with time and this can be attributed to factors such as changes in the economic growth of the region, threat of war or strikes, government policies or political changes. These factors are non deterministic in nature and highly autocorrelated.

Share prices movements in the NSE market are measured by an index based on 20 representative companies and is calculated on a daily basis. The index is a general price movement indicator based on a sample or upon all the stock market companies and the sale and purchase decisions are based on its movements.

The forecasts of future trends of share prices are often based on subjective factors, thus in this study appropriate forecasting models for determining the future share prices trends on the market are developed. The models are based on the stock market index as well as the share prices for Barclays Bank of Kenya Ltd, ICDC Investment Company Ltd, Kenya Commercial Bank Ltd, Standard Chartered Bank Kenya Ltd, BAT Kenya Ltd and Kenya Breweries Ltd.

Dedicated to

My Loving Parents, My Dear Wife

and

Lorraine My Beloved Daughter.

CONTENTS

CHAPTER ONE

INTRODUCTION AND LITERATURE REVIEW

1.1 Background

A stock exchange is a market which deals with the exchange between publicly quoted companies, government and municipal securities for money. The Nairobi stock exchange which was formed in 1954 as a voluntary organisation of stock brokers is now one of the most active capital markets in Africa.

The administration of Nairobi stock exchange limited is now under fully operational secretariat, located on the first floor of Nation centre, Kimathi street, Nairobi. As a capital market institution, the stock exchange plays a vital role in the process of economic development. It helps mobilize domestic savings thereby bringing about the reallocation of financial resources from dormant to active investors. Long term investments are made liquid as the transfer of securities between share holders is facilitated. The exchange has also enabled companies to engage local participation in the equity, thereby giving kenyans an opportunity to own shares.

The Nairobi stock exchange deals in both variables income securities and fixed securities. The former are the ordinary shares which have a fixed rate of dividend payable, as the dividend is dependent upon both proficability of the company and what the board of directors decide. The latter includes the preference shares, debentures stock, municipal and government stock and these have a fixed rate of interest (dividend) which is not dependent on profitability.

A share is a unit of ownership and represents the money which a shareholder originally put into building up a company. When investors invest in a company by buying shares, they become shareholders and they are entitled to vote on company policies, appoint and dismiss plant directors and if the company makes a profit, they are entitled to a share of it in form of dividend.

The share prices in the stock market usually vary with time. This can be attributed to factors such as changes in the economic growth of the region, government policies, threats of war and strikes within the region or in companies, political changes or the stability of companies. These factors are non deterministic in nature and are highly autocorrelated.

Share price movement in the Nairobi stock exchange market is measured by an index based on 20 representative companies and is calculated on a daily basis. The index is a general price movement indicator based upon a sample of the stock market companies or upon all of them and thus the sale and purchase decisions are based on its movement.

The forecast of future trends of the share prices is often based on subjective factors and it is therefore possible that any two people particularly stockbrokers may arrive at different subjective forecasts if presented with information that a particular share has reached a historically high value. Therefore it is for this particular reason that we wish to apply quantitative forecasting techniques to develop appropriate forecasting models for determining the future trends of the share prices in the market based on the past information of the share prices and hence this is what entitles this dissertation. The models developed are based on the stock market index as well as the share prices for Barclays Bank of Kenya Ltd, ICDC Investment Company Ltd, Kenya Commercial Bank Ltd, Standard Chartered Bank Kenya Ltd, BAT Kenya Ltd and Kenya Breweries Limited.

1:2 Stochastic Time Series Models

1.2.1 Linear Models

A set of observations obtained sequentially in time is known as a time series. An observed time series $(Z_1, Z_2, \ldots, Z_n)$ can be thought of as a particular realization of a stochastic process which can either be linear or non linear. When such observations are represented as a linear function of a sequence of mutually independent and identically distributed (iid) random variables, it is referred to as a linear process, otherwise it is a nonlinear process. Stochastic processes in general can be described by an n-dimensional probability distribution $p(Z_1, Z_2, \ldots, Z_n)$.

The autoregressive moving average processes abbrevited as (ARIMA(p,q)) are the most frequently and widely applied class of models in time series modelling. These types of models have provided the basis for much of the traditional model fitting methodology. A general autoregressive moving average model is a linear process given by the general equation

$$\Phi(B)X_t = \Theta(B)e_t$$

where B is the backshift operator such that

$$B_k X_t = X_{t-k}$$

for some integer k. The set (e_t) is a sequence of uncorrelated random variables with mean zero and constant variance. The polynomials

$$\Phi(B) = 1 + \sum_{i=1}^{p} \phi_i B^i$$

and

$$\Theta(B) = 1 + \sum_{i=1}^{q} \theta_i B^i$$

are the autoregressive and the moving average operators of order p and q respectively and with all the roots of the polynomial equations

$$\Phi(B) = 0 \text{ and } \theta(B) = 0$$

being outside the unit circle if the process is both stationary and invertible respectively.

The autoregressive moving average process is a composition of the autoregressive (AR(p)) and moving average (MA(q)) processes. The p^{th} order autoregressive process components is expressed as

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots \phi_p X_{t-p} + e_t$$

where ϕ_i's are the model parameters and e_t is as defined earlier.

The autoregressive models date back to Yule (1921, 1927) when he developed the first order autoregressive (AR(1)) process written as

$$X_t = \phi X_{t-1} + e_t$$

following his observation that any successive values which are autocorrelated can be represented as a linear combination of a sequence of uncorrelated random variables. The first autoregressive process is also called a *Markov process* because the observation X_t at time t only depends on the previous observation X_{t-1} at time t-1.

The moving average process developed by slutzky (1937) has a general functional form similar to the linear filter representation though with a finite order q. Thus its functional form is given by

$$X_t = e_t + \theta_1 e_{t-1} + \ldots + \theta_q X_{t-q}$$

while the first order moving average (MA(1)) process is expressed as

$$X_t = \theta e_{t-1} + e_t$$

where θ_i's are the model parameters and $\{e_t\}$ are as defined earlier.

A stochastic process which is not constant in its first and second order properties is said to be nonstationary. In particular, processes whose second order properties vary with time (heterogenous nonstationary) are appropriately transformed to attain stationarity (see for example Priestley, 1988). A more general method which leads to standard statistical inference about the choice of transformation was analysed by Box and Cox (1964) who considered the parametric family of *power transformations* given by

$$g(X_t) = \begin{cases} \dfrac{(X_t^{\lambda} - 1)}{\lambda} & if\ \lambda \neq 1 \\ \ln X_t & if\ \lambda = 0 \end{cases}$$

The values of the index λ can either be chosen before hand using the mean and the variance or the range and the median plots (see Mill, T.C (1990) pg 49) or estimated with other parameters (Φ, θ, σ) (see Nelson and Granger, 1979).

A nonstationary series in mean is typically characterised by occasional increasing or decreasing trends in mean level. Since power transformations preserve order, they cannot by themselves stabilise a time varying mean. Thus time varying first order processes are usually differenced to attain stationarity (Box and Jenkins (1970)). Polynomial trends of order d, can be removed by taking the d^{th} difference

$$\nabla^d X_t = (1-B)^d X_t.$$

Seasonal nonstationary can also be removed by *seasonal* differencing. The s^{th} difference is defined as

$$\nabla^s X_t = X_t - X_{t-s} = (1-B^s) X_t$$

where s is the seasonal period and it is equal to 4 or 12 for quarterly or monthly data respectively.

Differencing of a stationary series still yields another stationary series, but *overdifferencing* can lead to serious difficulties. For one, it leads to complicated models with more parameters than the previous stationary models and it also has a larger variance than the previous differenced stationary process.

Thus the behaviour of the sample variance associated with different values of d can provide a useful means of deciding on the appropriate degree of differencing. Infact Anderson (1976) indicated that the sample variance tends to decrease until a stationary sequence has been attained but tends to increase on overdifferencing. However, this is not always the case but the idea can be employed as an *auxilliary* method of determining the appropriate values of d.

A nonstationary ARMA (p,q) process differenced d times is said to follow an autoregressive integrated moving average process abbreviated as ARIMA(p,d,q) and is expressed as

$$\Phi(B)\nabla^d X_t = \Theta(B)e_t$$

where the difference operator ∇ is such that

$$\nabla^d = (1-B)^d$$

and $\Phi(B)$, $\theta(B)$ and e_t are as earlier defined. The simplest ARIMA process is the ARIMA(0,1,0) usually called the *random walk* process and is expressed as

$$X_t = X_{t-1} + e_t$$

1.2.2 Nonlinear Models

Not all time series data can be adequately modelled using linear models and this has led to a search for alternative models to the linear models where one possible direction has been to assume nonlinearity while retaining the normally assumption on the innovation sequence. A considerable number of nonlinear models have been developed as a result of this assumption. They include the *Bilinear models* (see Granger and Anderson, 1978) abbreviated as B(p,q,r,s) and which are a generalization of the univariate ARMA(p,q) models with the genaral form

$$\Phi(B)X_t = \Theta(B)e_t + \sum_{i=1}^{r}\sum_{j=1}^{s}\sigma_{ij}X_{t-i}e_{t-j}$$

where the term

$$\sum_{i=1}^{r}\sum_{j=1}^{s}\sigma_{ij}X_{t-i}e_{t-j}$$

is a bilinear form in e_{t-j} and accounts for the non-linear character of the model. However, if the σ_{ij} are zeros (i.e $\sigma_{ij}=0$ for all i and j) then the bilinear model reduces to a linear ARMA model.

Threshold autoregresssive models (TAR) (see Tong and Lim (1980), Tong (1983)) represent another set of nonlinear models which are widely utilized. These were developed by Tong and Lim (1980) to facilitate the modelling of series that exhibit limit cycles. The first order threshold autoregressive model denoted as TAR(1) has a functional form given by

$$X_t = \begin{cases} \phi^{(1)}X_{t-1} + e_t^{(1)}, & if \;\; X_{t-1} < d \\ \phi^{(2)}X_{t-1} + e_t^{(2)}, & if \;\; X_{t-1} \geq d \end{cases}$$

and this can be extended to a 'k-threshold' model of the form

$$X_t = \phi^{(i)}X_{t-1} + e_t^{(i)} \;\; if \;\; X_{t_1} \epsilon R_{(i)}, \;\; i=1,2,\ldots,k$$

where $\mathbf{R}_1,\ldots,\mathbf{R}_k$ are given subsets of the real line $\mathbf{R}^1$. Looked at in this way, the k-threshold model may be regarded as a *'piecewise linear'* approximation to the general nonlinear first order model

$$X_t = \lambda(X_{t-1}) + e_t$$

The higher order threshold autoregressive models are similarly defined. Thus the p^{th} order threshold autoregressive (TAR(p)) model has the form

$$X_t - \phi_1^{(i)} X_{t-1} - \ldots - \phi_p^{(i)} X_{t-p} = e_t$$

if $(X_{t-1}, .., X_{t-p}) \in R^{(i)}$, $i=1,..,k$ where $R^{(i)}$ is a given region of the p-dimensional Euclidean space R^p. Correspondingly, this model may be viewed as a piecewise linear approximation to

$$X_t = f(X_{t-1}, X_{t-2}, .., X_{t-p}) + e_t$$

Other nonlinear models include, the *state dependent* models (SDM) of Priestley (1980), the *exponential autoregressive* (EAR) models developed by Ozaki and Haggan (1981), *the Random coefficient autoregressive* models by Nicolls and Quinn (1982) and *the Doubly stochastic* models by Tjostein (1986).

1.2.3 Intervention Models

Economic time series measurements as is the case with share prices at the Nairobi stock exchange are highly affected by policy changes and other events that are known to occur at a particular point of time. As an example, the end of year dividends given by firms registered at the Nairobi stock exchange can in one way or other affect the prices of the shares. Events of this type whose timing are known are referred to as *interventions* (see Box and

Tiao, 1975). Interventions can affect a time series data in several ways. They can change the mean level either abruptly or after some decay, change the trend, or lead to a more complicated response pattern. It is obvious that ignoring these factors can lead to an inadequate model being fitted and consequently, poor forecasts being made. Interventions can be incorporated into a univariate model by extending it to include a deterministic or *dummy* input variable. For example if we consider a single intervention known to occur at time T, and X_t is generated by an ARMA(p,q) process, then an intervention model may be postulated as

$$\mathbf{X_t = V(B) I_t + U_t}$$

where

$$U_t = \frac{\theta(B)}{\Phi(B)} e_t$$

is the 'noise' model, V(B) is a (possibly infinite) polynomial which may admit a rational form, such as

$$V(B) = \frac{\omega(B)}{\varphi(B)} B^b$$

where

$$\omega(B) = \omega_0 - \omega_1 B - \ldots - \omega_s B^s$$

and

$$\varphi(B) = 1 - \varphi_1 B - \ldots - \varphi_r B^r$$

where b measures the delay in effect (or dead time) and I_t is an intervention variable usually a dummy or an indicator sequence taking the values 1 and 0 to denote the occurrence or non occurrence of the external (exogenous) intervention. The commonly used dummy variables in representing various forms of interventions include:

(i) a *pulse* variable, which models an intervention lasting only for the observation T,

$$I_t = \begin{cases} 1 & t = T \\ 0 & t \neq T \end{cases}$$

(ii) a *step* variable, which models step changes in X_t beginning at T,

$$I_t = \begin{cases} 1 & t < T \\ 0 & t \geq T \end{cases}$$

1:3 Statistical Modelling

The analysis of data that has been observed at different points in time leads to a new and unique problem in statistical modelling and inference. Statistical modelling in time series is an *iterative* process as shown in the algorithm fig 1.1 which encompasses the model identification, parameter estimation, diagnostic checking and forecasting.

Process *specification* involves various steps, the most basic being the determination of the class of parsimonious models to which a given time series belongs. In particular, this requires determining whether a given time series is generated by a linear or a nonlinear gaussian processes, finite or an infinite variance non gaussian processes or a combination of some of these processes.

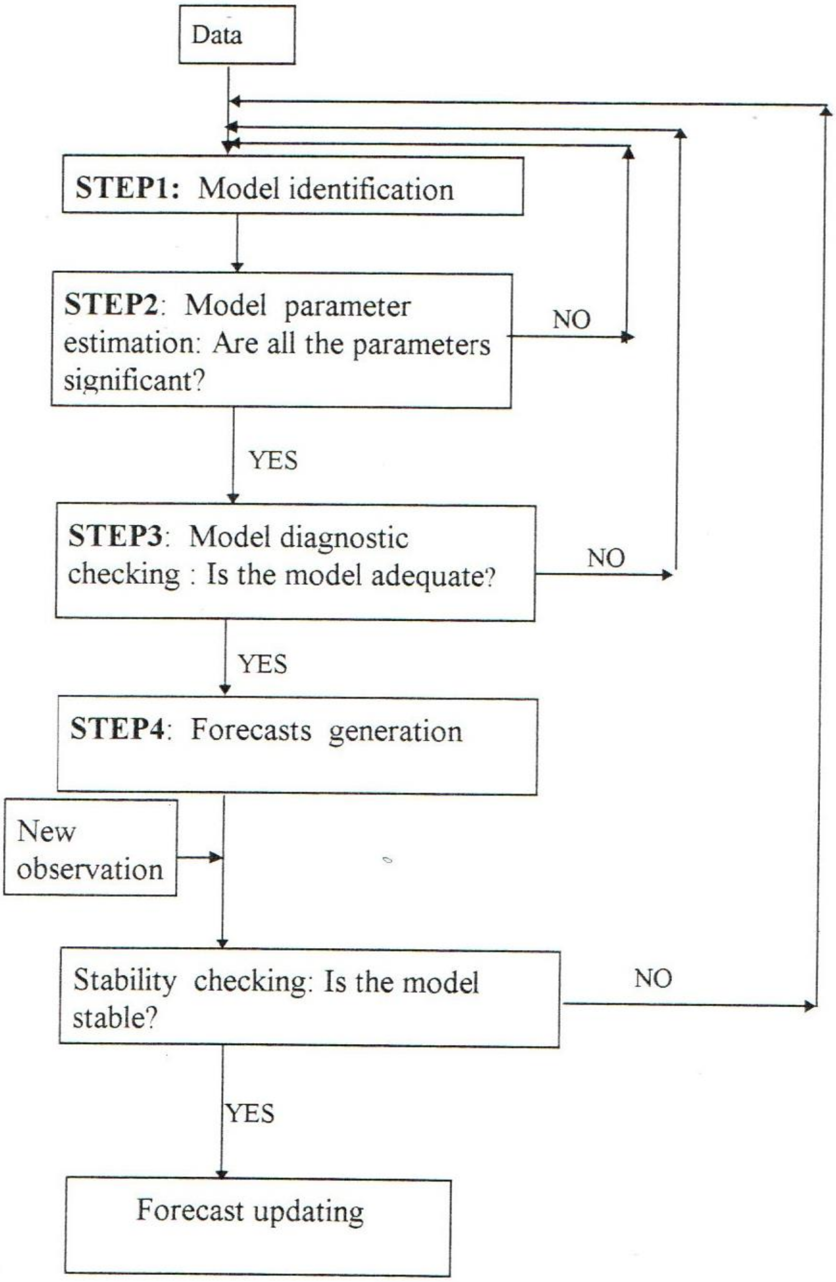

Fig. 1.1 Time series modelling algorithm

This initial identification stage is either based on past data and any prior information about the generating process or on subjective deductions from the timeplots of a series followed by some confirmatory objective tests. Once the form of the process is established, the next important step is to determine the specific subclass in the selected class to which the series belongs. This is followed by the determination of the orders of the model in the selected subclass where the objective techniques of Akaike (1970,1974), Schwarz (1978) and Hannan (1980) as well as simple graphical tools for the identification such as those developed by Box and Jenkins (1970) play a key role.

The second step in statistical modelling is *parameter estimation*. This is a crucial step in attaining some of the major goals in modelling and this is due to the fact that efficient estimation of the parameters leads to efficient forecasts. Several techniques on parameter estimation have been discussed in the time series literature. These include the maximum likelihood estimators, moment estimators, the conditional and unconditional estimators (see Klimko and Nelson, 1978), the optimal estimating function criteria (see Godambe, 1985) and nonlinear estimators.

After the parameters in the model have been estimated, it is necessary to check whether the model assumptions are satisfied. If the assumptions are not met, the model must be respecified. This step in statistical modelling is the third and is usually referred to as *diagnostic checking*. This phase, helps in selecting a parsimonious model among several competing models for the same process. The tests are based on the analysis of the residuals and a model is considered adequate if the residuals form a white noise sequence with zero mean and as small variance as possible (see Box and Pierce, 1970).

Finally, in the fourth and last step, the adequate model is used for control and *forecasting*. The commonest forecasting criteria is based on minimizing the mean square error, where for a process X_t, we aim to obtain the forecast X_t such that

$$E(X_t - \hat{X}_t)^2$$

is minimized.

1:5 Literature Review and Work Layout

The quest for an explanation on the kind of process that determines the prices of the common stock dates back to (1900) when Bachelier indicated that the common stock prices follow a random walk. However the burgeoning of modern work in this subject did not begin until 1959 when Robert suggested that stock prices appeared to follow a random process. Similarly, Osborne a distinguished physicist in the same year pointed out that there was a very high degree of conformity between movement of stock prices and the law governing Brownian motion.

Granger and Morgenstern (1963,1970) in their work on Predictability of stock market prices presented evidence that stock price returns are normally distributed in terms of transaction (i.e. per transaction) rather than per unit calendar time e.g. per day. Cootner (1964) in his work on the random character of stock market prices traced the development of the theory of random walk of stock prices from 1900, while Fama (1965,1976) studied the behavior of stock market prices and gave various types of evidence in support of the random walk theory and published studies suggesting that the rate of returns were distributed according to a stable symmetric distribution with infinite variance or Paretian tail and suggested the use of a normal distribution in analyzing stock prices.

Clark (1973) developed a subordinate stochastic model with finite variance for speculative prices. Westerfield (1977) in his work on the distribution of common stock price changes showed that the stock prices fit the subordinate normal generating process better than they fit Fama's paretian distribution.

Taylor (1986) examined the possibility of forecasting financial series through the use of time series models. In the case of the stock market prices, he examined the behavior of the daily prices of 15 individual US shares over the period 1966 to 1976 so that the number of the observations in each series was 2750. He found out that the daily prices follow a first order moving average process.

Chapter two of this dissertation explores the various theoretical concepts on model order specification and parameter estimation criteria and this is followed by the identification and parameter estimation of the models that fit the share price data for various firms.

In chapter three, various tests for checking the adequacy of the fitted models and forecasts techniques are disscussed. Moreover these tests are used to determine the appropriate models for the share prices data for the various firms. Chapter four gives a brief conclusion and suggestions for further study.

CHAPTER TWO

MODEL IDENTIFICATION AND PARAMETER ESTIMATION PROCEDURES

2.1 Introduction

Univariate ARIMA(p,d,q) processes are widely used to analyse stochastic properties of time series. In order to estimate the parameters of a fitted model, a decision must be made on the dimensions of the autoregressive moving average structure and the order of differencing (d) or any other appropriate transformation required to achieve stationarity.

Specification of a model requires finding estimates of the order (p,q) of the process. The true order of the process is rarely if ever known, and therefore a most difficult part of time series modelling is the specification of the order (p,q) of the process to be fitted based on a finite set of observations. It often happens that the selected model is a simplified form of the true model which is usually complicated. However, what is assumed is that the model choosen eventually adequately describes the underlying process and that it may be potentially useful for some purpose (i.e forecasting and control). Once the order has been specified, the parameters of the model and the variance (σ^2) of the error component can then be estimated.

Since there exists no universal paradigm to the question of determining the order of a time series model from empirical data, a large number of procedures have been put forth to help in choosing the most appropriate model structure. However, the Box and Jenkins approach to time series modelling remains the most widely used technique.

In this chapter the underlying theoretical concepts of model identification and parameter estimation are discussed in section 2.2. In section 2.3 interest is centred on the specification and parameter estimation of the appropriate models for the quoted companies of the Nairobi stock exchange. To achieves this, we will follow the Box and Jenkin approach to order specification. The Akaike information criteria (AIC) and Bayesian information criteria (BIC) are also used to place the proposed models in order of their preferrence.

2.2 Theoretical concepts of model identification and parameter estimation

2.2.1 Order determination

The determination of the order of a model requires finding the estimates of p and q of the process. The traditional method of choosing the best model has been the likelihood ratio test statistic. The test of the null hypothesis that the order is (p_0, q_0) against the alternative that (p_1, q_1) is suitable. However, this is true only when (p_0, q_0) and (p_1, q_1) have been specified a prior. If these are unknown, as usually is the case, then the testing procedure has to be applied repeatedly for different values of (p_0, q_0) and (p_1, q_1) (Hannan (1970); Potscher (1982)) with the consequent difficulty of determining the appropriate level of significance (Akaike, 1978).

In the traditional Box and Jenkins approach (see Box and Jenkins, 1970) this is done by matching the properties of the sample autocorrelation (r(h)) and sample partial autocorrelation (p(h)) functions with those of the theoretical autocorrelation (ρ(h)) and partial autocorrelation (ϕ(h)) functions with the hope of finding similar patterns. It is seldom in practice that the mean (μ) and the variance (σ^2) of the sampled data are known. However, with the stationarity assumptions, μ and σ^2 can be estimated by the sample mean and the sample variance

$$\hat{\mu} = \overline{X} = \frac{\sum_{t=1}^{n} X_t}{n}$$

and

$$\hat{\sigma}^2 = S^2 = \frac{\sum_{t=1}^{n} (X_t - \overline{X})^2}{n}$$

respectively. Consequently an estimate of the r(h) and p(h) can be obtained from the lag h sample autocorrelation

$$r(h) = \frac{\sum_{t=1}^{n} (X_t - \overline{X})(X_{t-h} - \overline{X})}{\sum_{t=1}^{n} (X_t - \overline{X})^2} \qquad h=1,2,...$$

and lag h sample partial autocorrelation

$$p(h) = \frac{\begin{vmatrix} 1 & \rho(1) & \cdots & \rho(h-2) & \rho(1) \\ \rho(1) & \rho(2) & \cdots & \rho(h-3) & \rho(2) \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ \rho(h-1) & \rho(h-2) & \cdots & \rho(1) & \rho(h) \end{vmatrix}}{\begin{vmatrix} 1 & \rho(1) & \cdots & \rho(h-1) \\ \rho(1) & 1 & \cdots & \rho(h-2) \\ \vdots & \vdots & \cdots & \vdots \\ \rho(h-1) & \rho(h-2) & \cdots & 1 \end{vmatrix}}$$

If there is no correlation among observations that are more than q steps apart (ρ(h)=0 for h>q), the variance of r(h) is approximated by (Bartlett, 1946)

$$Var(r(h)) \cong \frac{1}{n}(1 + 2\sum_{h=1}^{h=q} \rho^2(h)) \qquad for\ h > q$$

and in the special case when all observation are uncorrelated (ρ(h) = 0 for all h $\neq$ 0) then this equation reduces to

$$\mathbf{Var(r(h)) \cong n^{-1}}$$

If n is large and ρ(h)=0, r(h) will be approximately normally distributed with mean zero and var(r(h))= n^{-1} (Bartlett (1946) and Anderson (1971) pg.478). Therefore the absolute value of r(h) in excess of twice the standard error (s.e) may be regarded as significantly different from zero i.e

$$|\mathbf{r(h)}| > \mathbf{2s.e(r(h)) = 2var(r(h))^{1/2}}.$$

The properties of the autocorrelation and partial autocorrelation functions serve as a guide in identifying the type of process that is behind the generation of a particular set of emperical data. For an AR(p) model

$$(1-\phi_1 B - \ldots -\phi_p B^p) X_t = e_t,$$

its autocorrelation function (ACF) is given by

$$\rho(h) = \begin{cases} \phi_1\rho(h-1)+\phi_2\rho(h-2)+\ldots+\phi_p\rho(h-p) & h>0 \\ 0 & otherwise. \end{cases}$$

which decays exponentially (or sine wave decay), while its partial autocorrelation function (PACF) has the form

$$\phi_{hh} = \frac{\begin{vmatrix} 1 & \rho(1) & \cdots & \rho(h-2) & \rho(1) \\ \rho(1) & \rho(2) & \cdots & \rho(h-3) & \rho(2) \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ \rho(h-1) & \rho(h-2) & \cdots & \rho(1) & \rho(h) \end{vmatrix}}{\begin{vmatrix} 1 & \rho(1) & \cdots & \rho(h-2) & \rho(h-1) \\ \rho(1) & 1 & \cdots & \rho(h-3) & \rho(h-2) \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ \rho(h-1) & \rho(h-2) & \cdots & \rho(1) & 1 \end{vmatrix}}$$

for h =1,2,...,p and zero for h > p and it cuts off at lag p.

The MA(q) process

$$X_t = e_t + \theta_1 e_{t-1} + \ldots + \theta_q e_{t-q},$$

has its ACF

$$\rho(h) = \begin{cases} \dfrac{-\theta_h + \theta_{h+1}\theta_1 + \ldots + \theta_{q-h}\theta_q}{1 + \theta_1^2 + \ldots + \theta_q^2} & h=1,2,..,q, \\ 0 & h > q. \end{cases}$$

cutting off at lag q i.e the memory of the process extends only q steps with the observations more than q steps being uncorrelated whereas its PACF has a combination of exponential decay or damped sine wave decay for real and complex roots of $\theta(B)=0$ respectively.

Thus indeed, an important duality between the AR and the MA process is that, while the ACF of the AR(p) process is infinite in extent, its PACF cuts off after lag p. The ACF of the MA(q) process on the other hand cuts off after lag q, while the PACF is infinite in extent.

However, unlike the pure AR or MA models, the mixed ARMA model is characterised by both an ACF and PACF that tail off to infinity rather than cut off at a particular lag. For $h>q-p$, the ACF is determined from the AR part of the model, while for $h<p-q$, the PACF is determined from the MA part of the model. The theoretical properties of the AR(p), MA(q) and ARMA(p,q) processes are summarized in table 2.1.

Seasonal ARIMA(p,d,q)*(P,D,Q) processes tend to generate autocorrection and partial autocorrection functions that mimic the behaviour observed in the ordinary ARMA(p,d,q) process, except that there are peaks at multiples of the seasonal period **s**.

A Seasonal AR process of order P given as

$$\Phi_P(B^s)X_t = e_t$$

has a PACF which takes nonzero values at m = s, 2s,...,Ps and zero for m >Ps, while the MA process of order Q

$$X_t = \theta_Q(B^s)e_t$$

has an ACF with nonzero values at m = s, 2s,...,QS and is zero for m >QS.

Model	ACF lag (h).	PACF lag (h).
White noise.	All zero.	All zero.
AR(p).	Exponential or sine wave decay.	$\theta_{hh} = 0$
(0,d,q) MA(q).	ACF = 0 for h>1.	Dominated by damped exponential or sine wave.
(p,d,q) ARMA(p,q).	Tail off after (q-p) lags. Exponential and/or sine wave decay after (q-p) lags.	Tail off (p-q) lags. Dominated by damped exponential and/or sine wave after (p-q) lags.

Table 2.1 The ACF and PACF properties for ARIMA(p,d,q) models.

While an informal inspection of the sample autocorrelation (SACF) and partial autocorrelation (SPACF) functions plays a crucial part in model identification, it cannot stand by itself, since no standards of comparison are provided against which the observed descrepancies can be measured (Newbold and Granger, 1974; Chatfield and Prothero, 1973; Bhansali, 1983).

A number of model selection criteria have been proposed in the literature (see Abraham, et al., 1985). However, among them, the most commonly employed criteria includes the Akaike information criteria (AIC), Bayesian information criteria (BIC) and the Φ (Hannan) criteria, given by

$$AIC(p,q) = \ln\sigma_e^2 + 2(p+q)n^{-1}$$

$$BIC(p,q) = \ln\sigma_e^2 + (P+q)n^{-1}\ln(n)$$

and

$$\Phi(p,q) = \ln\sigma_e^2 + (p+q)cn^{-1}\ln\{\ln(n)\} \quad \text{for } c \geq 2$$

respectively. Where σ_e^2 is the estimate of the error variance σ^2 and (p,q) are the number of parameters in the autoregressive and moving average components respectively of the fitted model. These criteria are used in the following way. The upper bound, say **P**={0,1,...,P) and **Q**={0,1,...,Q) are fixed for the polynomial Φ(B) and θ(B), and order p_i and q_i are selected if they give the minimim value of AIC(p_i,q_i), BIC(p_i,q_i) and Φ(p_i,q_i). For example, the order p_i and q_i are selected through the BIC if

$$BIC(p_i,q_i) = \min[BIC(p_i,q_i),\ p_i \in P, q_i \in Q]$$

The application of this strategy has one possible drawback since no specific guidelines on how to determine P and Q seem to be available. However, they are tacitly assumed to be sufficiently large for the range of models to contain the true model which we may denote as having orders (p_o, q_o), and which will not necessarily be the same as (p_1, q_1), the orders chosen by the criterion under consideration. The BIC and Φ are strongly consistent in that they determine the model asymptotically, whereas for the AIC, an overparameterised model will always emerge no matter how long the available realization (Mill, 1990).

2.2.2 Parameter estimation

Identification procedures are approximate methods applied to a set of empirical data to indicate the kind of model which warrant further investigation. The specific aim of these procedures is to obtain some idea of the values of p,d and q needed in the general ARIMA model. The tentative ARIMA (or AR, MA or ARMA) model so obtained by the identification method provides a starting point for the model parameter estimation procedure.

Various techniques of parameter estimation of time series have been proposed in the literature (Abraham and Ledolter, 1980), but since the theory of estimation per se is not our primary aim in this dissertation, we will only apply the techniques to estimate the parameters of the proposed model. However, among the commonly used estimation criteria, the maximum likelihood (ML) estimation criterion gives parameter estimates which are consistent, asymptotically efficient and normally distributed. The criterion is usually preferred in small samples and particularly so when the parameter values approach the invertibility boundaries. The conditional least squares (CLS) method is comparable to the ML criterion when the parameter values are away from the invertibility boundaries. In estimating the error variance (σ^2) the CLS method tends to overestimate it, while the use of the unconditional least squares (ULS) method leads to underestimation. Once the parameters of the fitted model have been estimated, it is necessary to test whether the individual parameters are significantly different from zero. This is done by testing the hypothesis

$$H_0 : \beta_i = 0 \quad \text{Vs} \quad H_1 : \beta_i \neq 0$$

using the standard Z-test or t-test. For the t-test, the statistic

$$t = \frac{\hat{\beta}_i - 0}{s\sqrt{c_{ii}}}$$

is used. This statistic has a t-distribution with (n-p-q-1) degree of freedom if an ARMA(p,q) process was fitted, with $s(c_{ii})^{1/2}$ being the standard error of the estimate. If

$$| t | > t_{\alpha/2}(n-p-q-1),$$

the null hypothesis that $\beta=0$ is rejected in favour of the altenative hypothesis $\beta_i \neq 0$ at level α. For an acceptable model, the parameters should all be significantly different from zero, i.e $\beta_i \neq 0$. If they are not, then the parameters concerned should be set to zero and the model re-estimated without them as indicated in the algorithm in figure 1.1. The stability of the parameters can be tested by re-estimating them using a sub-set of the data to see if they change.

2.3 Model Specification for the quoted Firm's share prices data

2.3.1 Barclays Bank Kenya Ltd.

Barclays bank (K) whose registered head office in Kenya is at Barclays plaza, Loita street, Nairobi was incorporated in Kenya in 1978 to provides an extensive range of banking, financial and related services. The company has a foreign holding of 68.51% and is among the 20 NSE index representative companies with 31.5% floated shares at the NSE.

A timeplot of the Barclays bank share prices for the years 1992 to 1996 is given in fig 2.1(a). The increasing and decreasing trend in the timeplot of the share prices and the slow decline of the SACF for the original series reveals that the series is mean nonstationary.

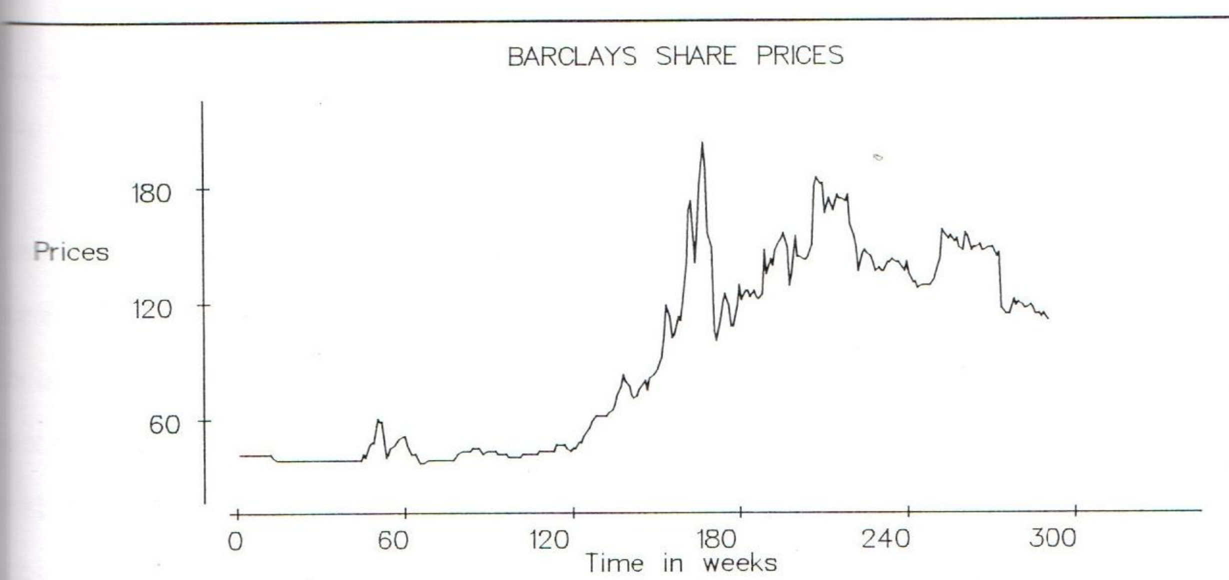

Fig 2.1(a) Timeplot for BARCLAYS BANK (K) share prices.

The stationarity in mean of the timeplot for the first difference (∇X_t) displayed in fig 2.1(b) indicates that the first difference is adequate. This is further confirmed by the minimum variance ($minV(\nabla^d X_t)$) criterion since the sample variance of the original series (X_t) and those associated with the series ∇X_t, $\nabla^2 X_t$ and $\nabla^3 X_t$ are 2375.778, 49.119, 113.901 and 170.520 respectively, implying that d=1 is an appropriate degree of differencing.

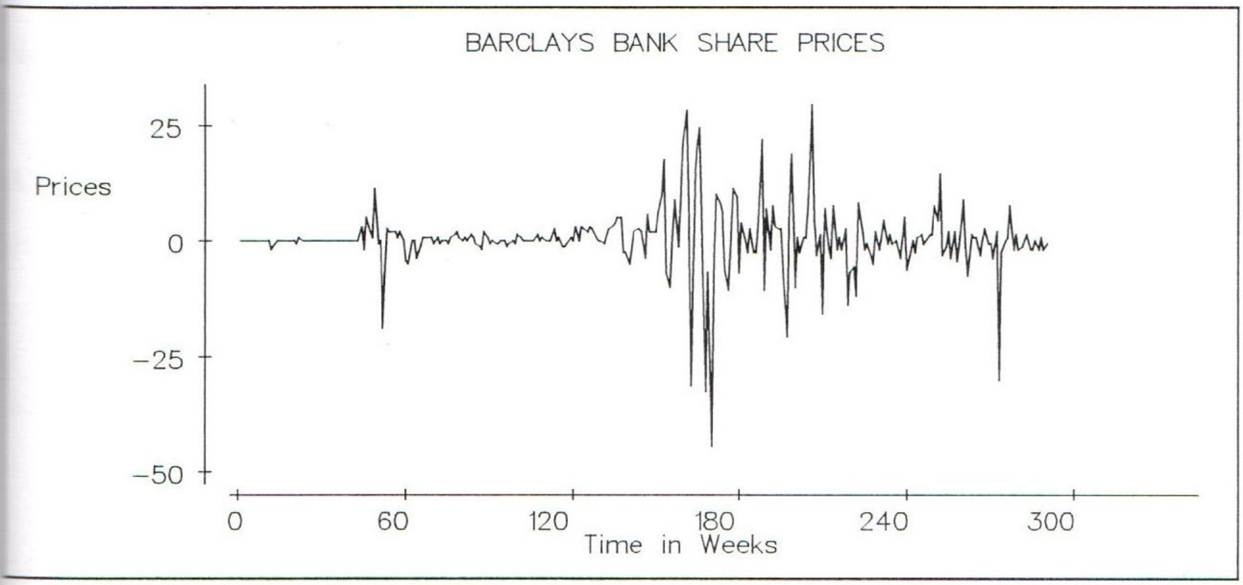

Fig 2.1(b) Timeplot for the first difference for the BARCLAYS share prices.

However, there are fluctuations between the 160th and the 225th week which can be attributed to the high share prices realized by the company between February 1994 and February 1995. This was as a result of the unstable high rates of inflation in the country's economy in that period, the increasing bank interest rates and the reforms and liberalization of the financial sector which relaxated the restrictions on foreign investors at the Nairobi Stock Exchange as well as the attractive dividends declared by the company at the end of 1993 financial year.

The significant peaks at lag 1, 3, 7, 10 and 13 of the SACF suggests seasonal nonstationarity of the series with seasonal period approximately equal to 3, but the SPACF with significant peaks at lag 1, 7 and 10 is rather difficult to interpret since there is no particular striking pattern. Closer examinination of the SACF, suggests that ARIMA(1,1,0)(1,1,0)$_3$ or ARIMA(0,1,1)(0,1,1)$_3$ processes could be possibilities. Ignoring the seasonality aspect of the series, the ARIMA(10,1,13), ARIMA(10,1,0) and ARIMA(0,1,13) processes could be best alternatives.

Estimating the parameters using the ML procedures, the following models were obtained

i) ARIMA(1,1,0)*(1,1,0)$_3$

$$\underset{(0.058)}{(1 - 0.230B)}(B^3)\nabla X_t = e_t \qquad \text{with } \sigma^2 = 107.078$$

ii) ARIMA(0,1,1)*(0,1,1)$_3$

$$(1 - B)X_t = \underset{(0.057)}{(1 + 0.250B)}(B^3)e_t \qquad \text{with } \sigma^2 = 105.826$$

iii) ARIMA(13,1,0)

$$(1 - \underset{(0.059)}{0.133B^7} + \underset{(0.059)}{0.536B^{10}} - \underset{(0.059)}{0.122B^{13}})\nabla X_t = e_t$$

with $\sigma^2 = 46.457$

iv) ARIMA(0,1,10)

$$\nabla X_t = (1 + \underset{(0.059)}{0.117B^7} - \underset{(0.058)}{0.210B^{10}})e_t \qquad \text{with } \sigma^2 = 46.615$$

v) ARIMA(3,1,10)

$$(1 + \underset{(0.089)}{0.726B} + \underset{(0.065)}{0.163B^3})\nabla X_t = (1 + \underset{(0.061)}{0.893B} - \underset{(0.061)}{0.147B^{10}})e_t$$

with $\sigma^2 = 44.785$

The parameters not included in the final models were found to be non-significant. The significance of the peaks in the SACF and SPACF were ignored and a random walk model fitted. The variance of the data based on the ARIMA(0,1,0) model was 49.012. The AIC and the BIC values for the above models are given in table 2.1 below.

Model	**AIC**	**BIC**
ARIMA(3,1,10)	1930.017	1944.697
ARIMA(0,1,10)	1939.685	1947.025
ARIMA(13,1,0)	1939.697	1930.707
$ARIMA(0,1,1)*(0,1,1)_3$	2153.470	2157.130
$ARIMA(1,1,0)*(1,1,0)_3$	2156.860	2160.520
ARIMA(0,1,0)	1951.683	1951.683

Table 2.1 The AIC and BIC values.

2.3.2 ICDC Investment Company Ltd.

The ICDC investment company limited with its registered head office in Uchumi house, Aga Khan walk, Nairobi was incorporated in Kenya in 1955. As a locally controlled investment company and parastatal body with foreign holding of 0.03%, the ICDC investment company limited enables its members to acquire interest in the existing projects including certain investments held by the corporation. The company has 100% floated share in the NSE.

From the timeplot for the ICDC share prices data for the years 1992 to 1996 shown in fig 2.2(a) it is clear that the mean level is changing with time which is an indication of homogeneous nonstationarity.

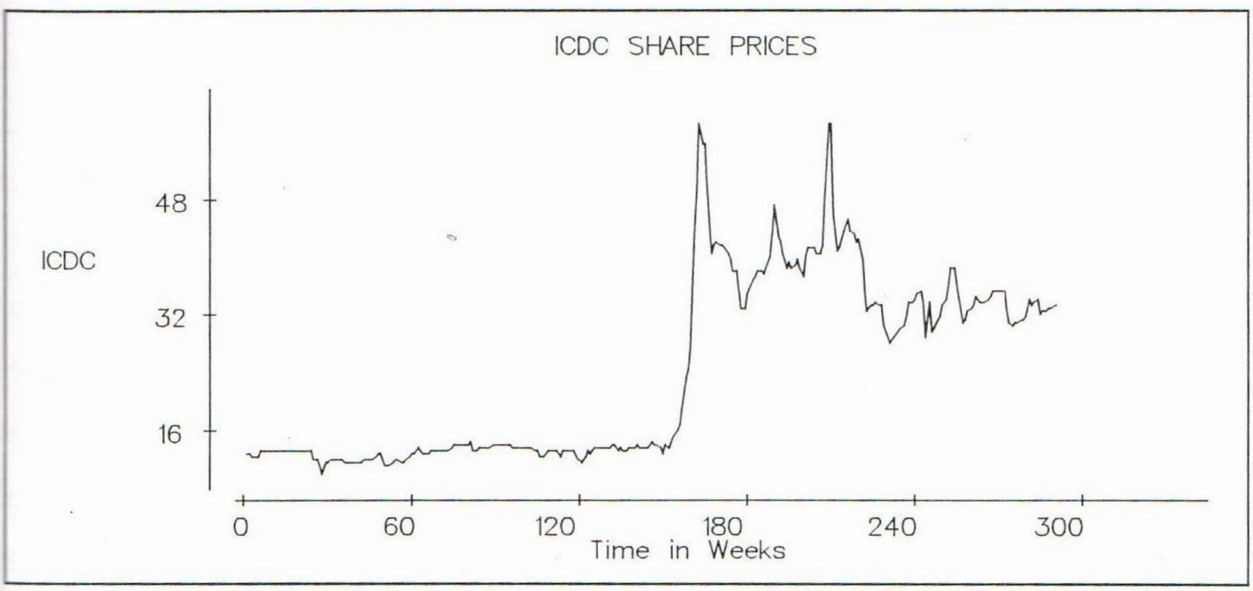

Fig 2.2(a) Timeplot for ICDC share prices.

The nonstationarity in mean of the data is further confirmed by the slow decay of the correlogram of the original series. The sample variance of the original series is 159.069 while those associated with the first, second and third differences are 4.075, 10.990 and 18.601 respectively, hence the first difference is suggested by the $\min V(\nabla^d X_t)$ criterion and its appropriateness is seen in the timeplot for ∇X_t series fig 2.2(b) which shows a fairly stationary series in mean.

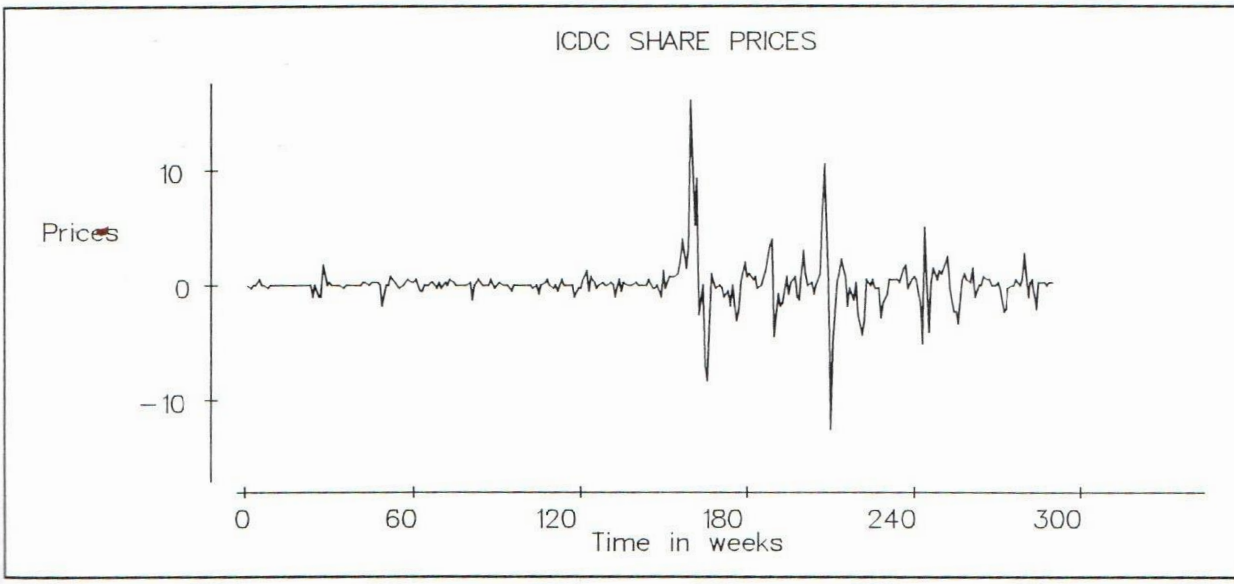

Fig 2.2(b) Timeplot for the first difference for the ICDC share prices.

The fluctuations between the 160th and the 225th week are due to the high share prices realized by the company between February 1994 and March 1995. This can mainly be attributed to the high rates of inflation in the country's economy in that time, the increasing bank interest rates and the liberalisation of the financial sector which relaxated the restriction on the foreign investors at the Nairobi Stock Exchange market.

The sharp cut-off at lag 1 in the SACF for the ∇X_t series point towards the ARIMA(0,1,1) process, whereas the corresponding SPACF has significant peaks at lag 1 and 3 suggesting that the ARIMA(1,1,0) or ARIMA(3,1,0) models could be tentatively entertained but on the grounds of parsimony we choose the ARIMA(1,1,0) process.

The Ml estimation technique applied on the ARIMA(0,1,1) and the ARIMA(1,1,0) processes showed that the constants for both processes were not significant. Estimating the models without the constants gave the following models

(i) ARIMA(1,1,0)

$$\underset{(0.055)}{(1 - 0.343B)}\nabla X_t = e_t \quad \text{with } \sigma^2 = 3.605$$

and

(ii) ARIMA(0,1,1)

$$(1 - B)X_t = \underset{(0.056)}{(1 + 0.310B)}e_t \quad \text{with } \sigma^2 = 3.648$$

The estimates obtained through the CLS method are almost the same as those given by the MLE criterion. The AIC and the BIC values for the two models are given in table 2.2 below.

Model	AIC	BIC
ARIMA(1,1,0)	1196.018	1199.688
ARIMA(0,1,1)	1199.363	1203.033

Table 2.2 The AIC and the BIC values.

2.2.3 Kenya Commercial Bank Ltd.

The Kenya Commercial bank limited was incoporated in Kenya in 1970 to provided provision of corporation and retail banking services. The locally controlled bank with a foreign holding of 0.05% has its registered head office at the 8^{th} floor, Kencom house, Moi Avenue, Nairobi. The company is among the 20 NSE index representative companies and has 40% floated share in the NSE.

The timeplot of the original series of the Commercial bank of Kenya limited share prices data for the years 1992 to 1996 shown in fig 2.3(a) exhibits a fluctuating trend that suggests a changing mean level. The nonstationarity in mean is further confirmed by the consequant slow decline of the SACF for the same series.

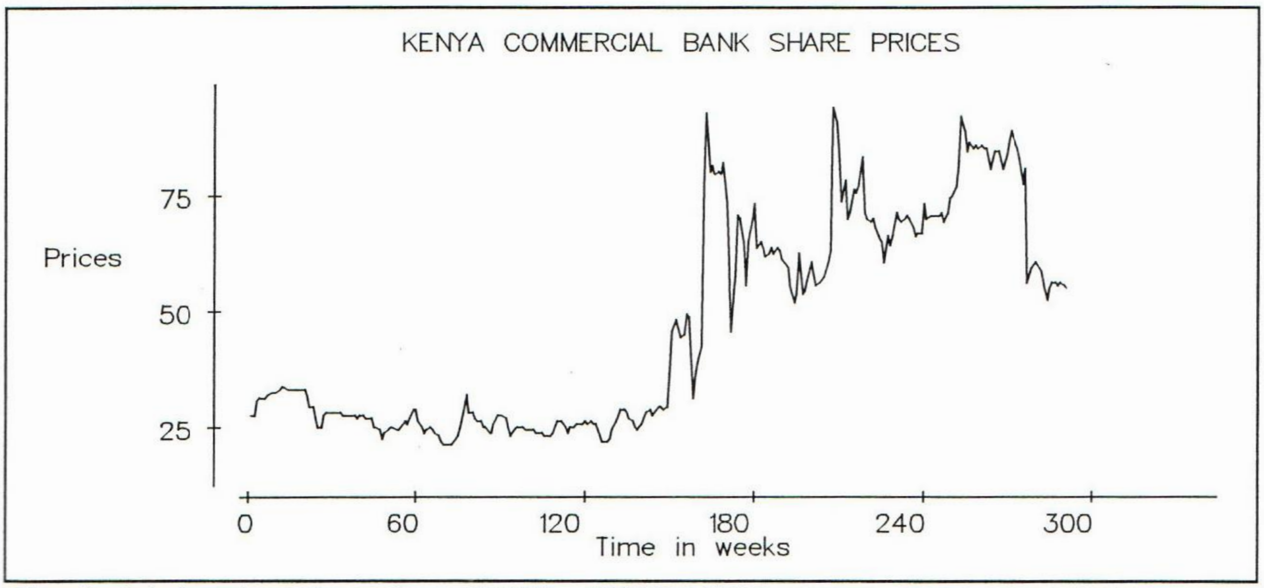

Fig 2.3(a) Timeplot for KENYA COMMERCIAL BANK share prices.

The sample variances for the series X_t, ∇X_t, $\nabla^2 X_t$ and $\nabla^3 X_t$ are 508.480, 20.762, 45.736 and 65.132 respectively, implying that by the $\min V(\nabla^d X_t)$ criterion the first difference is adequate as seen in the timeplot for the first difference fig 2.3(b).

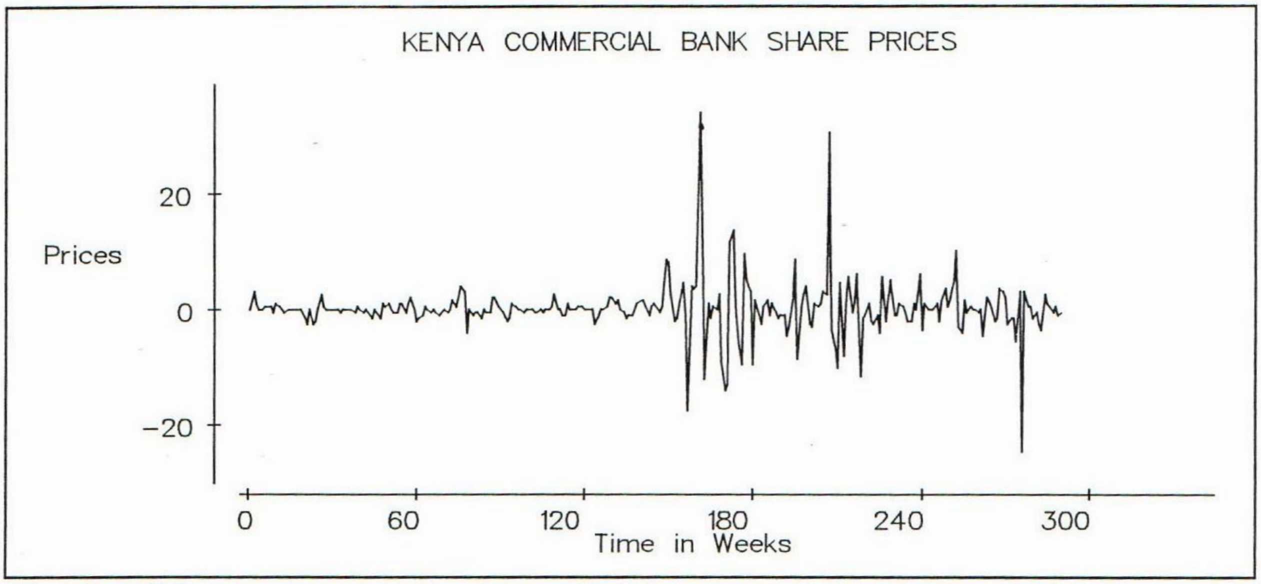

Fig 2.3(b) Timeplot for the first difference of the KCB share prices.

However, there are fluctuations between the 160^{th} and the 220^{th} week which can be attributed to the high share prices realized by the bank between February 1995 and February 1995. The high share prices were as a result of the high rates of inflation in the country's economy at that period, reforms and the liberalisation of the financial sector which allowed foreign investors to invest in the Nairobi Stock Exchange without much restriction and the increasing bank interest rates as well as the attractive dividends declared by the bank at the end of the 1993 financial year.

The significance of lags 2, 3, 8 and 12 for the SACF and of lags 2, 8 and 12 for the SPACF of the first difference suggests that an ARIMA(0,1,12) and ARIMA(12,1,0) with parameters at lag 2, 3, 8, 12, and at 2, 8 and 12 respectively or a combination of the two models i.e ARIMA(12,1,12) could be tentatively entertained.

Through the maximum likelihood estimation criterion the constants for all the models were not significant while the estimates of the rest of the parameters for the ARIMA(0,1,12) and ARIMA(12,1,0) processes were all significant and the models obtained are given below

(i) ARIMA(0,1,12)

$$\underset{}{(1 - B)X_t} = (1 - \underset{(0.059)}{0.132B^2} - \underset{(0.059)}{0.104B^3} - \underset{(0.059)}{0.130B^8} + \underset{(0.059)}{0.228B^{12}})e_t$$

with $\sigma^2 = 9.008$

(ii) ARIMA(12,1,0)

$$(1 + \underset{(0.059)}{0.130B^2} + \underset{(0.059)}{0.122B^8} - \underset{(0.058)}{0.196B^{12}})\nabla Xt = e_t$$

with $\sigma^2 = 19.396$.

When the ARIMA(12,1,12) model was fitted, the parameters at lag 2 for the autoregressive and at lags 2 and 8 for the moving average components were not significant. Re-estimating the model without these paramters gave the process

(iii) ARIMA(12,1,12)

$$(1 + \underset{(0.059)}{0.133B^8} + \underset{(0.231)}{0.280B^{12}})\nabla X_t = (1 - \underset{(0.059)}{0.111B^3} + \underset{(0.211)}{0.503B^{12}})e_t$$

with $\sigma^2 = 19.177$.

The significance of all the lags of the SPACF and SACF were ignored and a random walk model (ARIMA(0,1,0)) was also fitted. The variance of the data based on this model was 39.951. The AIC and the BIC values for the models are given in table 2.3

below.

Model	**AIC**	**BIC**
ARIMA(0,1,12)	1681.828	1696.507
ARIMA(12,1,12)	1684.232	1699.230
ARIMA(12,1,0)	1686.460	1697.470
ARIMA(0,1,0)	1702.587	1702.587

Table 2.3 The AIC and BIC values.

2.3.4 Standard Chartered Bank (K).

Standard Chartered bank of Kenya limited which has a majority foreign control and with foreign holding of 78.30% was incorporated in Kenya in 1953 to offer banking and provision of related services. The bank which has its registered head office in Stanbank house, Moi Avenue, Nairobi has 25.5% floated share in the NSE and it is among the 20 NSE index representative companies.

The slow cut-off of the SACF for the original series X_t clearly reveals nonstationary behaviour and this is also apparent from the timeplot for standard bank share prices for the years 1992 to 1996 as seen in fig 2.4(a) which show an increasing and decreasing mean levels.

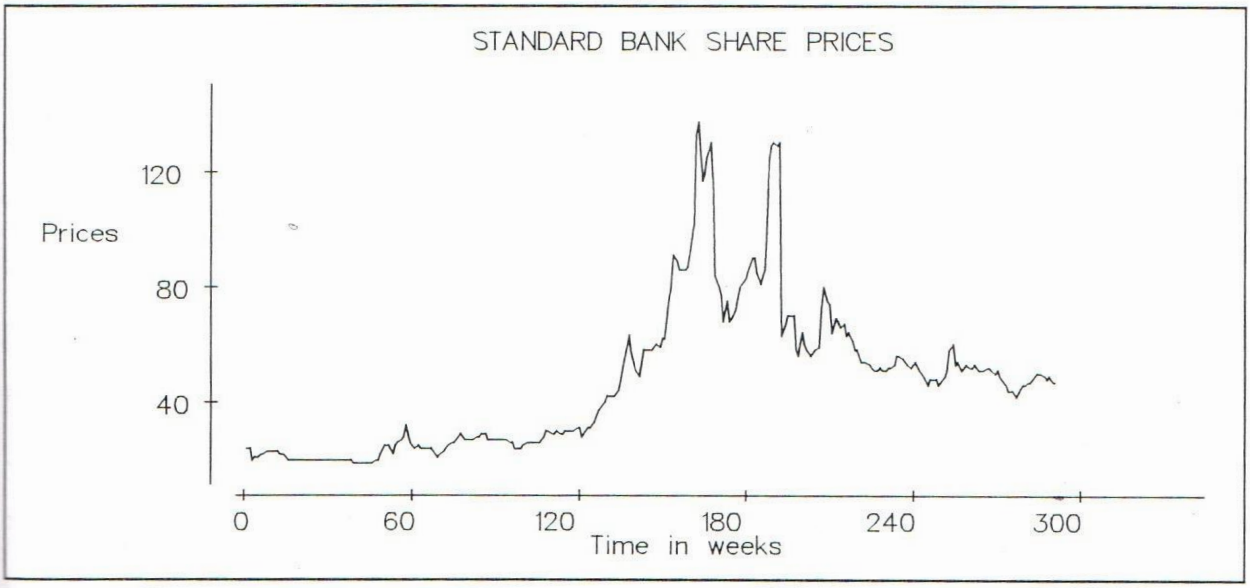

Fig 2.4(a) Timeplot for STANDARD BANK (K) share prices.

The sample variance for the original series is 669.082 and those associated with the first, second and third differences are 37.450, 82.632 and 124.745 respectively. Thus by the $\min V(\nabla^d X_t)$

criterion, the first difference is appropriate. The timeplot for the first difference given in fig 2.4(b) shows a fairly stationary series in mean.

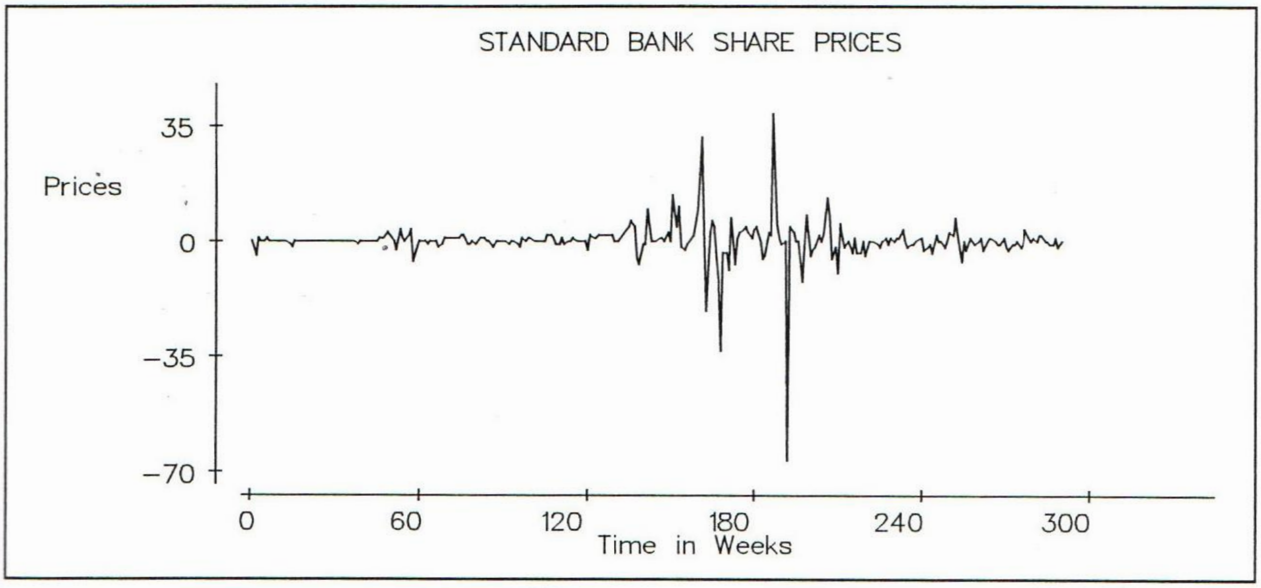

Fig 2.4(b) Timeplot for the first difference of the STANDARD share prices.

However, there are fluctuations between the 160th and the 200th week which can be attributed to the high share prices realized by the bank between February 1994 and January 1995. The high share prices were as a result of the high rates of inflation in the country's economy at that period, the reforms and liberalisation of the financial sector which allowed the foreign investors to invest in the Nairobi Stock Exchange market without much restriction and the increasing bank interest rates as well as the attractive dividends declared by the bank at the end of the 1993 financial year.

The SACF and SPACF for the ∇X_t series has both marginally significant values at lag 1 and prominent peaks at lag 7 and 14.

This suggests that an ARIMA(14,1,0), ARIMA(0,1,14) and ARIMA(14,1,14) could be possible models for the data.

The estimation of the parameters for the ARIMA(0,1,14) and the ARIMA(14,1,0) models using the maximum likelihood method revealed that the constant and the parameters at lag 14 for both procesess were not significant. Re-estimating the model excluding these parameters gave the following results

(i) ARIMA(0,1,14)

$$(1 - B)X_t = (1 + \underset{(0.058)}{0.131}B - \underset{(0.058)}{0.200}B^7)e_t \quad \text{with } \sigma^2 = 36.122$$

and

(ii) ARIMA(14,1,0)

$$(1 - \underset{(0.058)}{0.112}B + \underset{(0.058)}{0.147}B^7)(1 - B)X_t = e_t$$

with $\sigma^2 = 36.494$.

For the ARIMA(14,1,14) model, none of the parameters were significant suggesting that a random walk model (ARIMA(0,1,0)) could be tentatively entertained. The variance data based on the ARIMA(0,1,0) process was 37.45. The AIC and the BIC values for these models are given in table 2.4 below.

Model	**AIC**	**BIC**
ARIMA(0,1,14)	1865.485	1872.825
ARIMA(14,1,0)	1868.315	1875.650
ARIMA(0,1,0)	1873.660	1873.660

Table 2.4 The AIC and BIC values.

2.3.5 BAT Kenya Limited.

BAT Kenya limited is an industrial company which deals mainly with the manufacturing and importation of cigarettes and allied products. The foreign controlled company with 60.24% foreign holding was incorporated in Kenya in 1952 and its registered head office is along Likoni road, Nairobi. BAT Kenya limited is among the 20 NSE index representative companies with 39.76% floated share in the NSE.

The shape of the timeplot of the BAT share prices for the years 1992 to 1996 fig 2.5(a) makes it rather hard to make any subjective deductions on the stationarity of the series from it.

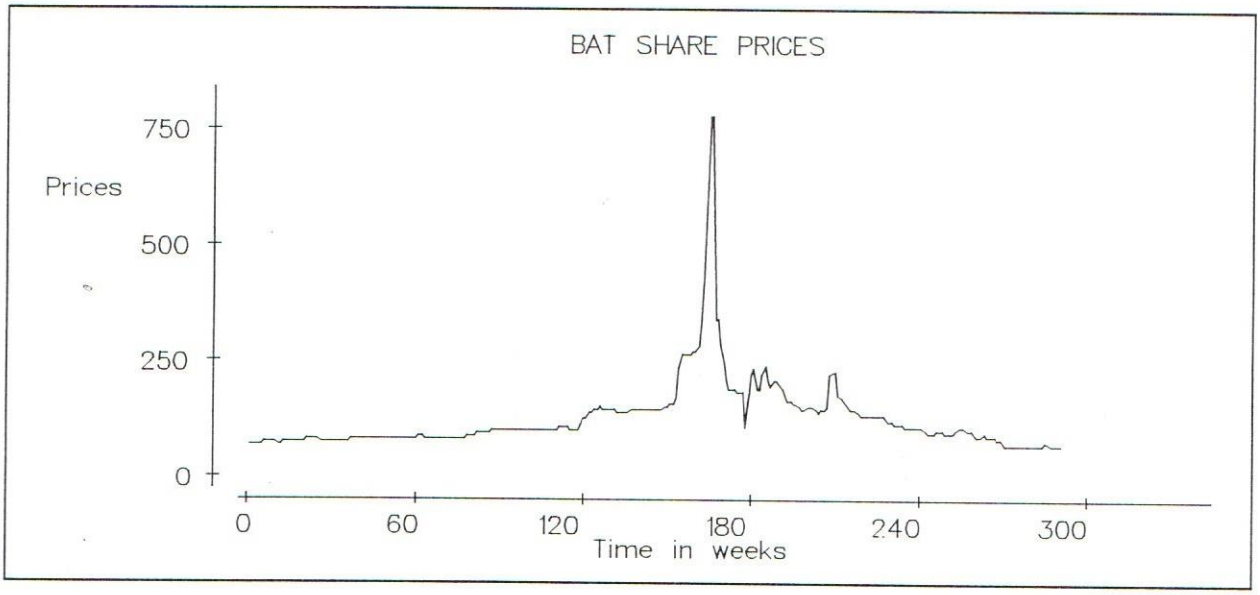

Fig **2.5(a)** Timeplot for BAT (K) share prices.

However, from the timeplot for the first difference shown in fig 2.5(b) and by the $\min V(\nabla^d X_t)$ criterion, it is clear that the first difference is appropriate. The sample variances associated with series X_t, ∇X_t, $\nabla^2 X_t$ and $\nabla^3 X_t$ are 6894.401, 1050.116, 2580.782

and 3947.934 respectively.

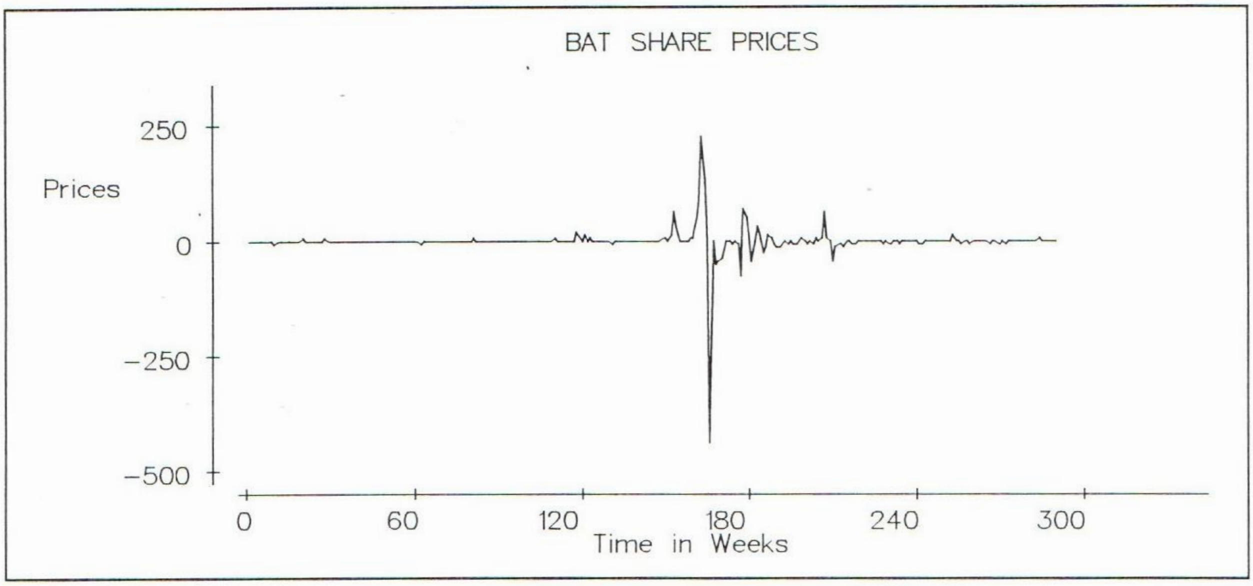

Fig **2.5(b)** Timeplot for the first difference of the BAT (K) share prices.

The sharp fluctuations seen in fig 2.b(b) between the 160th and the 200th week can be attributed to the high share prices realized by the company between December 1993 and November 1994. This was as a result of the high rates of inflation in the country's economy, liberalisation of the financial sector, the increasing bank interest rates and the attractive dividends declared by the company at the end of the 1993 financial year. The dumping of cheap imported cigarrettes onto the Kenyan market especially during 1995 adversely affected the company's trading environment and this led to the sharp drop on it's share prices from November 1994 as seen in fig 2.5(a).

The significance of lags 1, 3, and 13 for the SACF and 1, 3, 12 and 13 of the SPACF for the first differenced series suggest that the ARIMA(0,1,13), ARIMA(13,1,0) or ARIMA(13,1,13) models uld be fitted.

The parameters for the process ARIMA(13,1,13) were estimated sing the ML method and the constant together with the parameters t lag 1 and 13 for both the MA and AR component were not ignificant. These parameters were set to zero and the model re-itted. The following model was obtained

i) ARIMA(12,1,3)

$$\underset{(0.170)}{(1 - 0.287B^{3}} + \underset{(0.063)}{0.115B^{12}})\nabla X_t = (1 - \underset{(0.147)}{0.287B^{3}})e_t$$

ith $\sigma^2 = 950.56$.

The ARIMA(13,1,0) and the ARIMA(0,1,13) processess were also itted. All the parameters except the constant for the RIMA(13,1,0) were significantly different from zero and the model iven below was obtained.

ii) ARIMA(13,1,0)

$$(1 - \underset{(0.059)}{0.205B} + \underset{(0.057)}{0.238B^{3}} + \underset{(0.059)}{0.115B^{12}} + \underset{(0.058)}{0.163B^{13}})(1 - B)X_t = e_t$$

ith $\sigma^2 = 918.052$.

The ARIMA(0,1,13) had its constant and the lag 1 parameter eing non-significant. Re-estimating the model without these rameters produced the model

iii) ARIMA(0,1,13)

$$(1 - B)X_t = (1 - \underset{(0.055)}{0.342B^{3}} - \underset{(0.058)}{0.198B^{13}})e_t$$

ith $\sigma^2 = 933.975$.

e AIC and BIC values for the above models are given in table 2.5

below.

Model	**AIC**	**BIC**
ARIMA(13,1,0)	2806.133	2820.813
ARIMA(0,1,13)	2809.312	2816.652
ARIMA(12,1,3)	2815.139	2826.149

Table 2.5 The AIC and BIC values.

2.3.6 Kenya Breweries Ltd.

Kenya breweries limited incorporated in Kenya in 1922 is a locally controlled company with its registered head office in Tusker house, Thika road, Nairobi. As an industrial company the Kenya breweries limited main objective is to brew and malt. The company is among the 20 NSE index representative with 93% floated shares at the NSE.

The timeplot for Kenya breweries share prices for the years 1992 to 1996 shows a fluctuating trend in mean level as seen in fig 2.6(a) indicating nonstationarity in the data. The nonstationarity of the data is also confirmed by the slow decay of the correllogram.

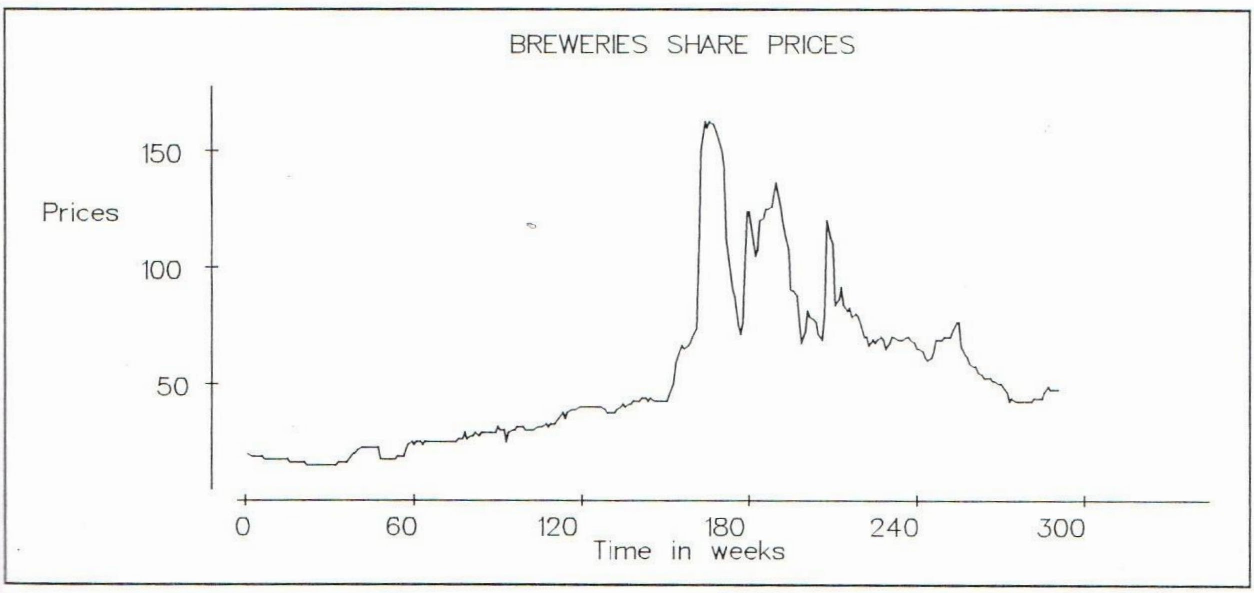

Fig 2.6(a) Timeplot for KENYA BREWERIES share prices.

The nonstationarity of the data suggests that the series should be transformed to attain stationarity. The $\min V(\nabla^d X_t)$ criterion point at d=1 as the appropriate degree of difference since the sample variances for the original data and those of the first, second and third differences are 1151.284, 40.750, 107.818 and 179.226 respectively. The appropriateness of this order of differencing is revealed in the timeplot fig 2.6(b) which shows a fairly stationary series in mean although with spontaneous fluctuation between the 160th and the 220th which can be attributed to the high share prices realized by the company between February 1994 and February 1995. The high share prices were as a result of the high rates of inflation in the country's economy in that period, the government reforms and liberalisation of the financial sector and the dropping of interest rates by the banks.

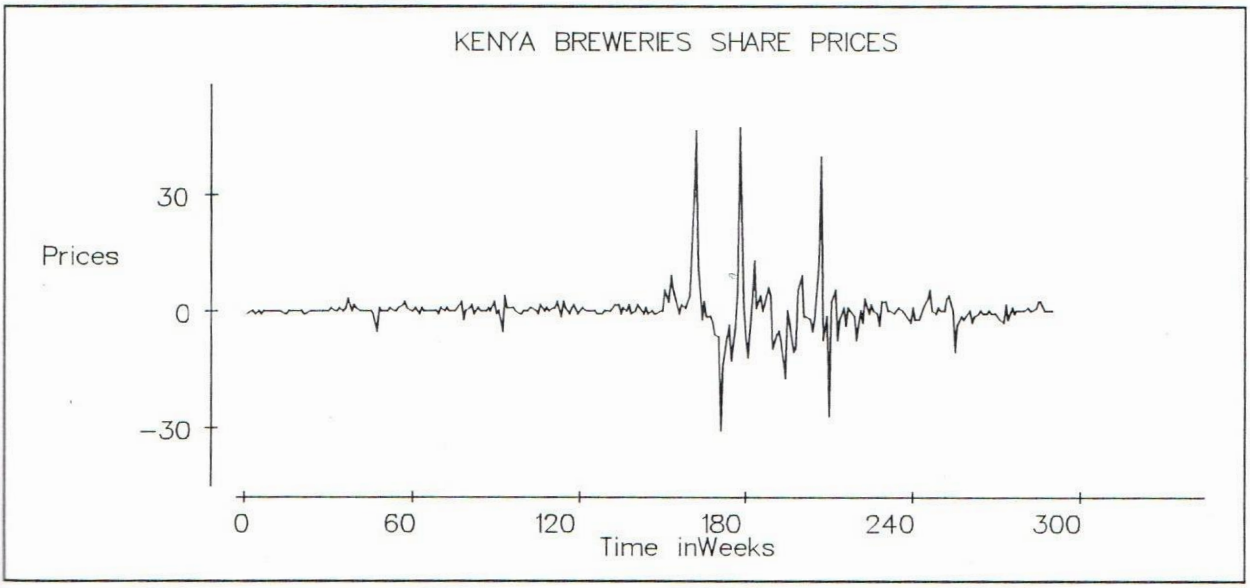

Fig 2.6(b) Timeplot for the first difference of the KENYA BREWERIES share prices.

The SACF and the SPACF for the first difference has significant peaks at lag 1, 9 and 1, 4, 9 and 12 respectively, suggesting that the ARIMA(0,1,9), ARIMA(12,1,0) or ARIMA(12,1,9) processes could be fitted.

The Ml estimation technique was used to fit the ARIMA(12,1,0) model and the constant together with the lags 4 and 12 parameters were not significant. The fitted model without these parameters gave the process

(i) ARIMA(9,1,0)

$$\underset{(0.055)}{(1 - 0.334B} + \underset{(0.058)}{0.149B^9)}\nabla X_t = e_t \quad \text{with } \sigma^2 = 34.620.$$

All the parameters of the ARIMA(0,1,9) model were significantly different from zero except for the constant and the model

(ii) ARIMA(0,1,9)

$$\nabla X_t = (1 + \underset{(0.056)}{0.313B} - \underset{(0.058)}{0.173B^9)}e_t$$

with $\sigma^2 = 34.616$ was obtained using the ML method.

When the ARIMA(12,1,12) model was fitted, all the parameters were not significant suggesting a random walk model. The variance of the data based on the ARIMA(0,1,0) was 39.95. The AIC and BIC values for the fitted model are given in table 2.6(a) below.

Model	**AIC**	**BIC**
ARIMA(9,1,0)	1853.184	1860.520
ARIMA(0,1,9)	1853.208	1860.548
ARIMA(0,1,0)	1892.402	1892.402

Table 2.6(a) The AIC and BIC value.

2.3.7 Nairobi Stock Exchange (NSE) Index.

An index generally represents a measure of the relative change from one point to another. Stock indices are constructed to measure the general price movement in the listed shares of the stock exchange. The NSE 20 share index has its base year as 1966 at 100. It was based on 17 companies and calculated on weekly basis. However, in 1992, the sample companies were increased to the current 20 to represent nearly 90% of the NSE market capitalization and the computation changed from weekly to daily basis.

Fig 2.7(a) of the original series for the NSE index for the years 1992 to 1996 shows a increasing and decreasing trend in mean level, revealing nonstationarity in the index data.

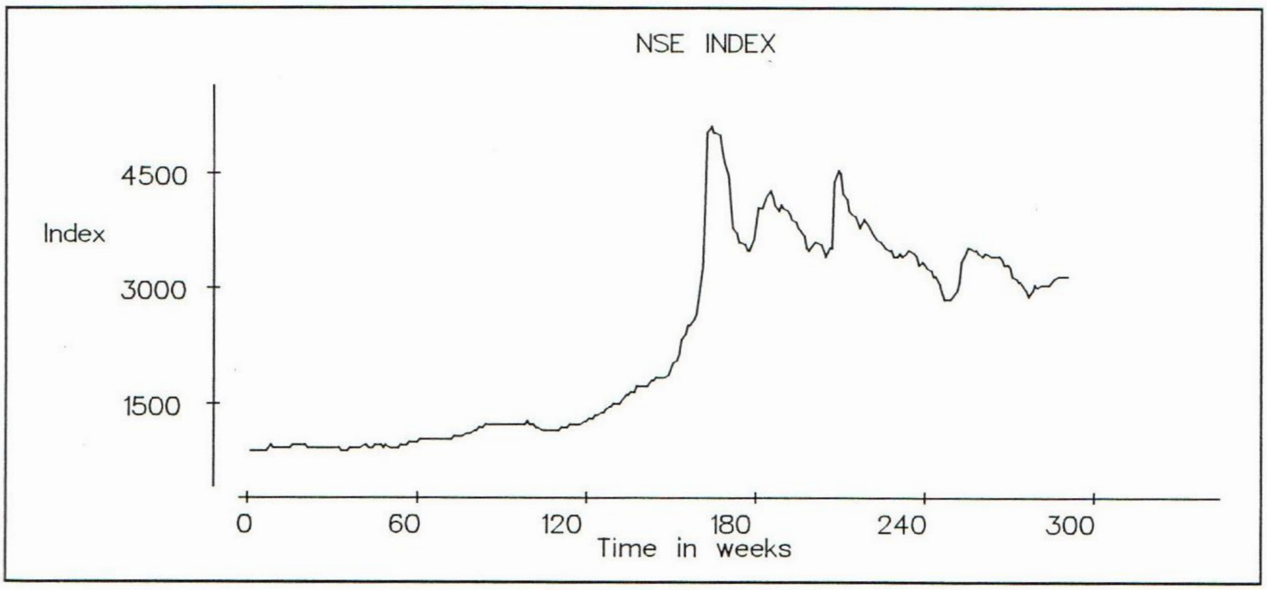

Fig 2.7(a) Timeplot for the NSE INDEX.

The minV($\nabla^d X_t$) criterion suggests that the first difference is appropriate owing to the fact that the sample variances associated with the series X_t, ∇X_t, $\nabla^2 X_t$ and $\nabla^3 X_t$ are 1,268,245.30, 12,146.91, 38,495.62 and 72645.29 respectively.

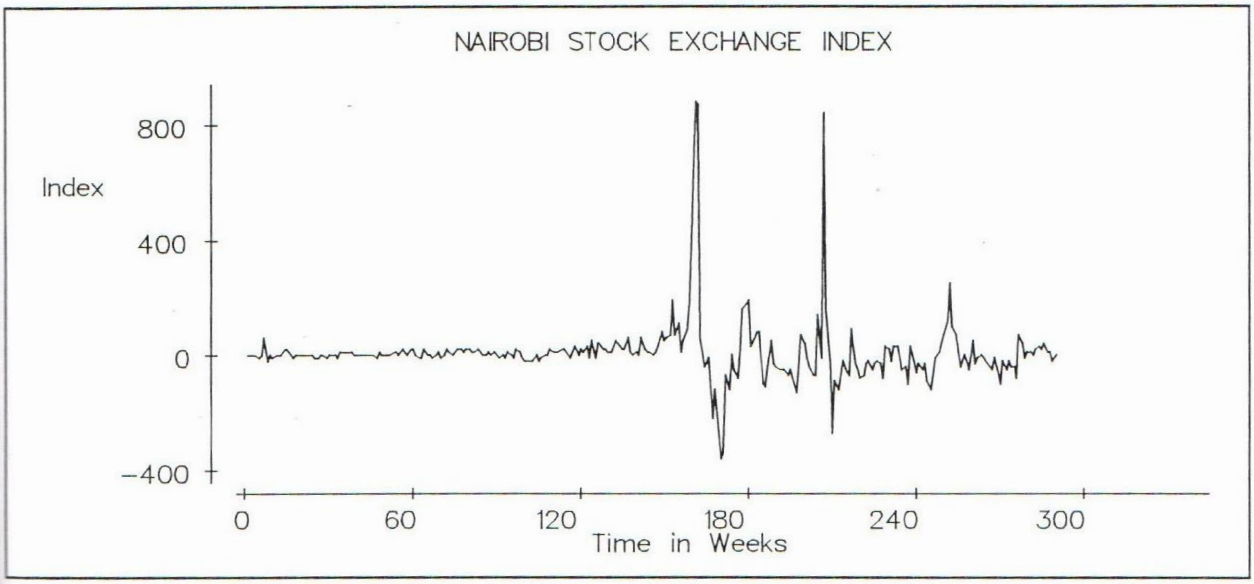

Fig 2.7(b) Timeplot for ∇X_t of NSE index.

The sharp fluctuations between the 160th and the 220th week can be attributed to the high share prices realized by the 20 NSE index representative companies between December 1993 and March 1995. This was as a result of the high rates of inflation in the country's economy, the increasing bank interest rates and the government reforms and liberalisation of the financial sector.

The SACF for the first differenced series tail-off at lag 2 pointing at the ARIMA(0,1,2) process while the corresponding SPACF has a sharp cut-off at lag 1 suggesting an ARIMA(1,1,0) process. The significance of the first two lags and lag 1 of the SACF and SPACF respectively suggests that an ARIMA(1,1,2) process could also be a possible model to fit.

All constants for the suggested models were not significant. Re-estimating the models without the constants using the ML procedures gave the following models

(i) ARIMA(1,1,0)

$$(1 - \underset{(0.048)}{0.577}B)(1 - B)X_t = e_t \quad \text{with } \sigma^2 = 8100.726$$

(ii) ARIMA(0,1,2)

$$\nabla X_t = (1 + \underset{(0.055)}{0.617}B + \underset{(0.055)}{0.344}B^2)e_t \quad \text{with } \sigma^2 = 7957.508$$

The lag 1 parameters for both the AR and MA components of the ARIMA(1,1,2) model were not significant.

The model

$$(1 - B)X_t = (1 + \underset{(0.056)}{0.305}B^2)e_t$$

with σ^2 = 11025.000 was obtained when the process was re-fitted without the nonsignificant parameters. The AIC and BIC for the three models are given in table 2.7 below.

Model	**AIC**	**BIC**
ARIMA(0,1,2)	3430.209	3437.549
ARIMA(1,1,0)	3434.303	3437.970
ARIMA(0,1,2)	3523.494	3571.163

Table 2.7 The AIC and BIC values.

The large variance of the index data and the large spontaneous fluctuations in the timeplot for the first difference of the NSE index fig 2.7(b) reveals the possibility of unstable variance. A transformation to stabilise the variance was the logarithmic transformation which was found the most appropriate. However, there was not much difference in timeplot for the first difference and that of the first difference of the transformed series as seen in fig 2.7(c) and for this reason no model was fitted for the transformed data.

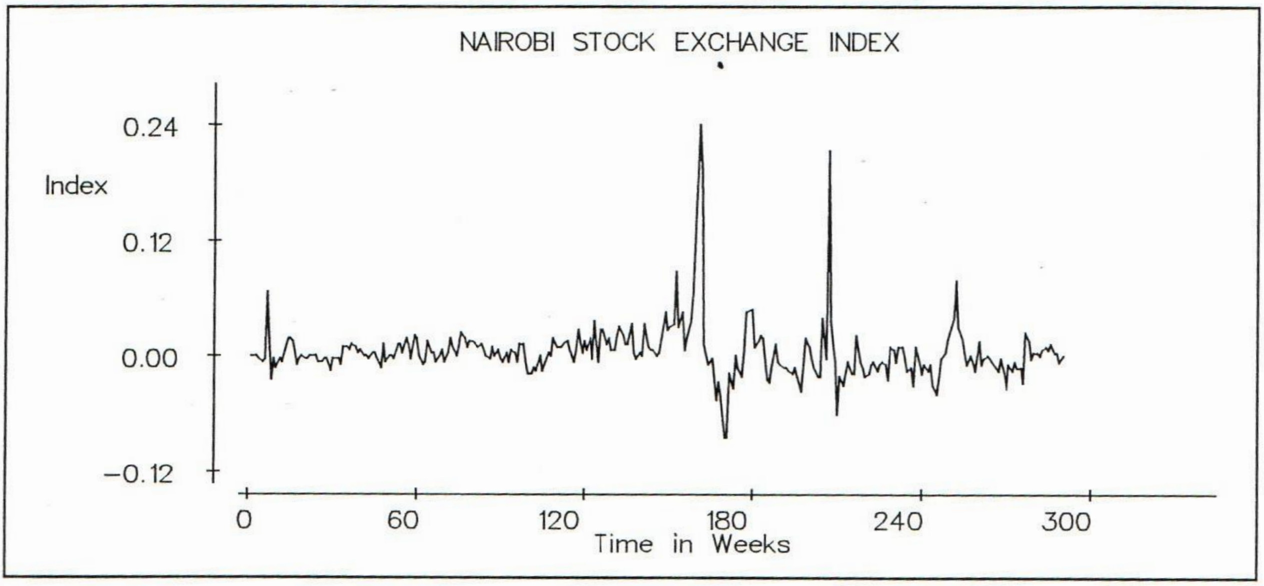

Fig 2.7(c) Timeplot for Log∇X_t for the NSEIndex.

CHAPTER THREE

DIAGNOSTIC CHECKING AND FORECASTING

3:1 Introduction

The ultimate goal in model building is to be able to utilize it for prediction purposes. Forecasts are required for two basic reasons. First, the future is uncertain and two, the full impact of many decisions taken now is not felt until later. Consequently, accurate prediction of the future improves the efficiency of the decision making process. However, before the fitted model is used for forecasting, it should be diagnosed to ascertain its adequacy.

Section 3.2 of this chapter discusses the various diagnostic tests and forecasting techniques whereas section 3.3 employs these techniques to choose the best model among a group of competing models. The models eventually chosen for each firm are used to generate the forecasts.

3.2 Diagnostic Tests and Forecasts Evaluation

3.2.1 Diagnostic tests

After fitting a provisional ARMA model, it is procedural to diagonise the model before it is eventually used for forecasting as suggested in the algorithm in fig 1.1. The usual approach in diagnostic checking is to extract from the data a sequence to correspond to the underlying, but unobservable, white noise sequence, and check whether the *statistical properties* of these residuals $\{a_t\}$ are indeed consistent with the white noise. The basic assumption in ARIMA models is that the residuals form a white noise process implying that $\{a_t\}$ are uncorrected random variables with mean zero and constant variance. Thus the goal in time series modelling (Box et al. (1978)) is to transform the presumably autocorrelated observed series to a structureless white noise process i.e

$$e_t = \Pi(B)\nabla^d X_t$$

where

$$\Pi(B) = \frac{\Phi(B)}{\Theta(B)}.$$

Therefore a check on whether a particular model is adequate or not revolves around ascertaining whether the calculated residuals,

$$a_t = \hat{\Pi}(B)\nabla^d X_t$$

mimic to a reasonable degree, the assumed properties of the error process e_t. This implies that

(i) the mean of the residual should be close to zero

$$E(a_t) = E(X_t - \hat{X}_t) \cong 0$$

(ii) the variance of the residual should be approximately constant

$$Var(a_t) = Var(X_t - \hat{X}_t) \cong \sigma^2$$

and (iii) the autocorrelations

$$r(h) = \frac{\sum_{t=h+1}^{T} (a_t - \overline{a})(a_{t-h} - \overline{a})}{\sum_{t=1}^{T} (a_t - \overline{a})}$$

of the residuals should be negligible compared to their standard errors. The standard errors depend on the form of the fitted model, the true parameter values and the lag h.

Test statistics such as the Box and Pierce (1970) statistic and the Ljung and Box (1978) statistic can also be used to test the adequacy of the fitted model. The Box and Pierce portmanteaus statistic

$$Q = T\sum_{j=1}^{m} r_j^2$$

is asysmptoticaly distributed as chi-square with (m-p-d-q) degrees of freedom if the stationary series $X_t=(1-B)^d W_t$ was correctly generated by an ARIMA(p,d,q) process, where T=(n-d) represents the total number of observation after differencing d times, m is the maximum number of the lags checked and is approximately equal to $T^{1/2}$ (see poskitt and Tremayna (1981)), r_j is the sample autocorrelation function of the j^{th} residual term and j represents the j^{th} autocorrelation being checked. If a constant is included in the fitted model, the degree of freedom reduces by one to (m-p-d-q-1). The test of the null hypothesis (H_0: model is adequate) is rejected if the statistic Q exceeds the chi-square tabular values of degree (m-p-d-q) or (m-p-d-q-1) if a constant is included in the model i.e reject H_0 if $Q > \chi^2(m-p-d-q)$ or if $Q > \chi^2(m-p-d-q-1)$.

A modified portmanteaus statistic

$$Q^* = T(T+2)\sum_{j=1}^{m}(T-j)^{-1}r_j^2$$

by Ljung and Box (1978) is a much better approximation to the $\chi^2(m-p-d-q)$ distribution and a model is considered adequate if the statistic Q* is less than the tabulated value χ_α^2 (m-p-d-q) at α level of significance.

If the fitted model is found to be inadequate, a new model must be specified, its parameters estimated and then diagonised as suggested in fig 1:1. However, a model may fail the diagnostic check but yet it gives better forecasts (see for example Giorgio C. and Pollard S. (1985)). Therefore to some extend, we will evaluate the selected models on the basis of their forecasting ability.

3.2.2 Forecasting

Most decisions are made with a view to influencing where one will be in the future. For example, workers decide to save part of their incomes in order to make provision for their future, while a stock market investor buys some shares now in the hope of receiving a worthwhile return in dividends in future. All these activities require some prior idea or forecasts of the future behaviour of the key *environmental* variables so that an assessment can be made of what will happen if nothing is done now and what is likely to happen if certain steps are taken. As a consequence, reliable forecasts enable timely decisions to be made which are based on sound plans. For example in most countries, weather forecasts and daily stock exchange are published by the media daily. These are of interest to the general public, farmers, travellers and investors.

To forecast is to declare beforehand or to predict. Forecast methods may be broadly classified into two: subjective or objective. *Subjective* forecasts are based on guesses, experience or intuition. They do not follow clear rules and rely on processing information in an informal way. These forecasts cannot be reproduced by someone else and thus it is possible for two people when given the same information to end up with different subjective forecasts. For example, two stockbrokers may reach different conclusions when presented with the information that a particular share has reached a historically high value. While one expects further increases, the other may expect decreases since each of stockbroker is forecasting the future trend after the historically high value using the available information and in the light of their experiences and their intuitive feel for the market, but no formal structure or method is being used.

Models based on objective forecasts on the other hand arise from mathematical rules or statistiacal models which formalise the relationships between the variables of interest. It is a more uniform and accurate method if the right model for the underlying data is used.

In evaluating the forecasts, suppose that our observed series $(X_1, X_2, \ldots, X_n)$ is regarded as a realization from the general ARIMA(p,d,q) process

$$\Phi(B)(1-B)^d X_t = \theta_0 + \Theta(B) e_t$$

and we wish to forecast a future value X_{n+h}. This implies that

$$X_{n+h} = \beta_1 X_{n+h-1} + \beta_2 X_{n+h-2} + \ldots + \beta_{p+d} X_{n+h-p-d} + \theta_0$$
$$+ e_{n+h} - \theta_1 e_{n+h-1} - \ldots - \theta_q e_{n+h-p}$$

where

$$\beta(B) = \Phi(B)(1-B)^d$$
$$= (1 - \beta_1 B - \beta_2 B^2 - \ldots - \beta_{p+d} B^{p+d})$$

such that the h-step ahead forecast $f_n(h)$ is given by

$$f_n(h) = E[X_{n+h} / X_n, X_{n-1}, \ldots]$$

where

$$E(X_{n+j}/X_n, X_{n-1}, \ldots) = \begin{cases} X_{n+j}, & j \le 0 \\ f_n(j), & j > 0 \end{cases}$$

and

$$E(e_{n+j}/X_n, X_{n-1}, \ldots) = \begin{cases} e_{n+j}, & j \le 0 \\ 0, & j > 0 \end{cases}$$

Hence to evaluate $f_n(h)$, we only need to replace the past expectations ($j \le 0$) by the known values, X_{n+j} and e_{n+j} and future expectations ($j>0$) by forecast values, $f_n(h)$ and 0. Forecasts often have a tendency to lie either wholly above or below the values of the series when they eventually become available (see for example Mill, (1990) Pg 106).

The h-step ahead *forecast error* $e_n(h)$ for the forecast X_{n+h} is

$$e_n(h) = X_{n+h} - f_n(h)$$

and its associated variance $V[e_n(h)]$ is

$$V[e_n(h)] = V[X_{n+h} - f_n(h)]$$

The reliability of the forecasts get smaller and smaller as the forecasts are projected further and further into the future, with the corresponing confidence interval becoming larger and larger. Hence for the forecasts to be relied upon, they should be *updated* as new observations become available.

Suppose that we are at time n and we are predicting (h+1) steps ahead (i.e forecasting X_{n+h+1}). If an ARIMA(p,d,q)

$$\Phi(B)(1 - B)^d X_t = \theta(B) e_t$$

was fitted and used also to generate forecasts, then if

$$\eta(B) = \theta(B)\Phi^{-1}(B)(1 - B)^{-d}$$

the linear filter representation of the above model is given by

$$X_{n+1} = e_{n+1} + \eta_1 e_{n+h-1} + \ldots + \eta_{h-1} e_{n+1}$$

$$+ \eta_h e_n + \eta_{h-1} e_{n-1} + \ldots$$

and the h-step ahead forecasts is

$$f_n(h+1) = \eta_h e_n + \eta_{h+1} e_{n-1} + \ldots$$

With the availability of the $(n+1)^{th}$ observation, the prediction of X_{n+1+h} is updated to

$$f_n(h+1) = X_n(h+1) + \eta_h e_{n+1}$$

which can be generally written as

$$f_{n+1}(h) = f(h+1) + \eta_h [X_{n+1} - f_n(h)].$$

Hence the updated forecast is a linear combination of the previous forecasts of X_{n+1+h} made at time n and the most recent one step ahead forecast error

$$e_n(1) = \{X_{n+1} - f_n(1)\} = e_{n+1}.$$

3.3 DIAGNOSTIC CHECK FOR THE FORECAST MODELS

3.3.1 Barclays Bank Kenya Ltd.

The ARIMA(1,1,0)(1,1,0)$_3$, ARIMA(0,1,1)(0,1,1)$_3$, ARIMA(13,1,0), ARIMA(0,1,10), ARIMA(3,1,10) and ARIMA(0,1,0) models were proposed for the Barclays bank(K) share prices in section 2.3.1. To verify their validity, their respective sample residual autocorrelations were examined. Both the sample autocorrelation and partial autocorrelation of the residuals for all the models except the ARIMA(3,1,10) had large values compared to their respective standard errors implying that the residuals are autocorrelated. This suggests that the considered models were inadequate. The inadequacy of the models was also confirmed by the Box and Pierce Q statistic since all the calculated values exceeded the corresponing chi-square tabular values. However, the ARIMA(3,1,10) model proved adequate in both diagnostic tests.

The forecasts generated through the use of the ARIMA(13,1,0) and ARIMA(0,1,10) models were bad and therefore not given whereas those obtained from the ARIMA(1,1,0)(1,1,0)$_3$, and ARIMA(0,1,1)(0,1,1)$_3$, ARIMA(3,1,10) and ARIMA(0,1,0) processes are given below.

Obs	Forecast	Std Error	Lower 95%	Upper 95%	Actual	Residual
284	115.0728	10.3483	94.7905	135.3551	118.2500	3.1772
285	114.0271	16.4016	81.8806	146.1737	116.5000	2.4729
286	114.2617	21.0981	72.9102	155.6131	114.6000	0.3383
287	112.0759	31.7637	49.8203	174.3315	114.6000	2.5241
288	111.0233	41.1431	30.3845	191.6622	112.6000	1.5767
289	111.2513	49.0488	15.1177	207.3849	113.2500	1.9987
290	109.0591	61.5464	-11.5694	229.6876	111.2500	2.1909
291	108.0001	73.1766	-35.4231	251.4233	110.7500	2.7499
292	108.2216	83.4609	-55.3584	271.8016	110.0000	1.7784
293	106.0230	97.6075	-85.2838	297.3298	113.8000	7.7777
294	104.9575	111.0767	-112.7484	322.6634	112.2000	7.2425
295	105.1726	123.3197	-136.5291	346.8743	111.4000	6.2274
296	102.9675	138.9586	-169.3858	375.3208	111.3000	8.3325
297	101.8956	154.0299	-199.9968	403.7879	110.8000	8.9044
298	102.1042	167.9721	-227.1144	431.3229	108.4000	6.2958
299	99.8927	184.9799	-262.6605	462.4458	103.8000	3.9073

Table 3.1(a) ARIMA(1,1,0)(1,1,0)$_3$

Obs	Forecast	Std Error	Lower 95%	Upper 95%	Actual	Residual
284	114.8471	10.2872	94.6846	135.0096	118.2500	3.4029
285	113.8407	16.4675	81.5650	146.1164	116.5000	2.6593
286	114.0842	20.8933	73.1341	155.0344	114.6000	0.5158
287	111.6749	31.1813	50.5607	172.7891	114.6000	2.9251
288	110.6620	40.4189	31.4426	189.8814	112.6000	1.9380
289	110.8991	47.9072	17.0030	204.7953	113.2500	2.3509
290	108.4834	59.9288	-8.9748	225.9415	111.2500	2.7666
291	107.4640	71.2716	-32.2255	247.1535	110.7500	3.2860
292	107.6947	81.0421	-51.1445	266.5339		2.3053
293	105.2725	94.6336	-80.2056	290.7505		8.5275
294	104.2467	107.7087	-106.8580	315.3514		7.9533
295	104.4709	119.3600	-129.4699	338.4117		6.9271
296	102.0422	134.3746	-161.3266	365.4111		9.2578
297	101.0100	148.9643	-190.9540	392.9740		9.7900
298	101.2278	162.2473	-216.7704	419.2259		7.1722
299	98.7927	178.5683	-251.1941	448.7795	103.8000	5.0073

Table 3.1(b) ARIMA$(0,1,1)(0,1,1)_3$

Obs	Forecast	Std Error	Lower 95%	Upper 95%	Actual	Residual
284	122.9638	6.6921	109.8475	136.0801	118.2500	-4.7138
285	123.4077	10.2834	103.2527	143.5627	116.5000	-6.9077
286	124.0525	12.4385	99.6735	148.4315	114.6000	-9.4525
287	123.8768	14.0311	96.3764	151.3772	114.6000	-9.2768
288	123.3304	15.2147	93.5102	153.1505	112.6000	-10.7304
289	123.6564	16.4773	91.3615	155.9512	113.2500	-10.4064
290	123.9778	17.5993	89.4840	158.4717	111.2500	-12.7278
291	124.4191	18.7426	87.6843	161.1539	110.7500	-13.6691
292	125.0144	19.7589	86.2877	163.7411		-15.0144
293	125.1578	20.7587	84.4716	165.8441		-11.3578
294	125.2829	21.4185	83.3034	167.2623		-13.0829
295	125.5151	22.0379	82.3217	168.7084		-14.1151
296	125.7250	22.6560	81.3201	170.1299		-14.4250
297	126.0077	23.2841	80.3718	171.6436		-15.2077
298	126.2223	23.9092	79.3613	173.0833		-17.8223
299	126.4772	24.5086	78.4415	174.5130		-22.6772

Table 3.1(c) ARIMA(3,1,10)

Obs	Forecast	Std Error	Lower 95%	Upper 95%	Actual	Residual
284	115.2436	10.6160	94.4365	136.0506	118.2500	3.0064
285	114.2371	15.0134	84.8115	143.6627	116.5000	2.2629
286	114.4807	18.3875	78.4418	150.5195	114.6000	0.1193
287	112.4678	28.0874	57.4175	167.5180	114.6000	2.1322
288	111.4549	35.2094	42.4458	180.4640	112.6000	1.1451
289	111.6920	41.1158	31.1067	192.2773	113.2500	1.5580
290	109.6726	52.0078	7.7394	211.6059	111.2500	1.5774
291	108.6533	60.9846	-10.8740	228.1806	110.7500	2.0967
292	108.8840	68.7999	-25.9610	243.7289		1.1160
293	106.8582	80.8494	-51.6034	265.3198		6.9418
294	105.8324	91.3227	-73.1564	284.8212		6.3676
295	106.0566	100.7127	-91.3362	303.4494		5.3434
296	104.0244	113.8444	-119.1061	327.1549		7.2756
297	102.9922	125.6108	-143.1999	349.1842		7.8078
298	103.2099	136.3656	-164.0612	370.4811		5.1901
299	101.1713	150.5085	-193.8193	396.1618		2.6287

Table 3.1(d) ARIMA(0,1,0)

To determine the model with the best forecasts, the mean square of the residuals for each model were calculated. The mean square of the residuals for the ARIMA(0,1,0), ARIMA$(1,1,0)(1,1,0)_3$, ARIMA$(0,1,1)(0,1,1)_3$ and ARIMA(3,1,10) processes were 18.476, .005, 31.291 and 175.856 respectively. Therefore on the basis of the mean square of the residuals the ARIMA(0,1,0) process had the best forecasts and thus it the most appropriate model to use in predicting the Barclays bank (K) share prices in the Nairobi Stock Exchange market.

3.3.2 ICDC Investment Company Ltd

From section 2.3.2, the ARIMA(1,1,0) and the ARIMA(0,1,1) processes were provisionally identified as possible models for the ICDC share prices data, and basing on the AIC and BIC criteria, the ARIMA(1,1,0) model was seen as the better model.

To ascertain the adequacy of the two models, their sample residual autocorrelations were compared with their respective standard errors. Approximately all their sample autocorrelations were less than twice their standard errors, hence both models were adequate. Further, the calculated values for the two models using the Box and Pierce **Q** test statistic were compared with the tabular values at various lags and they were all less than their corresponing chi-square tabular values confirming that both models adequately fit the data. The forecasts for the two models are given in table 3.2(a) and (b) below.

Obs	Forecast	Std Error	Lower 95%	Upper 95%	Actual	Residual
284	33.6665	1.8988	29.9449	37.3881	34.00	0.3335
285	33.7702	3.1790	27.5396	40.0008	32.00	-1.7702
286	33.8523	4.2182	25.5848	42.1197	32.20	-1.6523
287	33.9270	5.0902	23.9504	43.9035	32.45	-1.4770
288	33.9992	5.8461	22.5411	45.4573	32.80	-1.1992
289	34.0705	6.5189	21.2938	46.8472	32.80	-1.2705
290	34.1415	7.1296	20.1677	48.1153	33.05	-1.0915
291	34.2124	7.6925	19.1355	49.2894	33.25	-0.9624
292	34.2833	8.2170	18.1783	50.3883	32.75	-1.5333
293	34.3542	8.7100	17.2829	51.4254	33.00	-1.3542
294	34.4250	9.1766	16.4393	52.4108	33.10	-1.3250
295	34.4959	9.6206	15.6400	53.3518	33.75	-0.7459
296	34.5668	10.0449	14.8791	54.2544	33.70	-0.8668
297	34.6376	10.4521	14.1519	55.1233	33.70	-1.3876
298	34.7085	10.8440	13.4547	55.9623	33.25	-3.7085
299	34.7793	11.2222	12.7843	56.7744	30.20	-4.5793

Table 3.2(a) ARIMA(1,1,0)

Obs	Forecast	Std Error	Lower 95%	Upper 95%	Actual	Residual
284	33.8325	1.9099	30.0893	37.5758	34.0000	0.1675
285	33.9034	3.1478	27.7338	40.0729	32.0000	-1.9034
286	33.9742	4.0211	26.0930	41.8555	32.2000	-1.7742
287	34.0451	4.7361	24.7626	43.3276	32.4500	-1.5951
288	34.1160	5.3564	23.6176	44.6144	32.8000	-1.3160
289	34.1868	5.9121	22.5994	45.7742	32.8000	-1.3868
290	34.2577	6.4198	21.6752	46.8402	33.0500	-1.2077
291	34.3285	6.8902	20.8241	47.8330	33.2500	-1.0785
292	34.3994	7.3304	20.0320	48.7668	32.7500	-1.6494
293	34.4703	7.7457	19.2890	49.6516	33.0000	-1.4703
294	34.5411	8.1399	18.5873	50.4949	33.1000	-1.4411
295	34.6120	8.5158	17.9214	51.3026	33.7500	-0.8620
296	34.6829	8.8758	17.2867	52.0790	33.7000	-0.9829
297	34.7537	9.2217	16.6795	52.8279	33.2500	-1.5037
298	34.8246	9.5552	16.0968	53.5523	31.0000	-3.8246
299	34.8954	9.8774	15.5362	54.2547	30.2000	-4.6954

Table 3.2(b) ARIMA(0,1,1)

Although the two models performed equally well, on the basis of the mean square of the residuals the ARIMA(1,1,0) process with a mean square of the residuals of 3.5764 gave the best forecasts as compared to the ARIMA(0,1,1) process with a mean square of the residuals of 3.9515. Therefore the ARIMA(1,1,0) model is the most appripriate model to use in predicting the ICDC share prices in the Nairobi Stock Exchange market.

3.3.3 Kenya Commercial Bank Ltd.

The ARIMA(0,1,12), ARIMA(12,1,0), ARIMA(12,1,12) and ARIMA(0,1,0) models were provisionally identified as the possible models for the Kenya commercial bank share prices. A diagnostic check using both the Box and Pierce **Q** statistic and the sample residual autocorrelation and partial autocorrelation revealed that all the models were adequate except the random walk model (ARIMA(0,1,0)). The forecasts for the accepted models are shown below.

Obs	Forecast	Std Error	Lower 95%	Upper 95%	Actual	Residual
284	55.6998	4.4041	47.0679	64.3317	52.6000	-3.0998
285	58.9580	6.2284	46.7506	71.1653	55.0000	-3.9580
286	58.3375	7.3135	44.0033	72.6717	56.0000	-2.3375
287	57.1466	8.2572	40.9627	73.3305	56.5000	-0.6466
288	57.7242	9.1351	39.8198	75.6285	55.8000	-1.9242
289	53.2875	9.9356	33.8141	72.7610	56.4000	3.1125
290	54.1251	10.6728	33.2068	75.0435	55.4000	1.2749
291	54.6427	11.3623	32.3731	76.9124	55.1000	0.4573
292	54.8319	11.8492	31.6080	78.0558	56.2500	1.4181
293	54.2327	12.3168	30.0923	78.3732	60.1000	5.8673
294	54.2389	12.7858	29.1792	79.2985	56.9000	2.6611
295	53.8753	13.2382	27.9289	79.8216	55.8000	1.9247
296	53.8549	13.9142	26.5836	81.1263	54.7000	0.8451
297	54.5387	14.5589	26.0037	83.0736	57.7000	3.1613
298	54.4752	15.1454	24.7908	84.1597	55.7000	1.4213
299	54.2770	15.7101	23.4860	85.0681	54.9000	0.6230

Table 3.3(a) ARIMA(12,1,0)

Obs	Forecast	Std Error	Lower 95%	Upper 95%	Actual	Residual
284	55.6132	4.3769	47.0347	64.1918	52.6000	-3.0132
285	58.8307	6.1899	46.6988	70.9625	55.0000	-3.8307
286	58.1268	7.2628	43.8919	72.3617	56.0000	-2.1268
287	57.0191	8.1966	40.9542	73.0840	56.5000	-0.5191
288	57.6799	9.0343	39.9731	75.3867	55.8000	-1.8799
289	52.2128	9.8007	33.0039	71.4217	56.4000	4.1872
290	53.1698	10.5113	32.5681	73.7716	55.4000	2.2302
291	53.8659	11.1769	31.9597	75.7721	55.1000	1.2341
292	54.1576	11.6441	31.3357	76.9795		2.0924
293	53.6533	12.0932	29.9510	77.3555		6.4467
294	53.4075	12.5448	28.8201	77.9949		3.4925
295	52.7987	12.9808	27.3570	78.2405		3.0013
296	52.8706	13.7055	26.0083	79.7328		1.8294
297	53.7906	14.3938	25.5793	82.0019		3.9094
298	53.7944	15.0103	24.3748	83.2140		2.1056
299	53.8640	15.6025	23.2838	84.4442		1.0360

Table 3.3(b) ARIMA(0,1,12)

Obs	Forecast	Std Error	Lower 95%	Upper 95%	Actual	Residual
284	55.3597	4.4049	46.7262	63.9932	52.6000	-2.7597
285	58.1673	6.2295	45.9576	70.3769	55.0000	-3.1673
286	57.4840	7.6296	42.5303	72.4376	56.0000	-1.4840
287	56.3607	8.8099	39.0937	73.6277	56.5000	0.1393
288	57.0045	9.8497	37.6994	76.3096	55.8000	-1.2045
289	51.2945	10.7898	30.1469	72.4422	56.4000	5.1055
290	52.2578	11.6544	29.4157	75.0999	55.4000	3.1422
291	52.9017	12.4590	28.4824	77.3209	55.1000	2.1983
292	53.2732	13.0425	27.7104	78.8360		2.9768
293	52.4270	13.6010	25.7696	79.0844		7.6736
294	52.2013	14.1374	24.4925	79.9100		4.6787
295	51.5700	14.6542	22.8483	80.2916		4.2300
296	51.5973	15.4743	21.2683	81.9264		3.1027
297	52.4145	16.2531	20.5590	84.2700		5.2855
298	52.4022	16.9963	19.0901	85.7142		3.4978
299	52.4295	17.7083	17.7219	87.1371		2.4705

Table 3.3(c) ARIMA(12,1,12)

Among the accepted models, the ARIMA(12,1,0) process with a mean square of the residuals of 6.6710 gave better forecasts as compared to the ARIMA(0,1,12) and ARIMA(12,1,12) processes with mean square of residuals of 9.213 and 14.106 respectively. Thus the ARIMA(12,1,0) model is the best model to use in predicting the Kenya Commercial bank share prices in Nairobi Stock Exchange market.

3.3.4 Standard Chartered Bank Kenya Ltd.

In section 2.3.4. the ARIMA(7,1,0), ARIMA(0,1,7) and ARIMA(0,1,0) models were proposed for the standard bank share prices. The diagnostic check on all the models revealed that they were all adequate for the data since the sample residual autocorrelations and the partial autocorrelations for each model had negligible values. The values obtained using the Box and Pierce Q statistic were also less than the corresponding chi-square tabular values confirming that the models are all adequate. The forecasts generated from each model are given below.

Obs	Forecast	Std Error	Lower 95%	Upper 95%	Actual	Residual
284	48.1281	6.1197	36.1338	60.1224	49.7500	1.6219
285	48.2062	8.6545	31.2437	65.1687	50.0000	1.7938
286	48.2843	10.5996	27.5095	69.0591	49.9000	1.6157
287	48.3624	12.2393	24.3738	72.3510	49.0500	0.6876
288	48.4405	13.6840	21.6204	75.2606	48.2000	-0.2405
289	48.5186	14.9901	19.1387	77.8986	48.9000	0.3814
290	48.5967	16.1911	16.8627	80.3307	47.3000	-1.2967
291	48.6748	17.3091	14.7498	82.5999	47.0500	-1.6248
292	48.7529	18.3590	12.7700	84.7359	46.9000	-1.8529
293	48.8310	19.3521	10.9017	86.7604	46.5000	-2.3310
294	48.9091	20.2967	9.1285	88.6898	47.3500	-1.5591
295	48.9872	21.1992	7.4377	90.5368	47.0500	-1.9372
296	49.0653	22.0648	5.8192	92.3115	47.2500	-1.8153
297	49.1434	22.8977	4.2648	94.0221	46.3000	-2.8434
298	49.2216	23.7014	2.7678	95.6753	45.6500	-3.5716
299	49.2997	24.4787	1.3224	97.2769	44.3000	-4.9997

Table 3.4(a) ARIMA(0,1,0)

Obs	Forecast	Std Error	Lower 95%	Upper 95%	Actual	Residual
284	48.5059	6.0102	36.7261	60.2856	49.7500	1.2441
285	47.9559	9.0737	30.1719	65.7400	50.0000	2.0441
286	47.9752	11.3376	25.7540	70.1965	49.9000	1.9248
287	48.0544	13.2193	22.1450	73.9637	49.0500	0.9956
288	48.0732	14.8647	18.9390	77.2075	48.2000	0.1268
289	48.2245	16.3453	16.1883	80.2606	48.9000	0.6755
290	48.1160	17.7025	13.4198	82.8122	47.3000	-0.8160
291	48.1683	18.5664	11.7789	84.5577	47.0500	-1.1183
292	48.2464	19.3470	10.3270	86.1659		-1.3464
293	48.3245	20.0974	8.9344	87.7146		-1.8245
294	48.4026	20.8207	7.5949	89.2104		-1.0526
295	48.4807	21.5197	6.3029	90.6586		-1.4307
296	48.5588	22.1968	5.0541	92.0636		-1.3088
297	48.6369	22.8537	3.8446	93.4293		-2.3369
298	48.7150	23.4923	2.6710	94.7591		-3.0650
299	48.7932	24.1140	1.5306	96.0557		-4.4932

Table 3.4(b) ARIMA(0,1,14)

Obs	Forecast	Std Error	Lower 95%	Upper 95%	Actual	Residual
284	48.4427	6.0410	36.6026	60.2828	49.7500	1.3073
285	48.0151	9.0343	30.3082	65.7219	50.0000	1.9849
286	47.9735	11.3034	25.8193	70.1277	49.9000	1.9265
287	48.0265	13.1920	22.1706	73.8823	49.0500	1.0235
288	48.0203	14.8427	18.9292	77.1114	48.2000	0.1797
289	48.1394	16.3274	16.1383	80.1404	48.9000	0.7606
290	48.0300	17.6879	13.3624	82.6976	47.3000	-0.7300
291	48.0618	18.6499	11.5087	84.6148	47.0500	-1.0118
292	48.2144	19.5348	9.9270	86.5018		-1.3144
293	48.3101	20.3781	8.3699	88.2504		-1.8101
294	48.3920	21.1875	6.8653	89.9186		-1.0420
295	48.4825	21.9671	5.4279	91.5371		-1.4325
296	48.5545	22.7199	4.0244	93.0847		-1.3045
297	48.6603	23.4486	2.7019	94.6186		-2.3603
298	48.7452	24.1872	1.3393	96.1511		-3.0952
299	48.8123	24.9073	-0.0050	97.6297		-4.5123

Table 3.4(c) ARIMA(14,1,0)

To determine the best model the mean square of the residuals were calculated. The mean square of the resuduals for the ARIMA(0,1,14), ARIMA90,1,14) and ARIMA(0,1,0) processes were 3.617, 3.621 and 4.853 respectively. On the basis of the mean square of the residuals the forecasts obtained from the ARIMA(0,1,14) process were the best, therefore it is the most appropriate model to use in predicting the standard Chartered bank share prices in the NSE market.

3.5 BAT Kenya Limited.

The models proposed for the BAT(K) share prices in section 2.3.5 were the ARIMA(13,1,3), ARIMA(0,1,13) and ARIMA(13,1,0) models. To discriminate between the adequate and inadequate models, both the Box and Pierce test statistic and sample residual autocorrelation check were used. Approximately all the sample residual autocorrelations and partial autocorrelations for each model were less than their corresponding standard errors revealing that all the models are adequate. On the other hand the p-values calculated from the Box and Pierce **Q** statistic (i.e $P(X^2(df) > Q)$ for each model were greater than the α-values (i.e 0.05) confirming the adequacy of each model. The forecasts given by the models are shown in table 3.5(a), (b) and (c) below.

Obs	Forecast	Std Error	Lower 95%	Upper 95%	Actual	Residual
284	68.7018	30.8312	8.2740	129.1296	69.9000	1.1982
285	70.0703	43.6018	-15.3876	155.5281	74.5000	4.4297
286	70.4395	53.4011	-34.2246	175.1036	72.7000	2.2605
287	70.1787	57.6883	-42.8881	183.2454	70.4000	0.2213
288	70.4739	61.6782	-50.4129	191.3606	70.6000	0.1261
289	70.5534	65.4252	-57.6774	198.7841	70.7000	0.1466
290	70.4160	68.1943	-63.2421	204.0741	70.2500	-0.1660
291	70.5087	70.8553	-68.3648	209.3822	70.8000	0.2913
292	70.5387	73.4199	-73.3613	214.4387	70.5000	0.0387
293	70.5617	75.7128	-77.8325	218.9558	70.4000	-0.1617
294	70.5650	77.9384	-82.1912	223.3211	70.3000	-0.2650
295	70.5610	80.1021	-86.4360	227.5580	69.4000	-0.1610
296	70.5925	81.4453	-89.0371	230.2222	70.0000	-0.5925
297	70.4399	82.7668	-91.7797	232.6594	70.8000	0.3601
298	70.3984	84.0674	-94.3703	235.1672	69.2000	-1.1984
299	70.4266	85.5219	-97.1930	238.0461	68.2000	-2.2266

Table 3.5(a) ARIMA(13,1,3)

Obs	Forecast	Std Error	Lower 95%	Upper 95%	Actual	Residual
284	70.0965	30.5610	10.1981	129.9948	69.9000	-0.1965
285	70.1042	43.2198	-14.6048	154.8132	74.5000	4.3958
286	71.8241	52.9332	-31.9229	175.5711	72.7000	0.8759
287	71.8592	56.6209	-39.1156	182.8340	70.4000	-1.4592
288	71.4795	60.0828	-46.2803	189.2393	70.6000	-0.8795
289	71.5189	63.3557	-52.6557	195.6935	70.7000	-0.8189
290	71.4870	66.4677	-58.7870	201.7610	70.2500	-1.2370
291	71.2612	69.4403	-64.8390	207.3615	70.8000	-0.4612
292	71.3132	72.2908	-70.3739	213.0004	70.5000	-0.8132
293	71.4130	75.0331	-75.6490	218.4749	70.4000	-1.0130
294	71.6111	77.6787	-80.6360	223.8582	70.3000	-1.3111
295	71.5993	80.2370	-85.6621	228.8607	69.4000	-2.1993
296	71.9086	82.7163	-90.2120	234.0293	70.0000	-1.9086
297	71.8813	83.9004	-92.5601	236.3226		-1.0813
298	71.8517	85.0679	-94.8780	238.5814		-2.6517
299	71.7271	86.2196	-97.2600	240.7142		-3.5271

Table 3.5(b) ARIMA(0,1,13)

Obs	Forecast	Std Error	Lower 95%	Upper 95%	Actual	Residual
284	69.7604	30.4607	10.0586	129.4622	69.9000	0.1396
285	69.5241	47.3094	-23.2004	162.2486	74.5000	4.9759
286	70.4305	60.2321	-47.6219	188.4830	72.7000	2.2695
287	70.4276	67.2873	-61.4528	202.3079	70.4000	-0.0276
288	70.1433	73.1220	-73.1728	213.4595	70.6000	0.4567
289	70.1152	78.4305	-83.6053	223.8358	70.7000	0.5848
290	70.0683	84.0281	-94.6235	234.7601	70.2500	0.1817
291	69.8882	89.3901	-105.3129	245.0892	70.8000	0.9118
292	69.9282	94.4687	-115.2267	255.0831		0.5718
293	69.9275	99.1532	-124.4087	264.2638		0.4725
294	69.9685	103.6020	-133.0873	273.0242		0.3315
295	69.9378	107.8632	-141.4697	281.3453		-0.5378
296	69.9194	111.9913	-149.5792	289.4179		0.0806
297	69.7911	114.7663	-155.1462	294.7285		1.0086
298	69.8298	117.2766	-160.0276	299.6872		-0.6298
299	69.6776	119.6929	-164.9156	304.2708		-1.4776

Table 3.5(c) ARIMA(13,1,0).

Since the three models performed equally well to determine the best model, the mean square of the residuals for the models were calculated. The mean square of the residuals for the ARIMA(13,1,3), ARIMA(13,1,0) and ARIMA(0,1,13) processes were 2.085, 2.244 and 3.623 respectively. Thus on the basis of the mean square of the residuals the ARIMA(13,1,3) process had the best forecasts and thus it is the most appropriate model to use in predicting the BAT Kenya Limited share prices in the Nairobi Stock Exchange market.

3.3.6 Kenya Breweries Ltd.

The ARIMA(9,1,0), ARIMA(0,1,9) and ARIMA(0,1,0) processes were proposed for the Kenya breweries share prices. On diagnostic checking, none of the models was adequate. The forecasts obtained from each model are given below.

Obs	Forecast	Std Error	Lower 95%	Upper 95%	Actual	Residual
284	43.8734	5.8839	32.3412	55.4056	43.5000	-0.3734
285	43.8851	9.8082	24.6613	63.1088	44.2500	0.3649
286	44.1390	12.9806	18.6976	69.5804	46.2000	2.0610
287	44.2087	15.6382	13.5583	74.8590	48.3000	4.0913
288	44.3358	17.9414	9.1715	79.5001	48.0000	3.6642
289	44.4474	19.9915	5.2649	83.6299	48.1000	3.6526
290	44.5588	21.8533	1.7272	87.3905	48.0000	3.4412
291	44.5216	23.5696	-1.6739	90.7170	48.0000	3.4784
292	44.6106	25.1694	-4.7204	93.9416		3.3894
293	44.6516	26.3970	-7.0856	96.3887		3.2984
294	44.7611	27.4873	-9.1129	98.6352		3.2389
295	44.8347	28.5100	-11.0438	100.7131		1.9653
296	44.9356	29.4889	-12.8615	102.7327		1.3644
297	45.0280	30.4337	-14.6208	104.6769		3.1220
298	45.1227	31.3491	-16.3203	106.5658		2.0773
299	45.2175	32.2383	-17.9683	108.4033		1.6325

Table 3.6(a) ARIMA(9,1,0)

Obs	Forecast	Std Error	Lower 95%	Upper 95%	Actual	Residual
284	43.9010	5.8835	32.3695	55.4325	43.5000	-0.4010
285	43.8990	9.7112	24.8654	62.9325	44.2500	0.3510
286	44.1935	12.4096	19.8712	68.5158	46.2000	2.0065
287	44.2883	14.6181	15.6374	72.9392	48.3000	4.0117
288	44.4479	16.5342	12.0415	76.8543	48.0000	3.5521
289	44.6146	18.2502	8.8449	80.3843	48.1000	3.4854
290	44.8136	19.8182	5.9707	83.6565	48.0000	3.1864
291	44.8491	21.2709	3.1589	86.5393	48.0000	3.1509
292	44.9097	22.6306	0.5546	89.2647		3.0903
293	45.0040	23.6034	-1.2577	91.2656		2.9460
294	45.1008	24.4523	-2.8247	93.0264		2.8992
295	45.1977	25.2727	-4.3357	94.7312		1.6023
296	45.2946	26.0673	-5.7962	96.3855		1.0054
297	45.3915	26.8384	-7.2107	97.9937		2.7585
298	45.4884	27.5879	-8.5828	99.5597		1.7116
299	45.5853	28.3177	-9.9161	101.0868		1.2647

Table 3.5(b) ARIMA(0,1,9)

Obs	Forecast	Std Error	Lower 95%	Upper 95%	Actual	Residual
284	43.4969	6.3207	31.1087	55.8851	43.5000	0.0031
285	43.5938	8.9388	26.0742	61.1134	44.2500	0.6562
286	43.6907	10.9477	22.2336	65.1477	46.2000	2.5093
287	43.7876	12.6413	19.0111	68.5641	48.3000	4.5124
288	43.8845	14.1334	16.1835	71.5854	48.0000	4.1155
289	43.9814	15.4824	13.6365	74.3262	48.1000	4.1186
290	44.0783	16.7229	11.3021	76.8545	48.0000	3.9217
291	44.1752	17.8775	9.1359	79.2144	48.0000	3.8248
292	44.2721	18.9620	7.1074	81.4368		3.7279
293	44.3690	19.9877	5.1939	83.5440		3.5810
294	44.4659	20.9633	3.3787	85.5530		3.5341
295	44.5628	21.8954	1.6486	87.4769		2.2372
296	44.6597	22.7895	-0.0068	89.3261		1.6403
297	44.7566	23.6497	-1.5960	91.1091		3.3934
298	44.8534	24.4798	-3.1260	92.8329		2.3466
299	44.9503	25.2826	-4.6026	94.5033		1.8997

Table 3.6(c) ARIMA(0,1,0)

Among the three processes, the ARIMA(0,1,9) model with a mean square of the residuals of 6.725 gave the best forecasts as compared to the ARIMA(9,1,0) and ARIMA(0,1,0) with mean square of the residuals 7.955 and 9.908 respectively. Therefore the ARIMA(0,1,9) is the most appropriate model to use in predicting the Kenya breweries share prices in the NSE market.

3.3.7 Nairobi Stock Exchange (NSE) Index.

The ARIMA(1,1,0) and ARIMA(0,1,2) models were proposed for the NSE index in section 2.3.7. The sample residual autocorrelations and the partial autocorrelations for both models were all less than twice their corresponding standard errors while the calculated values using the Box and pierce Q statistic were also less than their corresponding chi-square tabular values revealing that both models adequately describe the data. The forecasts generated by each model are given in table 3.7(a) and (b) below.

Obs	Forecast	Std Error	Lower 95%	Upper 95%	Actual	Residual
284	3022.8250	89.2049	2847.9870	3197.6629	3051.0600	28.2350
285	3023.1283	169.5759	2690.7662	3355.4904	3081.6400	58.5117
286	3030.7906	243.6442	2553.2578	3508.3234	3100.2700	69.4794
287	3038.4528	299.9482	2450.5663	3626.3394	3135.4300	96.9772
288	3046.1151	347.2397	2365.5392	3726.6911	3149.2700	103.1549
289	3053.7774	388.8212	2291.7035	3815.8513	3159.2500	105.4726
290	3061.4397	426.3665	2225.7784	3897.1009	3139.0900	77.6503
291	3069.1020	460.8632	2165.8286	3972.3753	3138.8200	69.7180
292	3076.7642	492.9516	2110.5987	4042.9297	3138.8200	62.0448
293	3084.4265	523.0753	2059.2198	4109.6332	3126.5500	42.1235
294	3092.0888	551.5562	2011.0606	4173.1169	3126.5500	34.4612
295	3099.7511	578.6370	1965.6457	4233.8564	3130.6700	30.9189
296	3107.4133	604.5058	1922.6062	4292.2204	3096.7500	-10.6633
297	3115.0756	629.3121	1881.6491	4348.5021	3148.9100	33.8344
298	3122.7379	653.1770	1842.5371	4402.9386	3077.6500	45.0879
299	3130.4002	676.2001	1805.0749	4455.7254	3061.3500	-69.0502

Table 3.7(a) ARIMA(0,1,2)

Obs	Forecast	Std Error	Lower 95%	Upper 95%	Actual	Residual
284	3030.3989	90.0040	2853.9946	3206.8032	3051.0600	20.6611
285	3034.1229	168.0800	2704.6927	3363.5530	3081.6400	47.5171
286	3039.5121	240.4413	2568.2568	3510.7675	3100.2700	60.7579
287	3045.8625	305.9790	2446.1560	3645.5691	3135.4300	89.5675
288	3052.7676	365.1220	2337.1430	3768.3922	3149.2700	96.5024
289	3059.9928	418.7304	2239.2979	3880.6878	3159.2500	99.2572
290	3067.4029	467.6873	2150.7545	3984.0512	3139.0900	71.6871
291	3074.9196	512.7683	2069.9142	4079.9250	3138.8200	63.9004
292	3082.4978	554.6157	1995.4733	4169.5224	3138.8200	56.3222
293	3090.1116	593.7479	1926.3895	4253.8337	3126.5500	36.4384
294	3097.7459	630.5801	1861.8342	4333.6576	3126.5500	28.8041
295	3105.3920	665.4446	1801.1473	4409.6368	3130.6700	25.2780
296	3113.0450	698.6086	1743.8000	4482.2899	3096.7500	-16.2950
297	3120.7019	730.2888	1689.3650	4552.0387	3148.9100	28.2081
298	3128.3610	760.6621	1637.4937	4619.2284	3077.6500	-50.7110
299	3136.0215	789.8748	1587.8986	4684.1445	3061.3500	-74.6715

Table 3.7(b) ARIMA(1,1,0)

To choose the best model the mean square of the residuals of the two models were evaluated. The ARIMA(1,1,0) process with a mean square of the residuals 3622.680 give the best forecasts as compared to the ARIMA(0,1,2) process with a mean square of the residual of 7.183.535 and thus it is the best model to use predicting the NSE share index.

CHAPTER FOUR

CONCLUSIONS AND RECOMMEDATIONS

In this dissertation, we applied the time series modelling techniques to the Nairobi Stock Exchange share prices data to develop appropriate forecasting models. In choosing the best models, emphasis was laid on their forecasting ability and adequacy. Therefore in some cases, inadequate models were used to generate the forecasts for some of the quoted firms. The best models selected for each firm are given in the table 4.1 below.

Firm	**Model**
Barclays bank (K)	ARIMA(0,1,0)
ICDC Investment (K)	ARIMA(1,1,0)
Kenya Commercial bank	ARIMA(12,1,0)
Standard Bank (K)	ARIMA(0,1,14)
BAT (K)	ARIMA(13,1,3)
Kenya Breweries Ltd	ARIMA(0,1,9)
NSE index	ARIMA(1,1,0)

Table 4.1 Selected models

All the selected models for the quoted firms gave reliable 8-weeks ahead forecasts which may be used to help a stock investor to arrive at a sale or purchase decision of his stock securities. The forecasts obtained from the models had reasonable confidence intervals (C.I) with the exception of Barclays Bank (K), BAT (K) and the NSE Index which had forecasts with large confidence intervals due to the their dispersed share prices data. Although the forecasts were generally good for all the firms, they were affected by the high share prices between December 1993 and March 1995 which were as a result of the high rates of inflation in the country's economy at that period, the reforms and liberalisation of the financial sector which relaxated the restriction on foreign investors at the Nairobi Stock Exchange market and the increasing bank interest rates.

Thus we can conclude that time series modelling techniques can effectively be used to model the stock prices data and the forecasts generated from the selected models used to guide the stock investors on when to sell or purchase the stock securities.

In building the stock models, we maintained the Gaussian assumption on the innovation sequence and only fitted the linear ARMA models. However, the continued realization that for many practical situation the Gaussian laws are inadequate and that the stable laws may be more appropriate (see for example Fama, 1965; Granger and Orr, 1972; Stuck and Kleiner, 1965) may help to explain why for example the fitted linear models with Gaussian assumption on the innovation sequence for some firms like Barclays bank (K), Kenya Breweries and NSE Index performed poorly.

This implies that alternative models to linear ARMA processes like the Linear ARMA processes with infinite variance, Nonlinear models and the Intervention models could be possible alternatives.

REFERENCES

Abraham, B. and Ledolter, J. (1983), Statistical Methods of Forecasting, *New York; Wiley.*

Akaike, H.(1970), Statistical Predictor Identification; *Ann inst stat math. 22, 203-217.*

Akaike, H.(1974), A New look at the Statistical Identification; *IEEE Trans Autom control. 9, 716-723.*

Akaike, H. (1978), Comment on 'On Model Structure Testing in System Identification', *Int. J. Cont. 27, 323-324.*

Anderson, O.D.(1976), Time Series Analysis and Forecasting, London: *Butterworths.*

Anderson, T.W. (1971), The Statistical Analysis of Time Series, New York: *Wiley.*

Bachelier, L. (1900), Theory of Speculation; Paris: *Gauthier villar.*

Barlett, M.S. (1946), 'On the Theoritical Specification of Sampling Properties of Residual Autocorrelationed Time Series', *j. Roy statist. soc. ser. B, 8, 27-41.*

Bhansali, R.J. (1983), Estimation of the order of a Moving Model from Autoregressive and Window estimates of the Inverse correlation function: *J. Time ser. Anal. 4, 137-162.*

Box, G.E.P. and Cox, D.R. (1964), 'An Analysis of Transformations', *Journal of the Royal Statistical Society, Series B, 26, 211-43.*

Box, G.E.P. and Jenkins, G.M. (1970), Time Series Analysis: Forecasting and Control; *San francisco; Holden day.*

Box, G.E.P. and Pierce, D.A. (1970), Distribution of Autocorrelated Moving Average Models; J. *Amer Stat ass 65, 1509-1526.*

Box, G.E.P. and Tiao, G.C. (1975), 'Intervention Analysis with Application to Economic and Environmental Problems', *journal of the American Statistical Association, 6, 70-79*

Chatfield, C. and Prothero, D.L. (1973), Box and Jenkins Seasonal Forecasting: Problems in a case-study. *J. Roy. Statist. Soc A 136, 295-315.*

Clark, P.K. (1973), "A Subordinated Stochastic Process Model with Finite Variance for Speculative Prices", *Econometrica, 5, 135-155;*

Cootner, H. (1964), The Random Characher of Stock Market Prices; *Cambridge mass: Them. I.T. press.*

Fama, E. (1965), Behavior of Stock Market Prices; *Journal of buss 38, 34-105.*

Giorgio, C. and Pollard, S.K. (1985), ARIMA Modelling of the "New" U.S. Monetary Aggregates.

Godambe, V.P. (1985), Conditional Likelihood and Unconditional Optimum Estimating Equations. *Biometrika 63, 277-284.*

Gooijer, J.; Abraham, B.; Ann, G. and Robinson, L. (1985), Methods for Determining the order of an Autoregressive Moving Average Process: A survey. *National statistic reveiw (1985) 53, 300- 329 Great Britain international statistical institute.*

ranger, C.W.J. and Anderson, A.P. (1978), An Introduction to Bilinear Time Series Models, *Gottingen: Vandenhoeck and Ruprecht*.

ranger, C.W.J. and Morgenstern, O. (1963), "Predictability of Stock Market Prices", *Lexington, Mass, :Heath*.

ranger, C.W.J. and Orr, D. (1972), Infinite Variance and Research Strategy in Time Series Analysis. *J. Am. statist. assoc. 67, 275-85*.

aggan, V. and Ozaki, T (1981), 'Modelling Nonlinear Vibration using an Amplitude-Dependant Autoregressive Time Series Model', *Biometrika, 68, 189-96*.

annan, E.J. (1970), Multiple Time Series, New York: *Wiley*.

annan, E.J. (1980), The Estimation of the order of an ARMA Process: *Ann Statist 8, 1071 - 1081*.

annan, E.J. and Quinn, B.G (1979), The Determination of the order of an Autoregression: *J.R Statist Soc B41, 190-195*.

annan, E.J and Rissanan, J. (1982), Recursive Estimation of Mixed ARMA order: Biometrika 69, 81-94.

limko, L.A. and Nelson, P. (1978), On Conditional Least Squares Estimation for Stochastic Process. *Ann Statist 6, 629-642*.

jung, G.M. and Box, G.E. (1978), 'On a Measure of Lack of Fit in Time Series Models', *Biometrika, 65, 297-303*.

ill, T. C (1990), Time Series Techniques for Economists; *Cambridge University Press*.

Nelson, C.R. and Granger, C.W.J. (1979), 'Experience with Using the Box-Cox Transformation when Forecasting Economic Time Series', *Journal of Econometrics, 10, 57-69.*

Newbold, P. and Granger, C.W. (1974), Experience with Forecasting Univariate Time series and the Combination of Forecasts. *J. Roy. Statist. Soc A 137, 131-146.*

Nicolls, D.F. and Quinn, B.G. (1982), Random Coefficient Autoregressive Models, *An Introduction. Lecture Notes in Statistics No.11. Springer. New York.*

Osborne, M.F.M. (1959), Brownian Motion in the Stock Market; *Operation Research 7, 145-173.*

Ozaka, T. (1977), On the order Determination of ARIMA Models: *Appl. Statist 26, 290-301.*

Poskitt, D.S. and Tremayne, A.R. (1981), 'An Approach to Testing Linear Time Series Models', *Annals of Statistics, 9, 974-986.*

Potscher, B. M. (1982), Order Determination of the ARMA Systems by the Lagrange Multiplier Test. *Report No.5, Institute for Econometrics and Operations Research, Technology University.*

Priestley, M.B. (1980), 'State-Dependant Models: A General Approach to Nonlinear Time series Analysis', *Journal of Time Series Analysis, 1, 47-71.*

Priestley, M.B. (1988), Nonlinear and Nonstationary time series Analysis; *Academic Press, London.*

Quenouille, M.H. (1947), A Large Sample Test for the Goodness of Fit of Autoregressive Schemes: *J. R. Statist Soc 110, 123-129.*

Robert, H.V. (1959), Stock Market Patterns and Financial Analysis: Methodological Suggestions; *Journal of Finance 14, 1-14.*

Schwarz, G. (1978), Estimating the Dimension of a Model. *Ann Statist 6, 461-464.*

Slutzky, H. (1937), The Summation of Random Causes as the Source of Cyclic Process; *Econometricia 5, 105-146.*

Stuck, B.W. (1978), Minimumorror Dispersion Linear Filtering of the Scalar Symmetric Stable Processes. *IEEE Trans. Automot. Control 23, 507-9.*

Stuck, B.W. and Kleiner, B. (1974), A Statistical Analysis of the Telophone Noise. *Bell Syst. Tech. J. 53, 1263-1320.*

Taylor, S. (1986), Modelling Financial Time Series, Chichester: *John Wiley.*

Tjosteim, D. (1986), Some Doubly Stochastic Time Series Models, *Journal of Time Series Analysis 7, 51-72.*

Tong, H. and Lim, K.S. (1980), 'Threshold Autoregression Limit Cycles, and Cyclical Data', *Journal of the Royal Statist Society, Series B, 42, 245-292.*

Tong, H. (1983), Threshold Models in Non-linear Time Series Analysis, *Berlin: Springer-verlag.*

Westerfield, R. (1977), "The Distribution of Common Stock Prices Changes: An Application of Transactions Time and Subordinated Stochastic Models", *Journal of financial and*

Changes: An Application of Transactions Time and Subordinated Stochastic Models", *Journal of financial and Quantitative Analysis 5, 250-53.*

Wold, H. (1954), "A Study in the Analysis of Stationary Time Series (2nd Ed)": *Almquist and Wicksell uppsala.*

Yule, G.U. (1927), "Methods of Investigating Periodicities in Distrubed Series with Special Reference to Wolfer's Sunspot Number: *Philos Trans Roy Soc London Ser. V226, 267-298.*