ESSAYS ON AN EMERGING STOCK MARKET: THE CASE OF NAIROBI STOCK EXCHANGE

(Statistical Distribution of Returns, Market Seasonality and Reactions to Dividend Announcements)

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DECLARATION

This thesis is my original work and has not been presented for a degree in any university

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I, however, remain responsible for all the errors and inaccuracies which may remain.

ABBREVIATIONS

ARCH	Autoregressive Conditional Heteroskedasticity
EGARCH	Exponential Autoregressive Conditional Heteroskedasticity
EMH	Efficient Market Hypothesis
GARCH	Generalised Autoregressive Conditional Heteroskedasticity
NSE	Nairobi Stock Exchange
TGARCH	Threshold Autoregressive Conditional Heteroskedasticity
VAR	Vector Autoregression

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Abstract

The general objective of this thesis is to test the well known market efficiency hypothesis using daily data from the Nairobi Stock Exchange. This high frequency data permits a thorough testing of the efficiency hypothesis because the very short-period nature of the data, helps control for effects of other determinants of the stock market performance, which have been a persistent problem in previous studies.

The analysis of data reveals that the distribution of daily compounded returns on ordinary shares is not normal, and unlike what some previous studies have shown, the distribution of stock returns exhibits long tails. The shape of this distribution implies that the actual data fluctuates with a bigger margin than what would otherwise be expected from a standard normal distribution. It also renders linear models unsuitable tools for analyzing behavior of stock returns. There is strong evidence of volatility, clustering, and asymmetry of price dispersion, which further justifies the use of non-linear models in the analysis of stock markets.

With regard to asymmetry, it is found that big changes in returns follow big ones, and that small changes follow small ones, and negative changes in returns are more persistent than positive changes. On asset pricing models, the results show that the linear model fails to capture the relationship between daily returns on ordinary shares and market returns. As consistent with previous studies, there is evidence of ARCH effect, with TGARCH model outperforming the OLS, GARCH (1, 1) and the EGARCH models.

On calendar anomalies, the study shows that though methodologies play an important role in outcomes of tests of the null of the market efficiency hypothesis, the various methods deliver similar trends, such that the calendar effect is only evident when large periods are considered. The implication of this is that though there is no evidence of day-of-the-week effect, there is a weak pointer towards existence of month-of-the-year effect, and strong evidence of quarter-of-the-year effect. The

evidence that the quarter of the month effect exists, suggests that although investments in ordinary shares made on the basis of the day-of-the-week will yield capital gains by chance, profits from long term share investments are almost guaranteed.

As to sensitivity of stock returns to an event, a non-parametric test of this sensitivity outperforms the regression test. The test results show that there is need to use short estimation periods, since longer ones are subject to data smoothing, in addition to increasing the chances of the event of interest overlapping with other events. There is evidence that at the Nairobi Stock Exchange, ordinary share returns are sensitive to dividend announcements, with the announcements triggering market volatility, followed by normalization in about a week. This pattern of performance implies that it takes only a short period for publicly available stock information to get to all investors, so that only the investors who react within the first one week can make abnormal profits on the basis of such information. Finally, it is found that most investors at the Nairobi Stock Exchange are speculators who have no allegiance to particular firms.

CHAPTER ONE
Background, Research Problem, and Study Objectives

1.0 Introduction

1.1 The stock exchange market

The roots of stock markets can be traced to the periods of industrial revolution in England. Many merchants wanted to start big businesses yet individually they could not raise the required initial capital. It thus became inevitable that they had to pool resources together and start businesses as partners. Contribution of each partner was to be represented by some unit of ownership which is the precursor to what is today called a share. Challenges arose when new capital was needed and also when old investors wanted to leave. While the former required a platform for lobbying for new investors, the latter needed a method for allowing the old share holder to exit without affecting the capital base of the firm. This implied creating a platform for direct swapping of shares. Initially, trading in shares began out of convenience as informal hawking in the streets of London. As the need for organized market escalated, traders decided to meet at a coffee house to transact businesses. Eventually in 1773, like the proverbial camel, they took over the coffee house to form the first stock exchange market in London.

Stock market as it is presently, is that market which deals in the exchange of shares, bonds and other instruments of money. Bonds and shares form securities. Shares are financial instruments that allow one to acquire ownership of a company, voting rights and entitlement to returns, which are neither fixed nor guaranteed. Holders of shares can gain from exceptional performance of the firm. Bonds on the other hand are loans, which attract and guarantee returns. Holders have no voting rights and do not benefit or lose from exceptional performance of the firm.

Stock exchange markets perform important roles in the economy including: (1) Promoting a culture of thrift by providing avenues through which savers can invest their money while consumers reduce consumption due to economic interests accompanying shares. (2) Facilitating transfer of securities among participating public. Under this function, the stock market provides a channel through which persons who may want to withdraw from firms can do so without affecting the capital base of such firms by simply transferring the shares to other persons who want to invest in the same firms. (3) Providing an extra source of finance for companies for expansion and development. Companies can raise funds through Initial Public Offers (IPO) and issuance of extra shares. (4) Enhancing flow of international capital.

Investors in the stock exchange markets can be classified as speculators who buy shares in anticipation of capital appreciation, those who buy for investment income and rely on dividend as compensation for their efforts, and those who use shares as a means of exchange. These investors can be individuals or organizations; thus the importance of stock markets in the economy cannot be overstated.

Emerging markets refer to all markets in developing countries (Balaban 1995). A stock market in any country whose per capita income is below US$ 7620 in 1990 prices is considered as an emerging market. These markets offer high expected return to capital with associated high risks (Anthony 2006). Their revitalization is often characterized by reforms such as modernization of trading systems, expansion of stock market membership by opening it to foreign participants and revamping the regulatory frameworks governing these markets.

1.2 The Nairobi Stock Exchange

Though dealing in shares started in Nairobi in 1920s, there was no formal market, no rules, and no regulations governing broking of shares at the time (NSE 2005). Trading was on a gentleman's agreement made over a cup of coffee. Clients were obligated to honor their contractual commitments of paying commission and making good delivery of stock. Trading was a sideline business conducted by people in other professions. It was not until 1951 that an estate agent named Francis Drummond established the first professional broking firm and approached the minister for finance with the idea of setting up a stock exchange market in East Africa. In 1953 the two approached authorities of the London Stock Exchange who agreed to recognize the setting up of Nairobi Stock

Exchange as an overseas stock market. The Nairobi Stock Exchange (NSE) was then constituted as a voluntary association under the societies act in 1954 (NSE 2005). Since its inception, NSE has undergone several experiences including an initial steady growth after post independent years, which was characterized by oversubscription of public issues. However, the oil crisis of 1972 slowed growth and led to depressed share prices. In the mid 1970s, losses were experienced at the NSE due to different and unfavorable government policies among the East African countries. For example, Uganda nationalized some of the companies that were listed in NSE. The loss was further accelerated by the introduction of a 35% capital gains tax which however was suspended in 1985. In 1989 a regulatory body, Capital Markets Authority was formed and charged with overseeing the development of NSE.

In the early 1990s, NSE regained its growth momentum after undertaking major modifications, including a move to spacious premises at the Nation Centre, the setting up of a computerized delivery and settlement system and a development of modern information centre. It is during this period that the number of stockbrokers increased to 20 from the original 5. In 1994, NSE was rated by International Finance Corporation (IFC) as the best performing stock market in the world with a return of 179% in dollar terms. In 1999, NSE was registered under the companies act and faced out the "call over" trading system in favor of the floor-based open cry system.

The first privatization to be handled by NSE was the sale of 20% Kenya Commercial Bank shares; however, the largest was the privatization of Kenya Airways in 1996. As at 2005 the number of listed companies at NSE was fifty four, forty eight of which were equities and the rest being bonds. Government bonds accounted for 7% of all bonds. The number of the listed companies at the NSE over the years has on the average ranged from 52 to 59 companies.

The listed companies at the NSE fall into main investment market segment, alternative investment market segment and fixed investment securities segment. The main difference between the first two is mainly in the requirement for the minimum authorized initial capital and net assets. The former is mainly for large companies. The segments are further divided into the following sectors: agriculture, commercial and services, finance and investment, industrial and allied, and alternative investment market (NSE 2005).

By 2007, the official market value for the NSE 20-share index, calculated as geometrical mean of 20 companies had increased to 5739.05. The constituent counters for the index were Tourism Promotion Services (TPS) Holdings, Bamburi Cement, Barclays Bank (K), British Oxygen Company (BOC), British American Tobacco (BAT), Unilever Tea, Diamond Trust Bank (DTB), East Africa Breweries Limited (EABL), National Industrial Credit (NIC) Bank, George Williamson, Kakuzi, Kenya Airways, Kenya Commercial Bank (KCB), Kenya Power & Lighting Company (KPLC), Sameer Africa Ltd., Nation Media Group, Sasini Tea and Coffee Ltd., Standard Chartered Bank (K) Ltd. (STANCHART), Total Kenya, and Uchumi Supermarkets Ltd (NSE 2005).

1.3 Efficient market hypothesis

The origins of Efficient Market Hypothesis (EMH) can be traced to the works of Bachelier (1964) and Cowles (1960). The modern literature has benefited from the works of Samuelson (1965) and Fama (1970).

Though used in many different ways, efficient market has a specific meaning in finance. A securities market is said to be efficient if the prices fully reflect all available market information. This definition rests on very strong assumptions and gives the impression that the cost of acquiring market information is zero. A more reasonable, and alternative view of EMH would be that prices reflect information until the marginal cost of obtaining market information and trading in stocks no longer exceeds the marginal benefit. The impetus is that prices must be unpredictable if they are properly anticipated. According to Fama (1998), efficiency in markets can be classified into three. First a market is weak efficient if all information contained in historical prices is fully reflected in current prices. This is to say that no investor can make excess profits from trading rules based on past prices. Second, a market is semi-strong efficient if prices and publicly available information is fully reflected in the current stock prices, hence no excess profits can be obtained when trading rules are based on past prices and publicly available information about the firms. Finally, a market is strong efficient if all information (past prices, publicly available information, and inside information) is fully reflected in current stock prices so that an investor cannot make excess profits from trading rules based on any information about the firm. Fama (1998) acknowledged that the test for EMH involves joint hypothesis of market efficiency and the underlying equilibrium asset pricing model. He concluded that market efficiency per se is not testable.

By 1970s there was consensus among financial economists that stock prices were approximated by random walk and that stock returns were unpredictable. In fact, Kendall (1953), Cowles (1960), Osborne (1964) and Samuelson (1965) provided evidence that in an informationally efficient market, price changes must be unpredictable.

Though initial studies showing evidence against random walk were dismissed as unimportant or statically suspect, increasing studies in the 1990s showed that stock returns over different horizons (days, weeks, and months) can actually be predicted to some degree by mean of interest and dividend yields (Pesaran 2005). This finding to some extent, throws out of gear the concept of the Efficient Market Hypothesis.

1.4 Statement of the problem

An efficient stock market is that which responds to new information and does not experience rapid price fluctuations or other instabilities, for it is assumed that all investors in the market have similar, accurate information (Fama 1998). If markets are efficient then anomalies are chance events and should disappear within a relatively short time. Some studies on stock markets including DeBondt and Thaler (1985), Lakonishok (1990), Laughran and Ritter (1995), Mitchell and Stafford (2000) conclude that markets appear to overreact to information. The common conclusion is that stock prices adjust slowly to information and that in some cases losers become winners. The impetus of these findings may be that overreaction is an alternative to market efficiency. Other studies, for example, Ball and Brown (1968), Bernard and Thomas (1990) and Jegadeesh and Titman (1993) suggest that stock prices tend to under-react.

This dialogue brings about the question whether the market efficiency concept is still relevant. Fama (1970) provides an answer to the question by giving two reasons as to why the market efficiency concept is still relevant:

1. Long-term return anomalies are sensitive to methodology. He argues that studies rarely test a specific alternative to market efficiency since the alternative hypothesis is vaguely market inefficiency.
2. Market under-reaction and overreaction to information are both common; but both could still be attributed to chance.

Literature does not lean clearly towards market efficiency or the behavioural alternative. This dilemma was well captured by Mechealy (1995) when he said, "we hope to understand why markets appear to overreact to some circumstances and under react in others".

In classical economic theory, equilibrium price and quantity are determined by the intersection of downward sloping demand curve and an upward sloping supply curve. However, in the securities market, there is evidence of high demand when prices are high and low demand when prices are low. This may be due to other intervening macroeconomic and market or firm-specific factors. It is evident that stock markets are characterized by information arrivals, i.e., mergers, initial public offerings (IPO), dividend announcements and share splits among others, which may have direct bearing on stock prices and returns. How these affect stock prices may differ between developed and emerging markets, and between markets or even between different industries in the same market. Though developed markets have been studied extensively, the same cannot be said of emerging markets; i.e., whether they exhibit similar general characteristics, including distribution of stock returns.

The economics of time series data has been dominated by Frisch-Slutsky paradigm which assumes linearity among variables. This linearity paradigm assumes that for every action there is a counter action. The strength of linearity models lies in two major arguments. First, simplicity: linear models are simple to work with, are predictable and are backed by a wide range of proven analytical techniques and computer software, capable of testing reliability of methodologies. Second, that there exists a direct relationship between stochastic economic theories and linear econometric models of the vector regression variety. However, economic theory is not emphatic that linear models best capture economic time series systems or that an economic system is linear. In the actual sense, stock markets are rarely orderly. Often, they unexpectedly exhibit exponential over-reaction to action. Moreover, linear systems lack the ability to capture shocks and are generally sensitive to outliers, rendering them inappropriate for forecasting time series variables that are history and shock dependent. When using linear models, strange answers have been attributed to noise. This demonstrates that noise is an important component in modeling, since it is known that when injected in a graph the data clustering neither appears as a straight line, nor are these data points predictable. Linear models thus fail to solve problems related to instability and oscillations of share prices. Economists have over time linearized certain models with a degree of success. Although the behaviour of certain physical non-linear systems can be effectively represented by linearization, through change of variables and detrending, this is often at a cost of essential dynamical properties of the real phenomenon.

From the classifications of market efficiency and the probable contradiction in the theory of demand from the literature, and experience with a variety of estimation techniques, the following research questions arise in the context of a stock market:

1. Is there evidence of stock price predictability? And if there is, how can market participants predict prices?
2. What techniques are available for the analysis of data that do not subscribe to the linear paradigm and are such techniques statistically superior to linear models?
3. Do stock returns and prices at NSE, and by extension, the emerging stock exchange markets exhibit market anomalies?
4. Do major announcements such as those related to dividends have effect on returns in emerging markets?

1.5 Objectives of the study

The general objective of this work is to test the market efficiency hypothesis using the Nairobi Stock Exchange (NSE) daily ordinary stock prices data and model stock returns using the same data. The specific objectives are:

1. To document statistical and modeling properties of returns on ordinary shares and to determine the most appropriate models and estimation techniques.
2. To test for the existence of calendar anomalies as a proxy for weak form efficiency.
3. To analyze the relationship between publicly available information and returns on ordinary shares.

1.6 Justification of the Study

Forecasting of stock market returns is important both to investors and policy makers. The specific calendar anomalies if documented would be useful to investors who will know what appropriate decisions to take at what time. Use of linear models for forecasting, though highly developed with good estimation and test of reliability techniques may not be theoretically appropriate. Stock market returns are characterized by leverage effect, fat tail distribution, and volatility clustering and hence may most likely exhibit non-linear trends. In fact, their trends are too complex to be determined by linear models. This presents an ideal platform for modeling stock prices using non-linear methods. The study will thus not only add to general knowledge about the securities market behavior, but also to the tools used to analyze such markets. Though the study uses data from the Nairobi Stock Exchange market, the results can be generalized to other emerging markets with similar characteristics. Finally, the study will be useful to the investor who may want to spread his portfolio and to the policy maker in the capital markets authority, intent to improve this institution.

1.7 Organization of the thesis

To meet the objectives of the study, each research objective is answered in its own chapter as an independent essay, complete with literature review, methodology, data analysis, results and a conclusion. Chapter two discusses statistical distribution properties of ordinary shares traded in the Nairobi Stock Exchange and documents the market volatility, its modeling, and the policy implications of the models formulated. Chapter three tests the presence of calendar anomalies and documents the possibility of making abnormal profits if investment rules are based on particular days, months or quarters of the year. Chapter four uses dividend announcement dates to measure the effect of publicly available information on returns to ordinary share prices.

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CHAPTER TWO

Ordinary Shares at the Nairobi Stock Exchange: Distribution of Returns, Share Pricing and Market Volatility

2.0 Introduction

This essay accomplishes the first objective of the study by synthesizing the relevant literature, documenting and modeling statistical properties of returns on ordinary shares, and by suggesting appropriate estimation methods for the models proposed.

2.1 Literature review

Efficient Market Hypothesis (EMH) often governs the modeling of financial markets. It assumes that investors are rational, orderly and tidy. This model reduces the mathematics of investment behavior to simple linear equations. Linear models borrow heavily from Euclidean geometry, which reduces nature to pure and symmetrical objects. Often, the assumption of linearity is followed by the use of regression analysis to estimate the coefficients of the population parameters. Regression analysis in turn assumes that the errors are normally distributed with a mesocurtic kurtosis, i.e., the distribution of the disturbance term neither has fat nor thin tails.

Osborne (1964) plotted the density function of stock market returns and noted that the tails were flatter than they should be, i.e., they follow Leptokurtic distribution. This suggests that use of linear regression would give biased results with large variances. The possible explanation given by Osborne of the fat tail for distribution of share returns is that information shows up in infrequent clumps rather than in smooth and continuous fashion, giving credence to the possibility that the stock market returns may not follow a linear pattern.

Diebold and Kamil (2009) proposes spillover index as a measure of linkages between asset return and return volatility. Using daily stock prices from seven developed markets and twelve emerging markets, they used variance decomposition in VAR to measure return spillovers and volatility spillovers. They found that there is divergent behavior in the dynamics of return spillovers and volatility spillovers in that the latter display clear bursts with no trend, while return spillovers display the exact opposite. The bursts displayed by volatility were found to be associated with identified crisis events.

In the 1970s, most option trading was in short term equity options lasting a few months. In this context, the assumption of constant volatility over the remaining period could produce good short term forecast. However, with the practice of active trading in long term options, this *ad hoc* method is unattainable. Despite its importance, volatility estimation and forecasting remain more of an art than a science among derivative traders (Figlewski 2004). This is because the in-sample models used are either too complicated to the stock traders or are not suitable for extrapolation. Autoregressive Conditional Heteroskedasticity (ARCH) family of models have been used successfully in characterizing non-linear dynamics in the analysis of exchange rates; however, they may not be suitable in capturing co-movements of variables associated with conditional volatility (Ho 2004). In addition, few studies have focused on multivariate modeling of exchange rate volatility (Anthony, 2006, Aggarwal, *et al.*, 2002, Fama and French, 1997).

Though time series theorists have made progress in developing theoretical properties of non-linear models, an efficient statistical method for estimating these models in a parametric form using a set of finite observations remains elusive (Hinich and Patterson 1995). Hinich and Patterson itemize practical iterative steps of estimating a non-linear function as follows: 1. Detection of non-linearity. They acknowledge that progress has been made in this direction especially in the case of non-zero third order cumulant functions. 2. Identification through use of data of candidate model tentatively considered. 3. Estimating the candidate model parameters using appropriate statistical methods. This may, for example, involve inversion of the model, i.e., expressing innovations as a function of past values of non-linear process. 4. Diagnostic checks to determine goodness of fit (see Schwert, 1993 & 1990).

There are several reasons for modeling and forecasting volatility in finance. First it helps in the analysis of risk of holding an asset. Second, it provides an accurate interval estimate. Third it allows for obtaining efficient estimates to be used in other estimates for example, in event studies. Variance of the errors is a measure of average deviation from the mean, and hence serves as an appropriate measure of variability.

Financial risk management has taken a central role thus making volatility forecasting a compulsory risk management exercise for many financial institutions around the world (Poon and Granger 2003). Banks for example set aside a reserve of several times the value-at-risk (VaR). This VaR can only be correct if volatility is forecast accurately. In addition financial market volatility has an effect on the economy for it can be viewed as a barometer for vulnerability of financial markets. It is known that monetary policies of some countries are made after considering volatility in stocks, bonds, currency and commodities. Though, there is wide literature on volatility forecasting, there seems not to be a consensus as to which is the best method. While some methods forecast correlation, others do not produce out-of-sample volatility, (see Bernard and Thomas, 1990; Black, 1972; Brav and Gompers, 1997; Brooks, 1996 and Brooks *et al*, 2001; LeRoy, 1973; Laughran and Ritter 1995; Kritzman, 1990; Kothari and Warner, 2004; Mackinlay, 1997; Tse 1997; Koulakiotis *et al*., 2006; Lakonishok, 1990; Paeran, 1994, 1995 and 2005).

According to EMH, prices move only when information is received. The implication is that today's change in prices is caused by unexpected news and that yesterday's news is not important because it is already known. This hypothesis oversimplifies modeling since it assumes lack of memory on the part of investors and that any variation is stochastic.
It is generally believed that thick distribution tails, volatility clustering, heteroskedasticity and asymmetry are stylized facts about financial data. It has also been believed for a long time that the linear market model effectively captures asset pricing of a stock market. All these assertions have implications for the estimation techniques in asset pricing models. Though developed markets have been studied extensively, the same cannot be said of emerging markets. From the above discourse, the following research questions arise:

(i). Does the linear model successfully capture the relationship between ordinary stock prices and the market returns?

(ii). is there evidence of stock price predictability?

(iii). what is the most appropriate method of modeling risk in stock markets?

2.2 Methodology

Security market players are either those who want to own part of the business or those investing in the secondary market with the aim of selling the stock when the market price is right. To both, a change in stock price represents a capital gain or loss depending on the direction of the price change. To the primary investor, a change in stock price represents a change in net worth, while to the secondary investor the same is an indication of profit opportunity. Assuming rationality, each stock holder would want to maximize gain on capital.

Denoting a stock holder's profit

by Π, we have:

$$\Pi = p_t - p_{t-1} \tag{2.1}$$

Where p_t is the price of the security at day t.

Since securities have different initial values, a better statistic for comparing performance of securities is the returns on securities, given as

$$R_{it} = \left[\frac{p_t - p_{t-1}}{p_{t-1}}\right] * 100 \tag{2.2}$$

This equation is based on the assumption that the price of a stock depends on performance of the economy and calendar effects. The former can be proxied by the daily stock index and specific events, while the former is represented by either day of the week, month of the year or week of the month. Since an investor may purchase more than one security, the behavioural problem becomes to maximize the average return from the various securities, as shown below

$$R_{it} = f(R_{mt}, C_t, E_k) \tag{2.3}$$

where R_{mt} is the stock exchange index for day t, C_t is calendar effect, and E_t is the ***k*** th specific event.

The calendar effect shows, if specific days, months or quarter of the year exhibit specific pattern in the behaviour of stock prices, and is summarized as:

$$C_t = f(D_w, M_y, Q_y) \text{ w= 1,2...5; y= 1,2...12; m=1,2...5} \tag{2.4}$$

Where D_w is day-of-the-week, M_y is month-of-the-year and Q_y is quarter-of-the-year

Equation (2.4) can thus be modified as:

$$R_{it} = f(R_{mt}, D_w, M_y, Q_y, E_k) \quad \textbf{(2.5)}$$

Though the variables can occur simultaneously, we assume that their impacts can be isolated such that the impact of calendar and event on share returns can be analyzed separately. Since the variables D_w, M_y W_m and E_k are qualitative factors, the main model is therefore

$$R_{it} = f(R_{mt}) \quad \textbf{(2.6)}$$

Equation (2.6) is actually a market model of measuring normal returns on an asset.

For a reliable test of hypothesis, an appropriate measure of variance is necessary but this will also depend on the distribution of the error term, an issue which this paper will also address.

2.2.1 Linearity and volatility of returns

Though the linear paradigm is useful, the observation by Campbell *et al* (1997) that payoffs to options, investors' willingness to trade off returns and risks are non-linear, provides a motivation that financial data is subject to non-linear relationships. Furthermore, features such as Leptokurtosis (fat tails), volatility clustering (bunching), and leverage effects (asymmetry) characterizing financial data cannot be handled by linear models. These arguments strongly support use of non-linear models in analyzing stock markets. However, the opposite of linearity, which is not necessarily non-linearity, the way we understand it, could as well be chaos in the relationship represented by the data. Before data is subjected to estimation it is thus important to test for non-linearity and/or chaos (see Browm and Warner, 1980; Debondt and Thaler, 1982; Cowles, 1960; Fama, 1998; Ball and Brown, 1968; Bernard and Thomas, 1990; Kim and Singal, 2000).

Campbell *et al.* (1997) broadly defines a non-linear data generating process as that where current values of the series are related non-linearly to current and previous values of the error term. This relationship can be represented more specifically as:

$$y_t = g(\mu_t, \mu_{t-1} \ldots) + \mu_t \sigma^2(\mu_{t-1}, \mu_{t-2} \ldots) \quad \textbf{(2.7)}$$

Where g is a function of past error terms only and σ^2 is variance term. Models with non linear g(.) are non-linear in mean, while the $\sigma^2(.)$ are non-linear in variance.

2.2.2 Test for non-linearity

The first test for non-linearity is to consider whether theory accommodates it. Using precedence it may be safe to say that from the authority of Campbell *et al* (1997) financial data is generally non-linear. Statistical time series tests which look at data in frequency domain like autocorrelation and partial autocorrelation can as well be used to test for non-linearity, but are weak (Brooks 2004). Other popular tests for linearity include Ramsey's RESET and BDS tests. In this study RESET test is applied, buttressed by the recursive least squares method (see Corrado and Zivney, 1992; Dejong *et al*, 1992; Lee, 1994; Ibbotson, 1975; Jegadeesh and Titman, 1993 and 2001; Lucas, 1978; Reynolds, 2006; Ritter, 1994; Rubinstein, 1976; Samuelson, 1965).

RESET Test

Regression Specification Error Test (RESET) was proposed by Ramsey (1969). It is actually an omnibus test and can test for omitted variables, incorrect specification and correlation between independent variables and the stochastic term. RESET tests the hypothesis that the classical normal linear equation is not representative of the relationship existing between the economic variables. Assuming that equation (2.6) defines the correct relationship characterizing prices of an ordinary share for the *i*th firm. The following market model can be specified:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \quad \varepsilon_{it} \sim N(0, \sigma^2) \qquad \textbf{(2.8)}$$

The hypotheses implicit in the model are:

$$H_0 : \varepsilon \approx N(0, \sigma^2 I)$$

$$H_a : \varepsilon \approx N(\mu, \sigma^2 I) \mu \neq 0$$

Accepting the null hypothesis implies that the classical linear model is representative. Since the test involves fitting the powers of the fitted values to data, it gives a strong indication of the nature of the relationship between the dependent and independent variables (see; Engel, 2002; Fama, 1970; Granger, 1998; Hsieh, 1989).

Recursive Least Squares

This method involves estimating the price equation repeatedly using larger samples. Recursive residuals are plotted about the zero line after estimation. Residuals outside the standard error band suggest instability of returns.

2.2.3 Test for volatility

Conceptually, there are infinite types of non-linear models in economics; however, only a few may be applicable in finance. The most popular of these are the ARCH and GARCH models.

The ARCH Model

Until the ground breaking seminal paper by Engel (1982), most macro-econometrics and financial modeling centered on conditional first moments. The importance of risk and uncertainty however necessitated the development of alternative modeling. Engel (1982) introduced ARCH model, whose insight is the distinction between the conditional variances and co-variances. ARCH model has been improved upon further by many scholars to what may be referred to as the ARCH family of models.

The ARCH (Autoregressive Conditional Heteroskedasticity) models are designed to model and forecast conditional variances as a function of past values of the dependent variable and independent or exogenous variables. ARCH evolved from two equations as follows:

$$y_t = \beta_0 + \sum_{i=1}^{T} \beta_i x_{it} + \mu_t,\ \mu_T \sim N(0,\sigma^2) \qquad \textbf{(2.9)}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{T} \alpha_i \mu^2_{t-i} \qquad \textbf{(2.10)}$$

where equation (2.9) is the conditional mean equation which describes how the dependent variable varies over time. The form it takes depends on the theory governing the relationship between the variables specified in the model. Equation 2.10 is the conditional variance equation.

In the literature, conditional variance (σ_t^2) is referred to as h_t ; hence equation 10 becomes:

$$h_t = \alpha_0 + \sum_{i=1}^{T} \alpha_i \mu^2_{t-i} \qquad \textbf{(2.11)}$$

Where h_t must be strictly positive. This is referred to as the non–negativity condition.

The ARCH model has important features, which make it appropriate for financial time series analysis. First, it takes account of volatility clustering (the tendency of large changes to follow large changes and small changes to follow small changes). Second, it takes care of heteroskedasticity. ARCH models however have three limitations. First, it is problematic settling on the lag length. Second, if the lag length is big, then the model may not be parsimonious. Lastly the non-negativity condition may be violated.

GARCH Models

The terminology stands for Generalized Autoregressive Conditional Heteroskedasticty. It addresses the limitations of ARCH. The original GARCH model was developed independently by Bollerslev (1986) and Taylor (1986) as a generalized form of ARCH. It explains variance by two sets of distributed lags, one on past residual to capture high frequency effects, and the second in lagged values of the variance itself to capture long term effects. The generalized version of the model, known as GARCH (q,p) is given as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \mu^2_{t-i} + \sum_{j=1}^{p} \beta_j \sigma^2_{t-j} \qquad \textbf{(2.12)}$$

This generalized GARCH model is hard to fit if more than one lag is anticipated. The most popular model in this class is GARCH (1, 1), which is given as:

$$\sigma^2_t = \omega + \alpha_1 \mu^2_{t-1} + \beta_1 \sigma^2_{t-1} \qquad \textbf{(2.13)}$$

GARCH (1,1) is parsimonious, can account for both leptokurtosis and volatility clustering and hence it is superior to the ARCH model. The major shortcoming of the GARCH model is that the use of variance and squared errors limits all the variables to positive values, thus implying that impact is independent of sign. Studies have shown that in finance, negative shocks are more persistent than positive ones. In addition, it may also not satisfy the non-negativity condition. Because of the aforesaid problems, there is need to address the asymmetry problem.

Asymmetric ARCH Models

This class of models takes into account the fact that downward movements in the market are followed by higher volatilities than upward movements of the same magnitude. In technical terms, they factor in leverage. The two main models at issue here are TGARCH and EGARCH models.

TGARCH Model

TGARCH is a variation of GARCH introduced independently by Zakoian (1990) and Glosten, Jaganathan and Runkle (1993). It is sometimes referred to as GJR. In this model, the impact of good new (ε_t<0) and bad news (ε_t>0) is tested to show if there is a different impact on conditional variance of news, depending on whether downward movements in the market are followed by higher volatilities than upward movements of the same magnitude. The conditional variance is modeled as:

$$\sigma^2_t = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} + \gamma\mu^2_{t-1}I_{t-1} \qquad \textbf{(2.14)}$$

Where γ is leverage effect and $I_{t-1} = 1$ if $\mu_{t-1} < 1$ and 0 otherwise.

EGARCH Model

EGARCH is an acronym for exponential GARCH proposed by Nelson (1991). It accounts for asymmetry by introducing the logarithm of conditional variances. It is given as:

$$\ln(\sigma^2_t) = \omega + \beta\ln(\sigma^2_{t-1}) + \gamma\frac{\mu_{t-1}}{\sqrt{\sigma^2_{t-1}}} + \alpha\left[\frac{|\mu_{t-1}|}{\sqrt{\sigma^2_{t-1}}} - \sqrt{\frac{2}{\pi}}\right] \qquad \textbf{(2.15)}$$

Apart from taking into account leverage, this model does not require non-negativity constraint.

Data and estimation methods

Data was drawn from the Nairobi Stock Exchange. It covers five years between 2001 and 2005. To capture the entire sections of the market, only firms included in the computation of Nairobi Stock Exchange index (NSE-20 Share index) are included in the sample. One firm, Uchumi supermarkets, is however excluded since it had been suspended from stock market at the time of this study.

An interesting but uncommon case is when change in share price is indicated as zero. This may imply two scenarios as follows: one that there was no trading at all, and second that trading occurred at constant prices. In an emerging market, where thin trading is common, for simplicity and without loss of generalization, we assume no trading.

Presented in the ensuing section are results derived from several methodologies, which include graphical, algebraic, and regression methods.

Table 2.1 Trading characteristics of the selected firms in NSE for the period 2001-2005

Name of Firm	Comparing Trading and Non-trading days for the data period
Bamburi	Non-trading days> Trading days
Barclays	Trading days> non-trading days
BAT	Trading days> non-trading days
BOC	Non-trading days> Trading days
DTB	Non-trading days> Trading days
EABL	Trading days> non-trading days
Firestone	Trading days> non-trading days
G.Williamson	Trading days> non-trading days
Kakuzi	Non-trading days> Trading days
Kenya Airways	Trading days> non-trading days
KCB	Trading days> non-trading days

Table 2.1 continued

KPLC	Trading days> non-trading days
NMG	Trading days> non-trading days
NIC	Trading days> non-trading days
Sasini	Non-trading days> Trading days
Stanchart	Trading days> non-trading days
Total	Trading days> non-trading days
TPS	Trading days> non-trading days
Unilever	Non-trading days> Trading days

2.3 Empirical Results

This section presents descriptive characteristics and the results of linearity and volatility tests. The descriptive statistics are in section 2.3.1 and the estimation results in section 2.3.2.

2.3.1 Descriptive Results

Introduction

In this section the characteristics of the share price data are explained using graphical presentation of daily compounded percentage changes in share prices for all the selected firms. Descriptive statistics, such as arithmetic mean, range and kurtosis are also presented.

In all the graphs, the vertical axis represents percentage change in daily share prices. On the horizontal axis, is presented the time period between 1st January 2001 and 31st December 2005. In all the cases, extreme values (>50%) have been excluded and this affects the variability of returns shown in the graphs.

Figure.2.1a Daily percentage change in ordinary share prices (Bamburi)

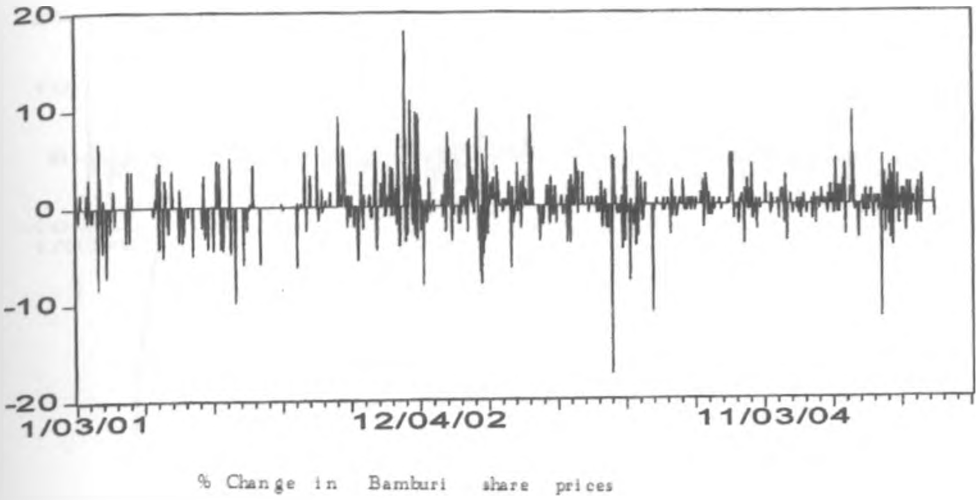


Figure.2.1b Daily percentage change in ordinary share prices (BOC)

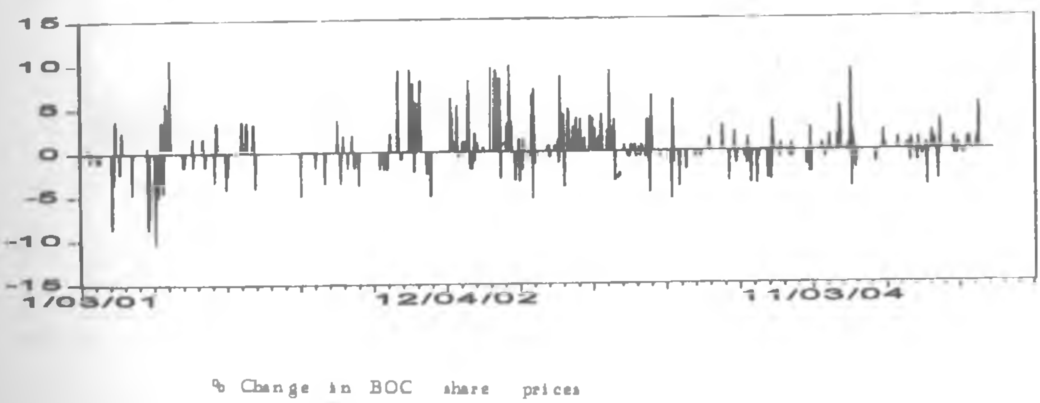


Figure.2.1c Daily percentage change in ordinary share prices (BAT)

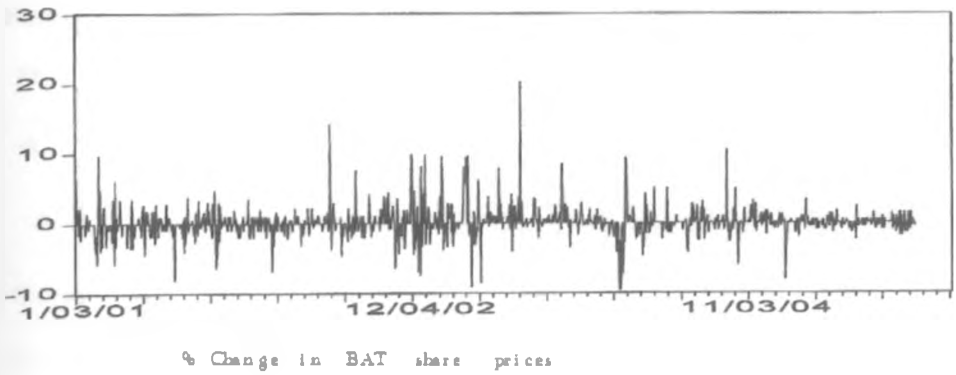


Figure 2.1d Daily percentage change in ordinary share prices (Barclays)

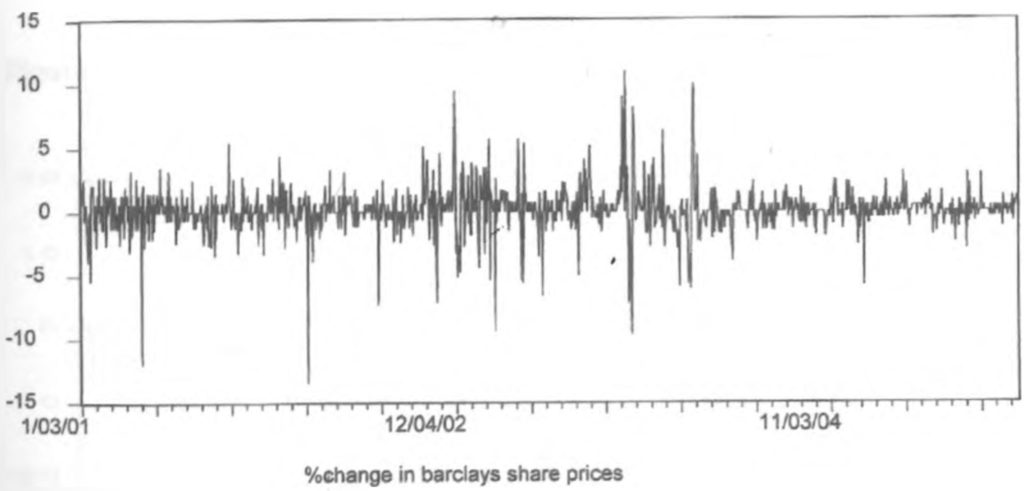


Figure 2.1e Daily percentage change in ordinary share prices (DTB)

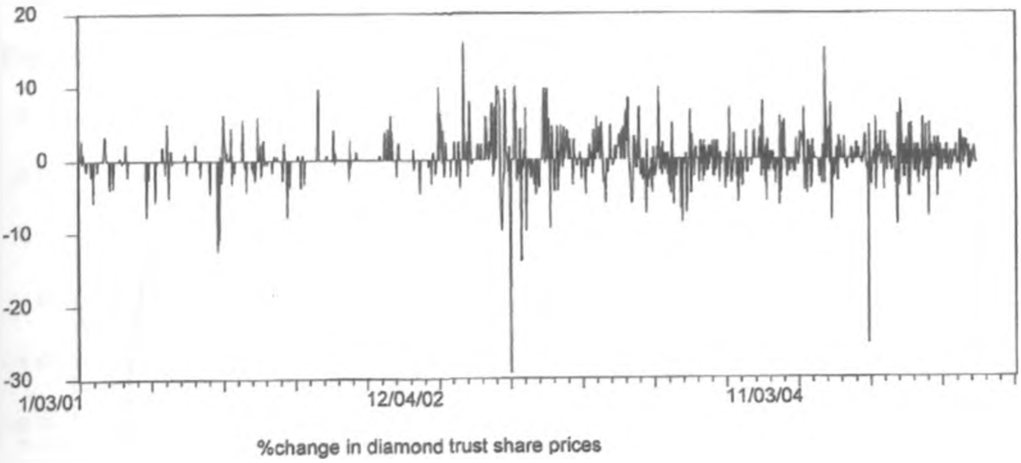


Figure 2.1f Daily percentage change in ordinary share prices (Unilever)

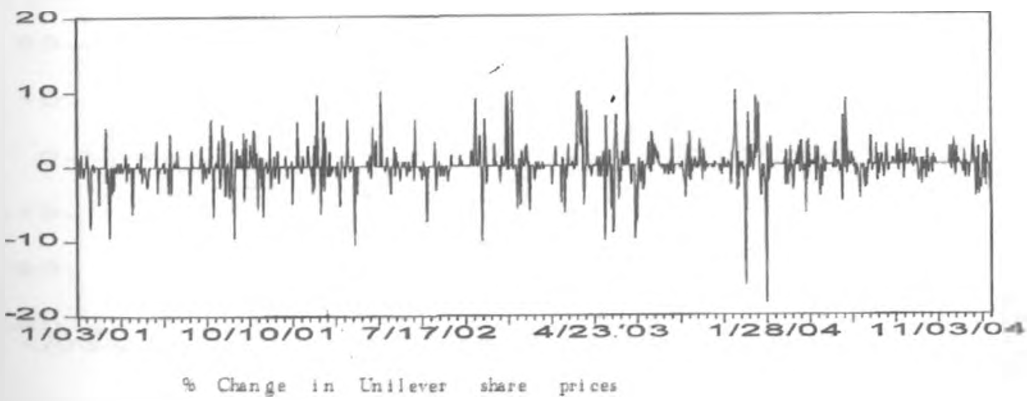


Figure 2.1g Daily percentage change in ordinary share prices (EABL)

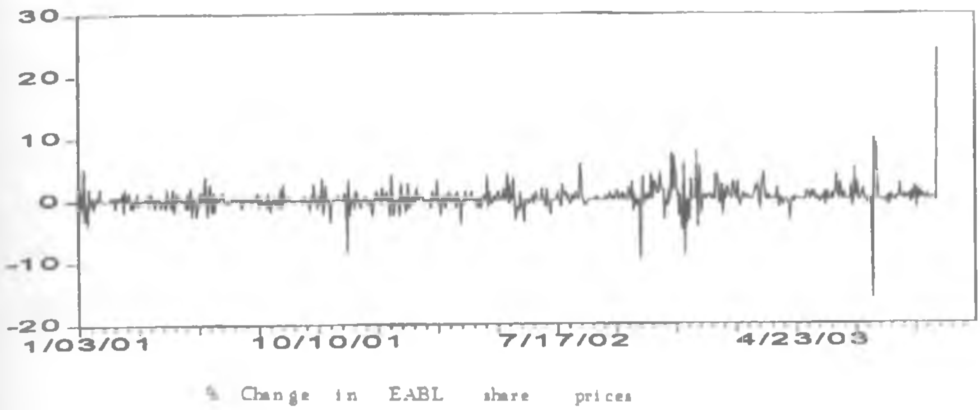


Figure 2.1h Daily percentage change in ordinary share prices (George Williamson)

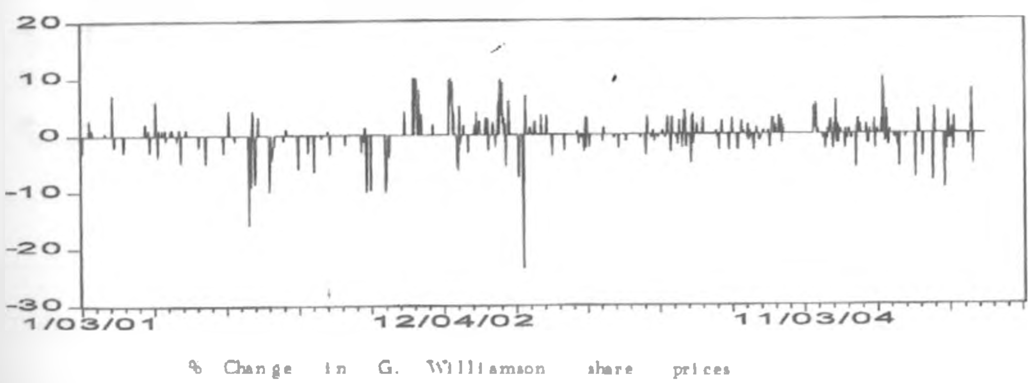


Figure 2.1i Daily percentage change in ordinary share prices (Kakuzi)

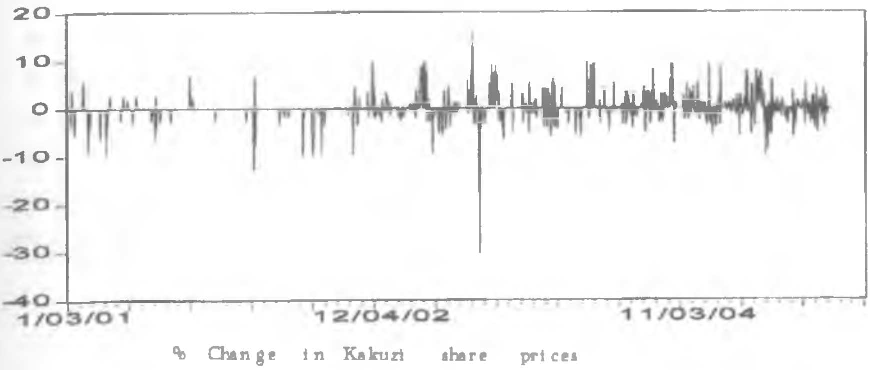


Figure 2.1j Daily percentage change in ordinary share prices (KCB)

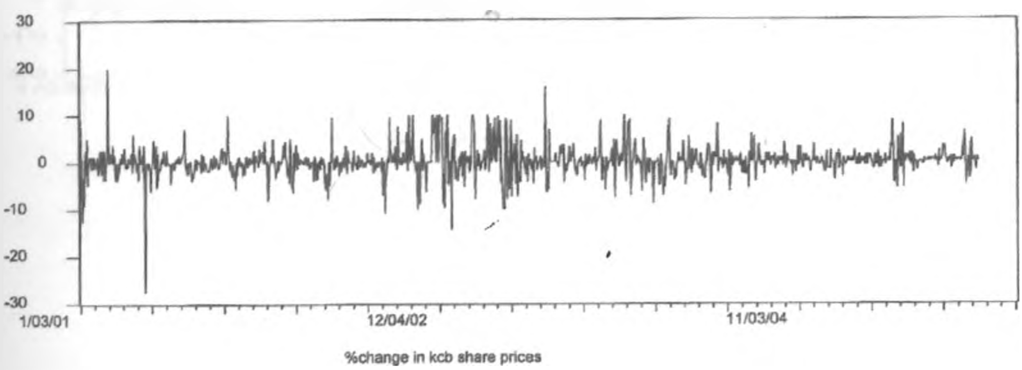


Figure 2.1k Daily percentage change in ordinary share prices (Kenya Airways)

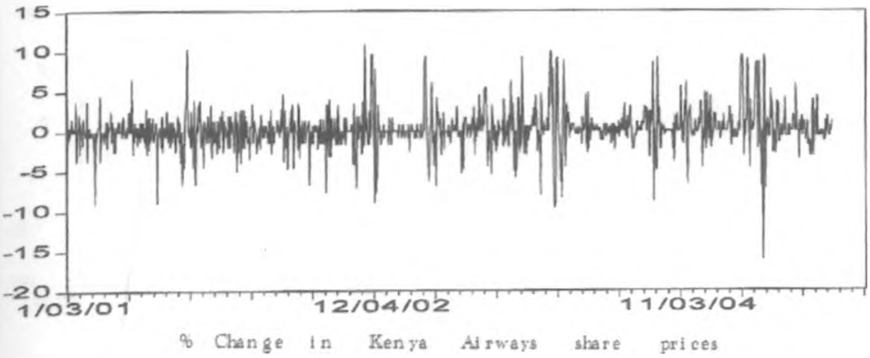


Figure 2.1l Daily percentage change in ordinary share prices (KPLC)

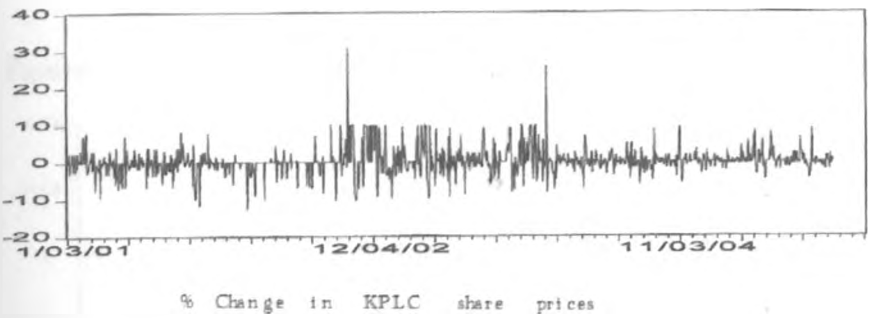


Figure 2.1m Daily percentage change in ordinary share prices (NIC)

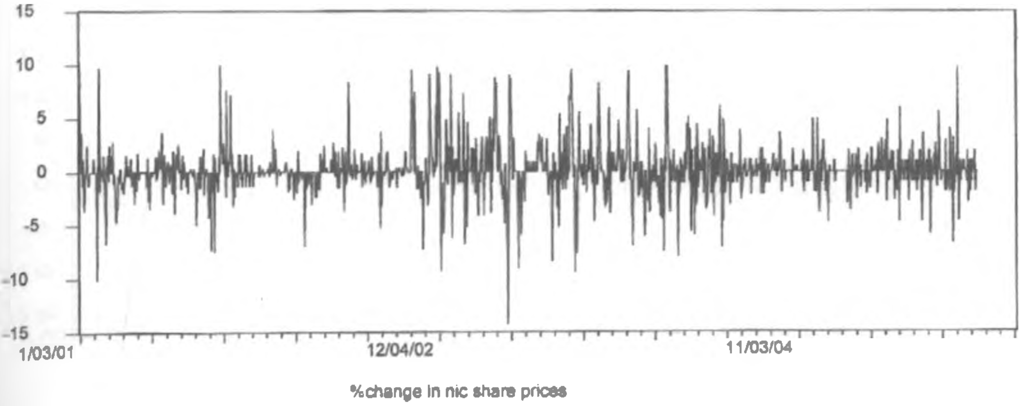


Figure 2.1n Daily percentage change in ordinary share prices (Nation)

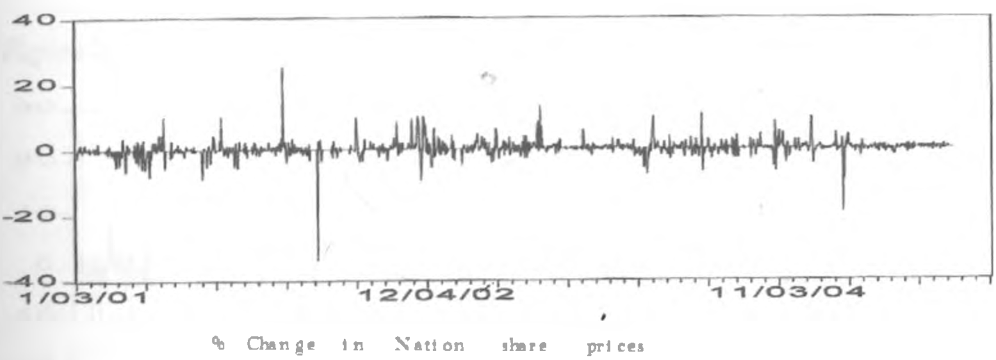


Figure 2.1o Daily percentage change in ordinary share prices (Sasini)

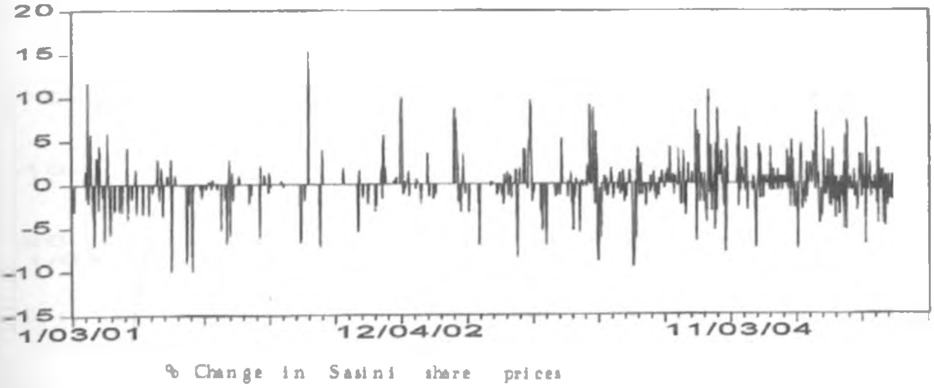


Figure 2.1p Daily percentage change in ordinary share prices (Total Kenya)

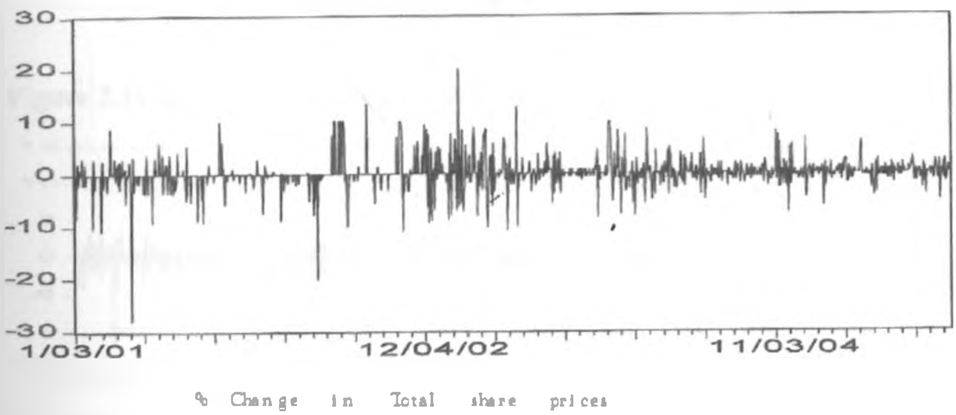


Figure 2.1q Daily percentage change in ordinary share prices (Firestone)

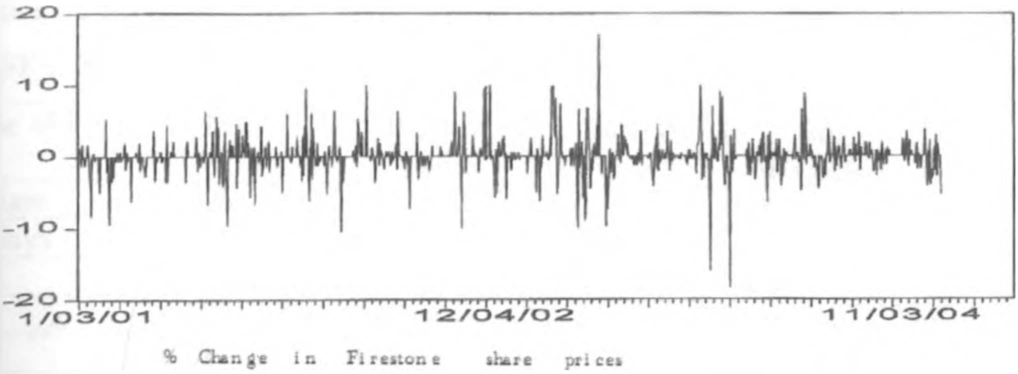


Figure.2.1r Daily percentage change in ordinary share prices (TPS)

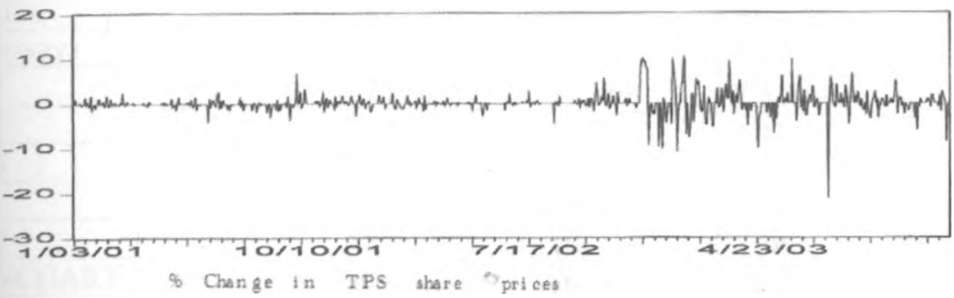
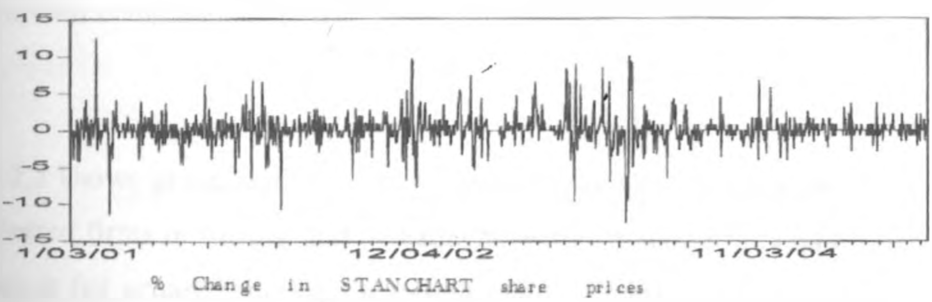


Figure 2.1s Daily percentage change in ordinary share prices (STANCHART)



From the graphs it can be noted that there are no wild swings but rather a cluster of changes seemingly similar in magnitude. Big changes tend to follow big ones and small ones tend to follow small changes. This evidence suggests that there is volatility clustering in the share price data.

Table 2.2 Descriptive group statistics for prices of ordinary shares of selected firms in NSE (2001-2005) (1248 observations)

Name of Firm	Mean	Highest Value	Lowest Value	Std deviation	Kurtosis
Bamburi	0.226	143.2	-60	5.3	>3
Barclays	0.116	10	-13.48	1.75	>3
BAT	0.18	94	-48	4.48	>3
BOC	0.122	48	-32	2.26	>3
DTB	0.231	162.8	-61	6.59	>3
EABL	0.28	24.36	-16	1.93	>3
Firestone	0.028	17	-18	2.4	>3
G.Williamson	0.0258	10	-23.5	1.95	>3
KAKUZI	0.13	192.6	-70	21	>3
K. Airways	0.30	180	-65.1	5.97	>3
KCB	0.330	175	-64.79	7.51	>3
KPLC	0.223	138	-58.7	5.41	>3
NMG	0.17	132	-57	4.7	>3
NIC	0.126	51.9	-34.5	2.98	>3
Sasini	0.11	51	-10	2.58	>3
STANCHART	1.25	900	-89	32.84	>3
Total Kenya	0.36	353	-78	12	>3
TPS	0.284	92.59	-21	4.47	>3
Unilever	0.028	17	-18	2.4	>3

Source: own computation.

Table 2.2 shows group statistics for percentage changes in prices for ordinary shares in the selected firms in finance and investment sector. It shows the highest percentage rise, the lowest fall achieved during the period, the arithmetic means and kurtosis. The table shows that in all cases, the range between the least and highest values are large. Due to the presence of the extreme values, the arithmetic mean and standard deviation may not give a good meaning of the distribution properties since they are sensitive to outliers. In all the cases, the kurtosis is greater than three (3) even when all the values greater than 50% are excluded from the data, implying that contrary to expectations the distribution governing returns in ordinary stock prices is leptokurtic (have long tails).

2.3.2. Linearity test results

Table 2.3 RESET Results for selected firms in NSE. (1248 observations)
Dependent variable: GROWTHPRICE

Firm	Variable	Coefficient	Std. Error	*t*-Statistic	Prob.	*p*-value for log likelihood ratio
BAMBURI	C	0.033947	0.058485	0.580445	0.5617	0.01
	GROWTHINDEX	0.791927	0.075905	10.43308	0.0000	
	FITTED^2	0.118260	0.043487	2.719468	0.0066	
BAT	C	-0.023704	0.056628	-0.41859	0.6756	0.00
	GROWTHINDEX	0.860247	0.072665	11.83847	0.0000	
	FITTED^2	0.150941	0.033654	4.485032	0.0000	
BARCLAYS	C	0.025689	0.048650	0.528025	0.5976	0.02
	GROWTHINDEX	0.800083	0.062694	12.76171	0.0000	
	FITTED^2	0.089260	0.037749	2.364545	0.0182	
BOC	C	0.067848	0.046336	1.464273	0.1434	0.17
	GROWTHINDEX	0.230861	0.064276	3.591720	0.0003	
	FITTED^2	0.457797	0.330478	1.385258	0.1662	
UNILEVER	C	-0.111327	0.076239	-1.46023	0.1445	0.00
	GROWTHINDEX	0.642160	0.092765	6.922456	0.0000	
	FITTED^2	0.285949	0.070776	4.040217	0.0001	
DTB	C	-0.021228	0.077960	-0.27229	0.7854	0.15
	GROWTHINDEX	1.015607	0.098712	10.28854	0.0000	
	FITTED^2	0.055769	0.039229	1.421631	0.1554	
EABL	C	0.216721	0.062918	3.444515	0.0006	0.00
	GROWTHINDEX	0.376331	0.078522	4.792656	0.0000	
	FITTED^2	0.033699	0.007252	4.646874	0.0000	
NIC	C	-0.070383	0.067040	-1.04985	0.2940	0.00
	GROWTHINDEX	0.904431	0.085449	10.58449	0.0000	
	FITTED^2	0.181947	0.033705	5.398241	0.0000	
G.Williamson	C	-0.057630	0.056964	-1.01168	0.3119	0.00
	GROWTHINDEX	0.764833	0.092115	8.303053	0.0000	
	FITTED^2	0.312724	0.107932	2.897418	0.0038	
	FITTED^3	-0.226081	0.064035	-3.53059	0.0004	
Kakuzi	C	-0.066988	0.070163	-0.95475	0.3399	0.03
	GROWTHINDEX	0.774223	0.088006	8.797415	0.0000	
	FITTED^2	0.123937	0.057956	2.138481	0.0327	
Kenya Airways	C	0.125403	0.072484	1.730072	0.0839	0.30
	GROWTHINDEX	0.960966	0.095424	10.07048	0.0000	
	FITTED^2	0.042306	0.040567	1.042865	0.2972	

Table 2.3 Continued

KCB	C	-0.001484	0.085412	-0.01738	0.9861	0.00
	GROWTHINDEX	1.909061	0.137240	13.91040	0.0000	
	FITTED^2	0.059469	0.020908	2.844279	0.0045	
	FITTED^3	-0.015120	0.004269	-3.54153	0.0004	
KPLC	C	-0.052696	0.089719	-0.58735	0.5571	0.00
	GROWTHINDEX	1.806335	0.113782	15.87547	0.0000	
	FITTED^2	0.043991	0.013709	3.208872	0.0014	
Firestone	C	-0.112423	0.076400	-1.47150	0.1415	0.00
	GROWTHINDEX	0.641745	0.092860	6.910871	0.0000	
	FITTED^2	0.286862	0.070929	4.044349	0.0001	
NMG	C	0.052200	0.069466	0.751448	0.4525	0.66
	GROWTHINDEX	0.745053	0.089614	8.314036	0.0000	
	FITTED^2	0.029536	0.067816	0.435534	0.6633	
Sasini	C	-0.096120	0.062681	-1.53347	0.1254	0.13
	GROWTHINDEX	0.538021	0.076930	6.993634	0.0000	
	FITTED^2	0.170496	0.112063	1.521423	0.1284	
STANCHART	C	0.001036	0.056398	0.018375	0.9853	0.01
	GROWTHINDEX	0.797315	0.072247	11.03596	0.0000	
	FITTED^2	0.107211	0.043010	2.492696	0.0128	
Total Kenya	C	-0.062024	0.081276	-0.763130	0.4455	0.94
	GROWTHINDEX	1.382689	0.101483	13.62480	0.0000	
	FITTED^2	0.001561	0.023896	0.065311	0.9479	
TPS	C	0.066074	0.079358	0.832607	0.4053	0.00
	GROWTHINDEX	0.661333	0.095565	6.920237	0.0000	
	FITTED^2	-0.244792	0.051524	-4.75100	0.0000	

In the estimations shown in Table 2.3 Schwartz criterion is used to choose the appropriate model. The Model is that with the least Schwartz Bayesian coefficient. The results show that among the firms where trading days exceed non-trading days, (BAT, Barclays, EABL, NIC, George Williamson, KPLC, Firestone, TPS, KCB, and Unilever), the coefficients of GROWTHINDEX and FITTED^2 (square of fitted values of GROWTHINDEX) are statistically significant implying the null hypothesis is rejected. In this category, only in three firms, Kenya Airways, the Nation Media Group and Total Ltd., is the null hypothesis not rejected. However, in all cases in this latter category, the log likelihood tests show that the model does not pass stability tests. Alternatively, among firms where non-trading days exceed trading days (BOC, DTB, and Sasini), the results show that the null hypothesis is rejected. These entire firms share a common characteristic, i.e., the non-trading days exceed the trading days by a large margin. Again in this category, two firms where the non-trading days exceed the trading ones by a small margin, the results show that the null hypothesis is rejected. However, the log likelihood tests show that the model does not pass stability test.

Similar results are obtained when all the firms considered are stacked together to form one big pool representing all listed firms. Second, the quadratic functional form fits the data best for most firms. The quadratic form shows that the relationship between returns on ordinary share prices and returns on market index is not effectively represented by a linear function.

It can be pointed out that the contradictions to this finding can partly be attributed to thin trading which in turn can lead to instability in a stock market. It is evident that in all the cases, where the null hypothesis was not rejected, the log likelihood test showed that the model was unstable implying that the linearity could not hold with added or reduced sample size.

Recursive Residual Test Results

The graphs show results for all the nineteen (19) of the twenty (20) firms used in the computation of NSE-20 index.

Figure 2.2a Recursive Residual Test (BAMBURI)

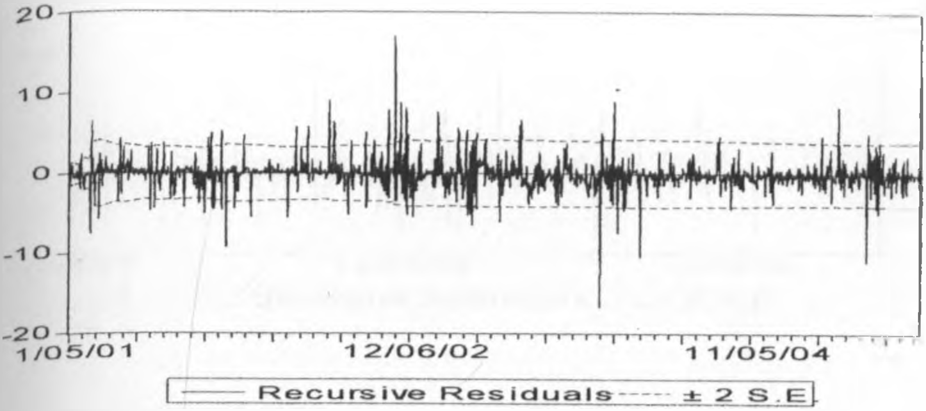


Figure 2.2b Recursive Residual Test (BOC)

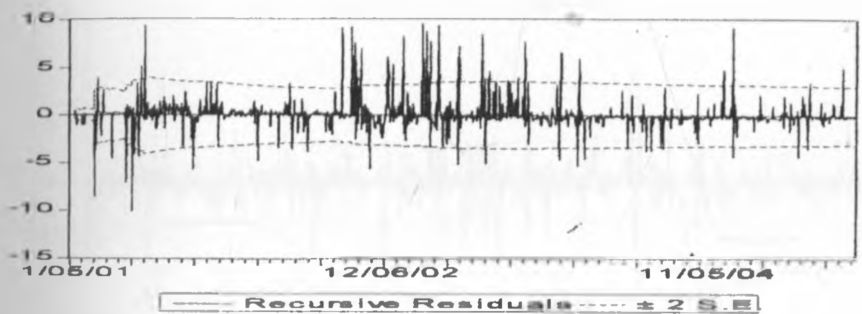


Figure 2.2c Recursive Residual Test (BAT)

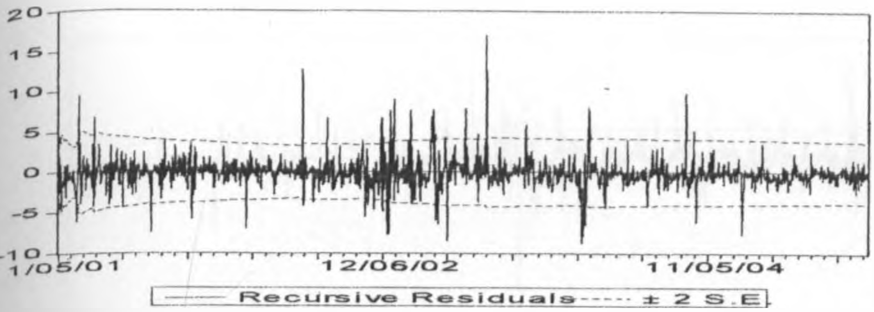


Figure 2.2d Recursive Residual Test (BARCLAYS)

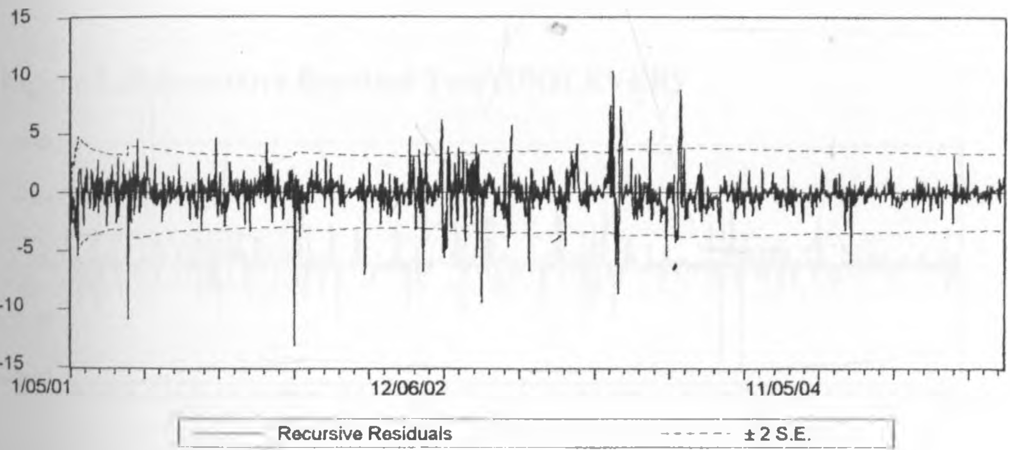


Figure 2.2e Recursive Residual Test (DTB)

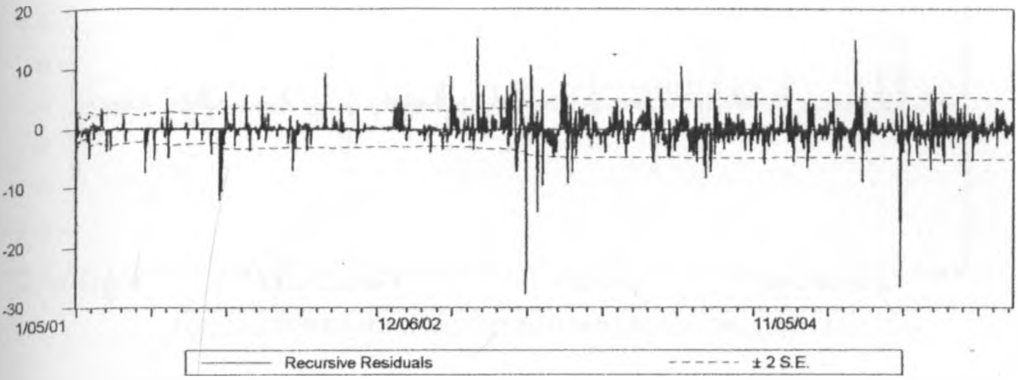


Figure 2.2f Recursive Residual Test (UNILEVER)

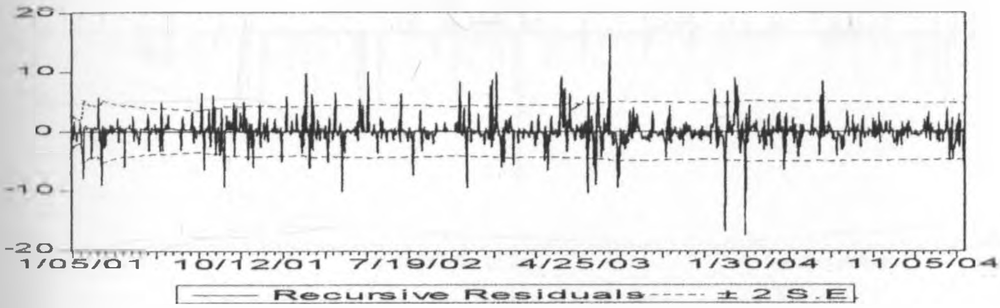


Figure 2.2g Recursive Residual Test (EAST AFRICAN BREWERIES)

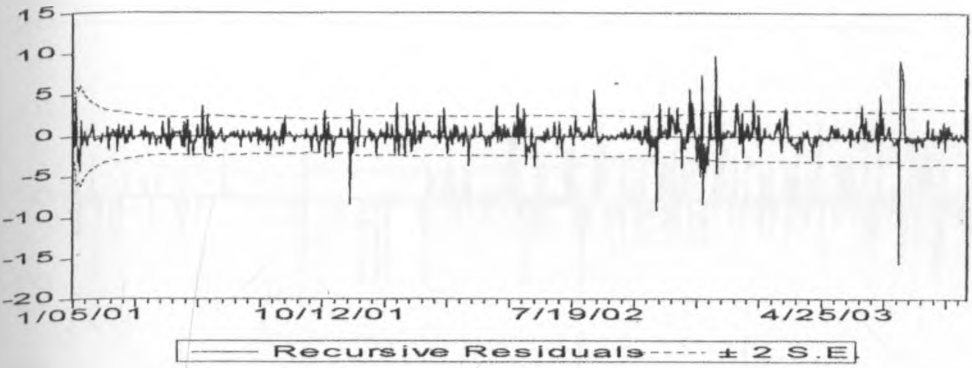


Figure 2.2h Recursive Residual Test (GEORGEWILLIAMSON)

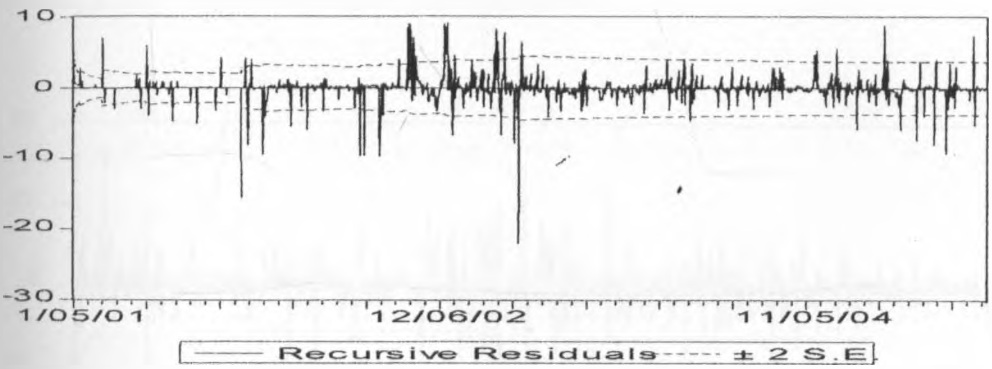


Figure 2.2i Recursive Residual Test (KAKUZ1)

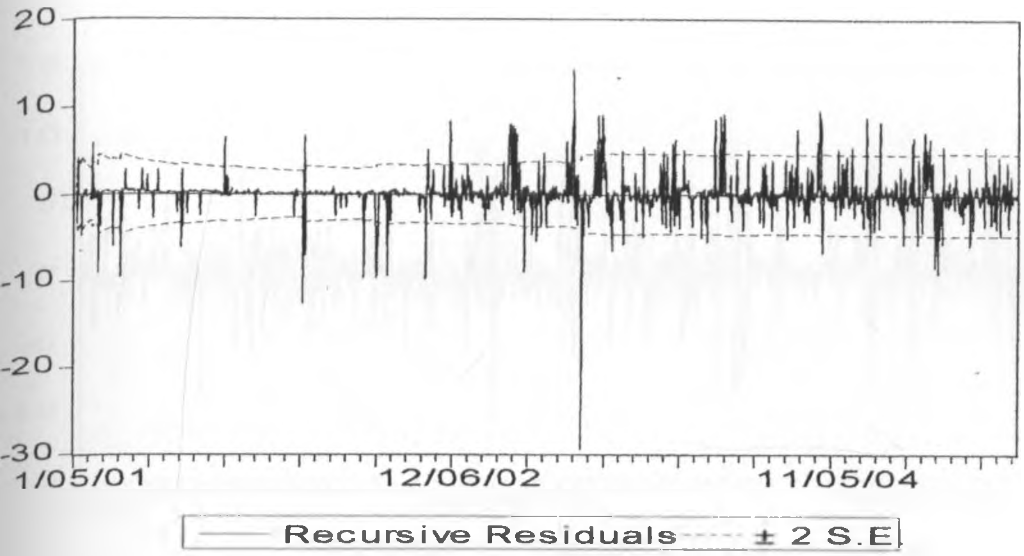


Figure 2.2j Recursive Residual Test (KCB)

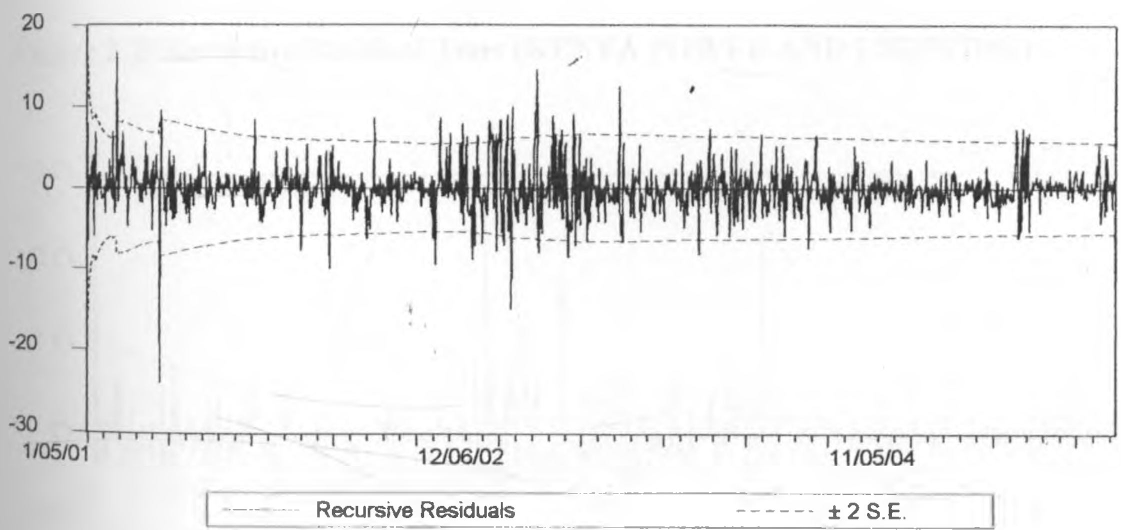


Figure 2.2k Recursive Residual Test (KENYA AIRWAYS)

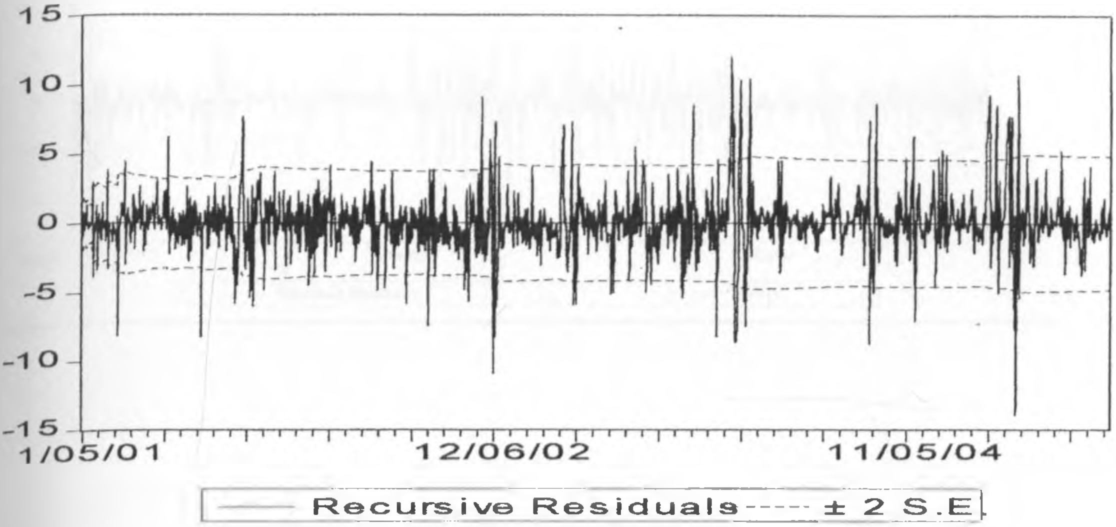


Figure 2.2l Recursive Residual Tests (KENYA POWER AND LIGHTING)

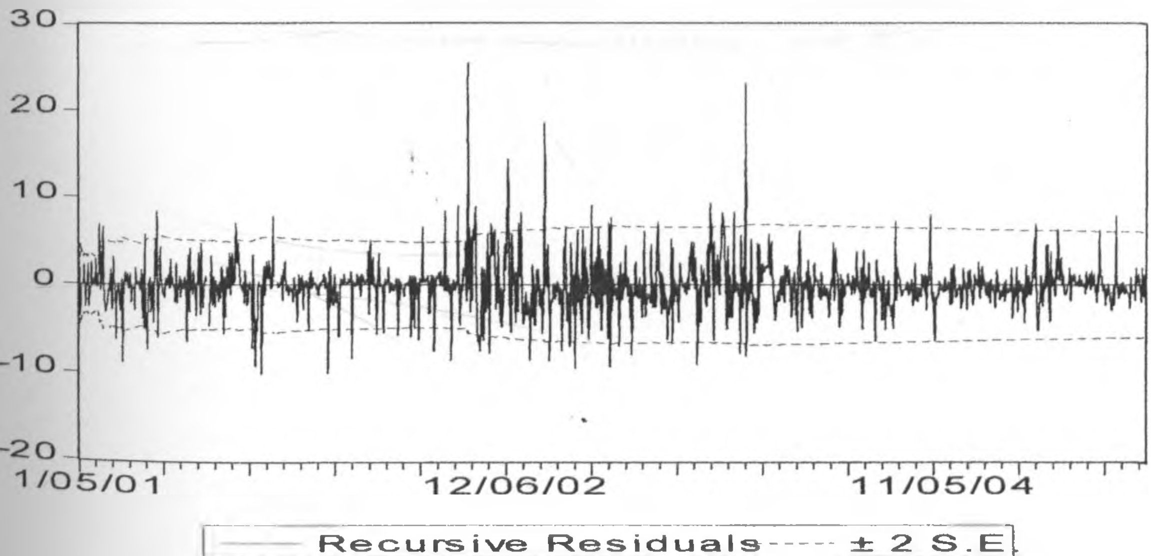


Figure 2.2m Recursive Residual Test NIC

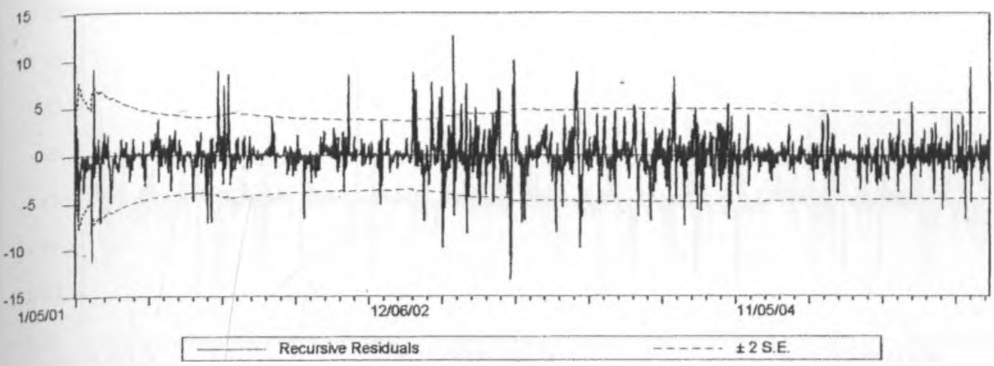


Figure 2.2n Recursive Residual Test (NATION)

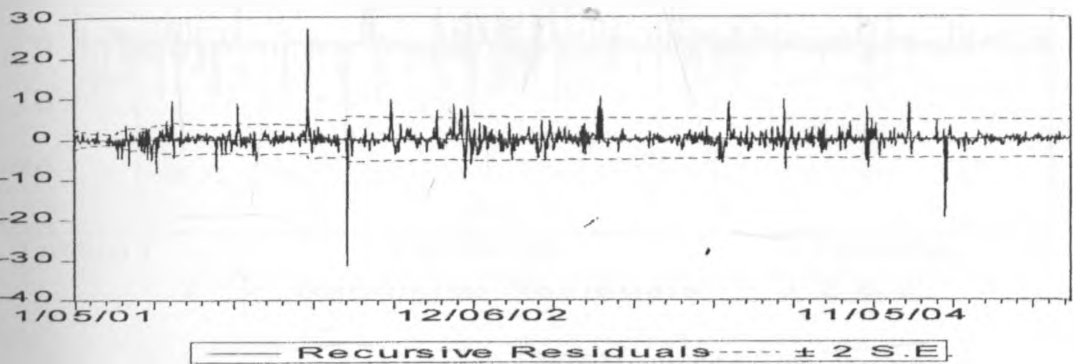


Figure 2.2o Recursive Residual Test (SASINI)

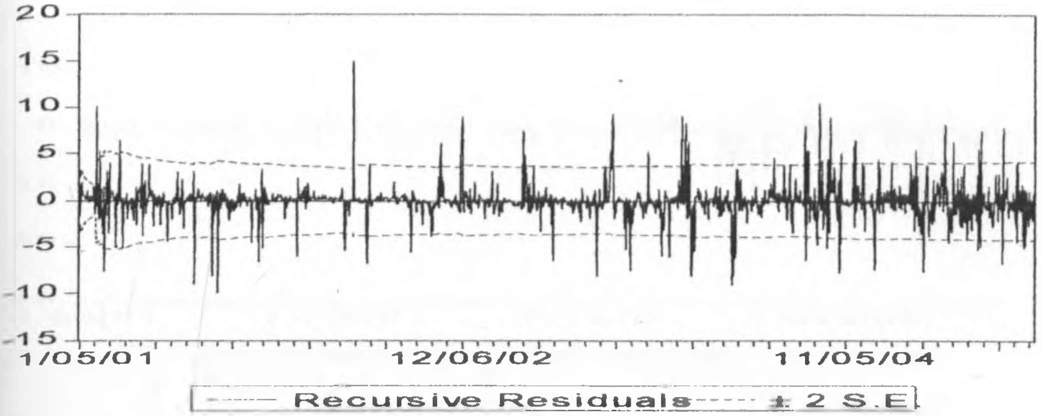


Figure 2.2p Recursive Residual Test (TOTAL KENYA)

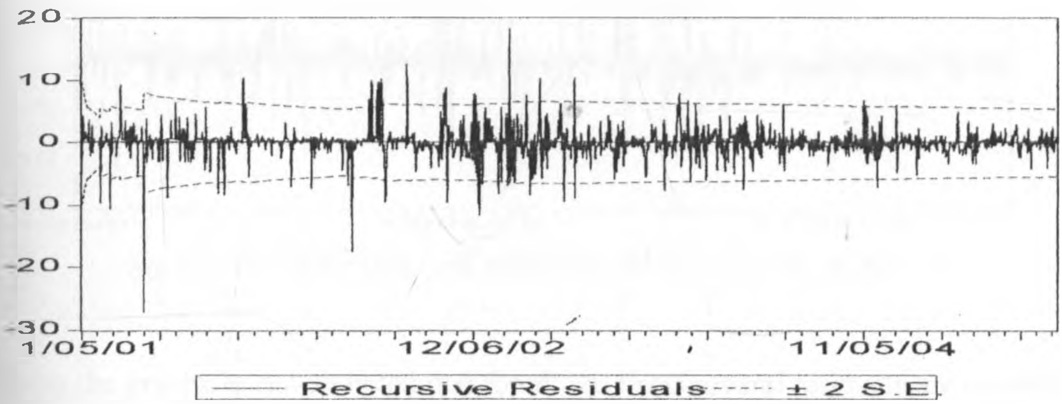


Figure 2.2q Recursive Residual Test (FIRESTONE)

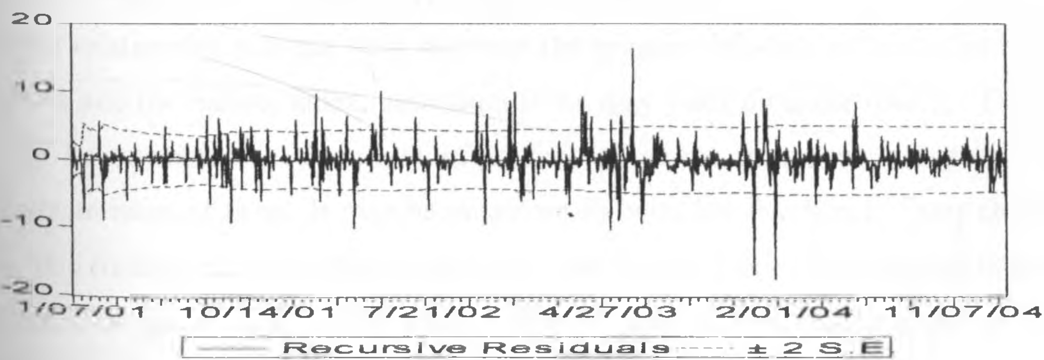


Figure 2.2r Recursive Residual Test (TPS)

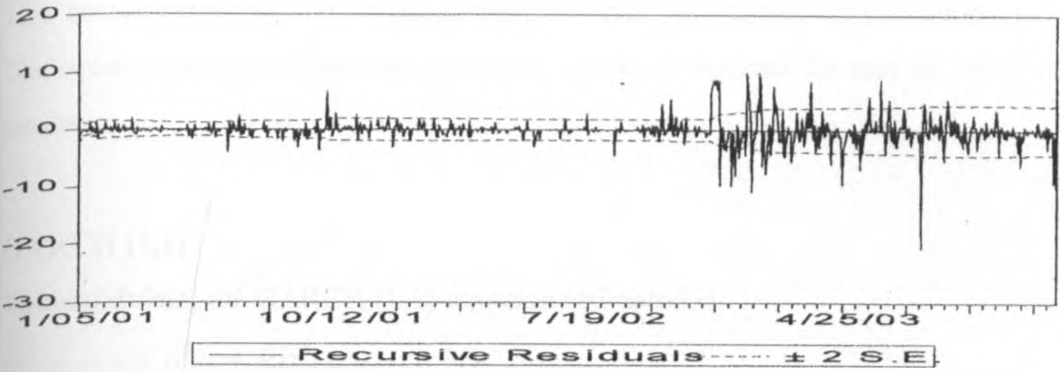
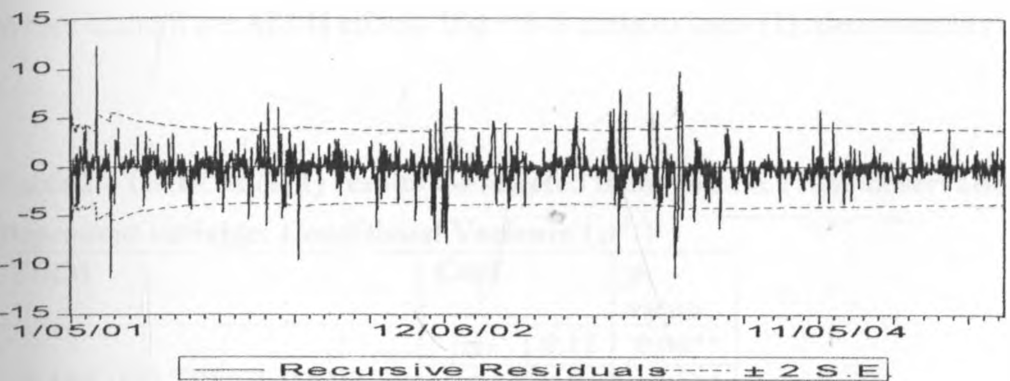


Figure 2.2s Recursive Residual Test (STANDARD CHARTERED)



From the graphs, it can be noted that for all the firms several residuals are outside the 5% significance band indicating that there is parameter variance instability in the residuals suggesting the presence of volatility. This is also true when all the firms are put together.

Considered together, RESET and recursive residual tests confirm that though, generally, linear relationship may not truly represent the behavior between returns on ordinary share prices and the market index, individual firms may yield different results. These results may be attributed to frequency of trading of shares in the market and to internal characteristics of firms. It may be important to point out that it is in firms characterized by thin trading that the difference is noted. Still, linearity cannot be rejected in these latter cases. The linear model is shown to be unstable, which supports the conclusion that this model is not appropriate.

2.3.3 Volatility Test Results

This section presents and compares results from the various ARCH family of models. The equation associated with each table of results is repeated for ease of interpretation of results.

GARCH (1,1)

To recapitulate, the GARCH (1,1) equation estimated is

$$\sigma^2_t = \omega + \alpha_1 \mu^2_{t-1} + \beta_1 \sigma^2_{t-1}$$

(See equations 2.9 and 2.10 for computation of σ^2_t and μ^2_{t-1})

Where α and,β are ARCH effects. If α + β is close to unity (1), then volatility persists.

Table 2.4 GARCH (1, 1) results for selected firms in NSE (1248 observations)
Dependent variable: Conditional Variance (σ^2_t)

FIRM	Coef		*p*-value
DIAMOND TRUST BANK	α	0.11	0.00**
	β	0.84	0.00**
	(α+β)	**0.95**	-
KCB	α	0.23	0.00**
	β	0.75	0.00**
	(α+β)	**0.98**	-
NIC	α	0.07	0.00**
	β	0.89	0.00**
	(α+β)	**0.96**	-
BARCLAYS	α	0.25	0.00**
	β	0.70	0.00**
	(α+β)	**0.95**	-
BAMBURI	α	0.05	0.00**
	β	0.89	0.00**
	(α+β)	**0.94**	-
BOC	α	0.03	0.00**
	β	0.95	0.00*
	(α+β)	**0.98**	-

Table 2.4 Continued

BAT	α	0.25	0.00**
	β	0.59	0.00**
	$(\alpha+\beta)$	**0.84**	-
UNILEVER TEA	α	0.14	0.00**
	β	0.83	0.00**
	$(\alpha+\beta)$	**0.94**	-
EABL	α	0.06	0.00**
	β	0.88	0.00**
	$(\alpha+\beta)$	**0.95**	-
GEORGE WILLIAMSON	α	0.11	0.00**
	β	0.72	0.00**
	$(\alpha+\beta)$	**0.83**	-
KAKUZI	α	0.09	0.00**
	β	0.87	0.00**
	$(\alpha+\beta)$	**0.96**	-
KENYA AIRWAYS	α	0.32	0.00**
	β	0.59	0.00**
	$(\alpha+\beta)$	**0.91**	-
KPLC	α	0.05	0.00**
	β	0.93	0.00**
	$(\alpha+\beta)$	**0.98**	-
NATION MEDIA	α	0.40	0.00**
	β	0.32	0.00**
	$(\alpha+\beta)$	**0.72**	-
SASINI	α	0.34	0.00**
	β	0.35	0.00**
	$(\alpha+\beta)$	**0.69**	-
TOTAL KENYA	α	0.16	0.00**
	β	0.62	0.00**
	$(\alpha+\beta)$	**0.78**	-
FIRESTONE	α	0.14	0.00**
	β	0.83	0.00**
	$(\alpha+\beta)$	**0.97**	-
TPS	α	0.04	0.00**
	β	0.96	0.00**
	$(\alpha+\beta)$	1.00	-
STANDARD CHARTERED	α	0.32	0.00**
	β	0.53	0.00**
	$(\alpha+\beta)$	**0.85**	-

** Indicates rejection of null hypothesis at better than 5% level.

The results in Table 2.4 show that in all the cases α + β is close to unity (1), suggesting that volatility persists. Hence we can confirm that there is ARCH effect in all firms in finance and investment sector.

TGARCH

The conditional variance equation estimated under TGARCH model is (2.14)

$$\sigma^2_t = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} + \gamma\mu^2_{t-1}I_{t-1}$$

Where γ is leverage effect and $I_{t-1} = 1$ if $\mu_{t-1} < 1$ and 0 otherwise. $\mu_{t-1}<1$ is considered good news while $\mu_{t-1t}>0$ represents bad.

Table 2.5 TGARCH results for selected firms in NSE (1248 observations)
Dependent variable: Conditional Variance (σ^2_t)

FIRM		Coef	*p*-value
BAMBURI	α	0.06	0.00**
	γ	**-0.03**	**0.01****
	β	0.89	0.00**
BARCLAYS	α	0.35	0.00**
	γ	**-0.21**	**0.00****
	β	0.72	0.00**
BOC	α	0.03	0.00**
	γ	**-0.01**	**0.00****
	β	0.95	0.00**
BAT	α	0.29	0.00**
	γ	**-0.07**	**0.01****
	β	0.58	0.00**
DIAMOND TRUST BANK	α	0.12	0.00**
	γ	**-0.02**	**0.00****
	β	0.84	**0.35**
UNILEVER TEA	α	0.18	0.00**
	γ	**-0.14**	**0.00****
	β	0.86	0.00**
EAST AFRICAN BREWERIES	α	0.09	0.00**
	γ	**-0.05**	**0.03****
	β	0.89	0.00**

Table 2.5 Continued

GEORGE WILLIAMSON	α	0.11	0.00**
	γ	**-0.009**	**0.67**
	β	0.71	0.00**
KAKUZI	α	0.12	0.00**
	γ	**-0.10**	**0.00****
	β	0.87	0.00**
KENYA AIRWAYS	α	0.37	0.00**
	γ	**-0.18**	**0.00****
	β	0.63	0.00**
KCB	α	0.31	0.00**
	γ	**-0.16**	**0.00****
	β	0.75	0.00**
KENYA POWER AND LIGHTING	α	0.06	0.00**
	γ	**-0.03**	**0.00****
	β	0.93	0.00**
NATION MEDIA	α	0.90	0.00**
	γ	**-0.83**	**0.00****
	β	0.33	0.00**
NIC	α	0.10	0.00**
	γ	**-0.03**	**0.00****
	β	0.89	**0.08**
SASINI	α	0.37	0.00**
	γ	**-0.08**	**0.20**
	β	0.36	0.00**
TOTAL KENYA	α	0.37	0.00**
	γ	**-0.37**	**0.00****
	β	0.61	0.00**
FIRESTONE	α	0.18	0.00**
	γ	**-0.14**	**0.00****
	β	0.86	0.00**
TPS	α	0.05	0.00**
	γ	**-0.03**	**0.00****
	β	0.97	0.00**
STANDARD CHARTERED	α	0.33	0.00**
	γ	**-0.03**	**0.30**
	β	0.55	0.00**

** Indicates rejection of null hypothesis at 5% level.

The results in Table 2.5 show that for the firms the coefficient representing leverage effect (γ) are significantly different from zero thus confirming the presence of asymmetry in the firms included in NSE 20 index. The same can be said for the entire market. In addition the same coefficient is negative implying that there is evidence of asymmetry and that bad news (negative changes in stock prices) tend to lead to more persistent volatility than good news (positive changes in stock prices).

EGARCH

The conditional variance equation estimated is (2.15)

$$\ln\left(\sigma_t^2\right)=\omega+\beta\ln\left(\sigma_{t-1}^2\right)+\gamma\frac{\mu_{t-1}}{\sqrt{\sigma_{t-1}^2}}+\alpha\left[\frac{\left|\mu_{t-1}\right|}{\sqrt{\sigma_{t-1}^2}}-\sqrt{\frac{2}{\pi}}\right]$$

Table 2.6 EGARCH results for selected firms in NSE

(1248 Observations)

Dependent variable: Log of Conditional Variance ln(σ^2_t)

FIRM		Coef	*p*-value
BAMBURI	α	0.13	0.00**
	β	-0.01	0.27
	γ	0.95	0.00**
BARCLAYS	α	0.33	0.00**
	β	0.93	0.00**
	γ	0.10	0.00**
BOC	α	0.13	0.00**
	β	0.03	0.00**
	γ	0.94	0.00**
BAT	α	0.37	0.00**
	β	0.03	0.02**
	γ	0.80	0.00**

Table 2.6 Continued

Diamond Trust Bank	α	0.07	0.00**
	β	0.92	0.00**
	γ	**0.07**	**0.57**
UNILEVER TEA	α	0.27	0.00**
	β	0.07	0.00**
	γ	0.93	0.00**
EAST AFRICAN BREWERIES	α	0.18	0.00**
	β	-0.06	0.00**
	γ	0.92	0.00**
GEORGE WILLIAMSON	α	0.23	0.00**
	β	0.028	0.04**
	γ	0.79	0.00**
KAKUZI	α	0.20	0.00**
	β	0.04	0.00**
	γ	0.93	0.00**
KENYA AIRWAYS	α	0.50	0.00**
	β	0.09	0.00**
	γ	0.85	0.00**
KCB	α	0.30	0.00**
	β	0.91	0.00**
	γ	0.06	0.00**
KENYA POWER AND LIGHTING	α	0.12	0.00**
	β	0.04	0.00**
	γ	0.97	0.00**
NATION MEDIA	α	0.50	0.00**
	β	0.37	0.00**
	γ	0.63	0.00**

Table 2.6 Continued

NIC	α	0.14	0.00**
	β	0.97	0.00**
	γ	0.01	**0.57**
SASINI	α	0.43	0.00**
	β	0.03	0.17
	γ	0.63	0.00**
TOTAL KENYA	α	0.23	0.00**
	β	0.23	0.00**
	γ	0.77	0.00**
FIRESTONE	α	0.27	0.00**
	β	0.07	0.00**
	γ	0.93	0.00**
TPS	α	0.098	0.00**
	β	0.03	0.00**
	γ	0.99	0.00**
STANDARD CHARTERED	α	0.29	0.00**
	β	0.05	0.00**
	γ	0.93	0.00**

** Indicates rejection of null hypothesis at 5%

The results in Table 2.6 show that in 16 out of the 19 firms considered, all the coefficients (α,β,γ) are significantly different from zero indicating that the null hypothesis is rejected. This indicates the presence of leverage effect, confirming the asymmetry of variance of share return.

From both Tables 2.5 and 2.6 we note that though the TGARCH and EGARCH models do not give identical results in terms of coefficients, their interpretation is similar to that of the pattern in changes in ordinary share prices, as both indicate existence of asymmetry in the variance of returns.

2.4 Conclusion

Though results from certain firms are conflicting, on average they show the following: First, that the distribution of returns on ordinary share prices is leptokurtic (have long tails) as demonstrated by the large kurtosis. This is contrary to findings in some of the literature.

Second, the linear model fails to capture the relationship between returns on ordinary share prices and the market share index. The model that seems to fit the data best is:

$$R_t = \alpha + \beta_1 R_{mt} + \beta_2 R^2_{mt} + \varepsilon_t$$

Third, there is evidence of volatility clustering in stock returns and, by extension, prices. This implies that though big changes tend to follow big changes and vice versa, there is no evidence of price predictability since the presence of ARCH effect confirms volatility in the stock market.

Fourth, that there is evidence of asymmetry in returns on ordinary shares, implying that most investors are in the secondary markets, where they put in money with the aim of benefiting from changes in share prices rather than from dividends.

Fifth, that TGARCH is a better method for modeling conditional variance since though its results are not very different from EGARCH ones, the former displays asymmetry in that a decrease in stock prices is more likely to trigger further rapid decreases than an increase in prices. This suggests that most investors in the market are more sensitive to a price fall than to a price increase. The possible explanation for this is that an increase in price is viewed as an opportunity to make more profit so that investors tend to hold on to shares with the expectation of making windfall gains. Alternatively, a fall in prices is met with panic selling, thus reducing prices further. Lastly, individual characteristics of the firm seem to play an important role in the response of firms to stock market conditions, and in modeling stock market behavior, since not all firms behave similarly.

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CHAPTER THREE

Stock Market Seasonality: Evidence from NSE

3.0. Introduction

This chapter addresses objective three of the thesis. It seeks to generate evidence on stock market seasonality by testing the presence of calendar anomalies in Nairobi stock exchange. The evidence would further show whether it is possible for investors to make abnormal profits if they base their investment rules on certain days, months or particular partitions of the year. The relevant literature is reviewed before the presentation of estimation methods and the empirical results.

3.1 Literature Review

Anomalies in stock markets generally refer to any occurrences that defy prevailing theory that is used to explain such markets i.e. EMH. Calendar anomalies in stock returns on the other hand specifically refer to the tendency of financial asset returns to display predictable seasonality at certain days of the week, week of the month and, month of the year. This systematic pattern permits trading strategies to earn excess profits and contradict efficient market hypothesis, and the claimed accuracy of the asset pricing model. Scholars have attributed such anomalies to tax loss hypothesis, settlement procedures, negative information releases and bid-ask spread biases (Alagidede and Panagiodis 2006). The major calendar anomalies include January, turn-of-the-year, day-of- the- week, turn-of-the-month and holidays anomalies. This study however investigates three anomalies; day-of-the-week, month-of-the-year and quarter-of-the-year effects on stock returns.

The day-of–the-week effect states that expected returns are not the same for all weekdays. This has been documented by many authors including Cross (1973), French (1980), Gibbons and Hess (1981) and Keim and Stambaugh (1983) among others. The

Monday effect, for example, considers return for preceding trading day to Monday's closing. Many studies have found the Monday effect to be negative (French 1980).

Month-of-the-year effect recognizes that returns seem to have a pattern such that some months have lower returns than others such that it is possible to achieve abnormal profits by consistently buying or selling shares in some months than others. Of these, January and turn-of-the-year effects are the most documented. Rozeff and Kinney (1976), Gultekin and Gultekin (1983), Keim (1983), Givoly and Ovadia (1983) and Griffiths and White (1993) all documented that for one reason or another stocks have a higher return in January compared to other months.

Quarter-of-the-year effect, though not frequently encountered in the literature, allows expected daily compounded returns to be consistently higher or otherwise on certain quarters of the year such that an investor can take advantage of this pattern to make abnormal profits.

Calendar anomalies have been widely studied mostly in developed markets, and have generated an exciting literature. Alagidede and Panagiotidis (2006) investigated day of the week and month-of-the-year effects in the ,Ghanaian stock exchange using continuously compounded daily and monthly index returns. They confirmed that stocks exhibit lower returns over periods between Friday's close and Monday's close. This is consistent with findings of Gibbons and Hess (1991), and Al-Loughani and Chappell (2001). The Monday effect is explained by the fact that most unfavorable news tends to occur during the weekend thus investors sell on Monday. Monday is also associated with pessimism unlike Friday when investors are optimistic. However they found that on the average, returns are higher in April contrary to most studies in developed markets which point at January effect.

Schwert (2002) acknowledges that evidence on anomalies indicates that either markets are inefficient in which case there are profit opportunities or that that there are inadequacies in the underlying asset-pricing model. He showed that size of the firm, value effect, weekend effect and dividend yield effects normally weaken and finally disappear after the publication of the paper stating so. This he attributed to the fact that when practitioners learn about anomalies they trade till profitable transactions vanish or that anomalies may not have existed in the first place. He therefore asserted that anomalies may be more apparent than real.

Chia *et al.* (2006) studied anomaly patterns in Malaysia using Ordinary Least Squares (OLS) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. They found that using OLS, different patterns of day-of-the-week specifically Monday and Friday effects, were revealed in the pre-crisis period even though there was, no evidence of January or any month seasonality during both pre and post crisis periods. They also found out that methodology plays a role in the analysis since some anomalies become insignificant when the GARCH method is used.

Hansen *et al.* (2005) asserts that discovery of calendar anomalies does not mean they actually do exist, but may be attributed to data mining. They stress their assertion by pointing out that extensive search across a number of possible calendar effects can yield significant results. They also noted that theoretical explanation about the said effect have been suggested subsequent to empirical discovery. In their study using a robust methodology, they found out that though end-of-the-year effect seems to be predominant, calendar effects have been diminishing since late 1980s with the possible exception of small-cap indices.

3.2 Methodology

Two sets of methodologies are used in this chapter to study stock market anomalies. The first is the OLS applied to data on daily compounded return in Nairobi Stock Exchange and the market index (NSE20). The second is the ARCH family of models that take volatility of returns into consideration. The methodologies test existence of day-of-the-week, month-of-the-year and quarter-of-the-year effects (see Ariel, 1987; Gao and Kling, 2005; Davidson, 2006, Barone, 1989; Bachelier, 1964).

the leverage effect (to test for asymmetry), whose sign and statistical significance have an implication on the impact of good news and bad news on volatilities of stock returns. The mean equation is actually adopted from the OLS function; however, as stated in equation 2.14, the specification of this equation is

$$\sigma^2_t = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} + \gamma\mu^2_{t-1}I_{t-1}$$

Where γ is leverage effect and $I_{t-i} = 1$ if $\mu_{t-1}<1$ and 0 otherwise; $\mu_{t-1}<1$ is considered good news while $\mu_{t-1t}>0$ represents bad news.

EGARCH

Exponential GARCH (EGARCH) is an asymmetric model which involves taking logarithms of variances thus ensuring that negative values are not reported. Like all the ARCH models, it has both the mean and variance equations. Whereas the mean equation is general, the specification for variance equation (see 2.15) is

$$\ln\left(\sigma^2_t\right) = \omega + \beta\ln\left(\sigma^2_{t-1}\right) + \gamma\frac{\mu_{t-1}}{\sqrt{\sigma^2_{t-1}}} + \alpha\left[\frac{\left|\mu_{t-1}\right|}{\sqrt{\sigma^2_{t-1}}} - \sqrt{\frac{2}{\pi}}\right]$$

Where α and β are ARCH effect, and γ is leverage effect.

3.3 Data and empirical results

3.3.1 Data

This study uses daily compounded returns on Nairobi stock exchange 20 (NSE 20) index. Since NSE 20 index is based on 20 most traded firms from the Nairobi stock Exchange, it gives a fair representation of the impact of all macroeconomic variables on the stock exchange and the average behavior of all the firms in the market.

Descriptive statistics in graphical form

This section is divided into two parts. The first part presents and discusses graphical representation of results from the four models of market anomalies. These results buttress

3.2.1 The OLS model

The standard methodology to test day-of-the-week, month-of-the-year, and quarter-of-the-year effects can be summarized by a set of mean equations stated, respectively, as follows:

$$R_{mt} = \sum_{w=1}^{4} \Phi_w D_w + \varepsilon_1$$

$$R_{mt} = \sum_{y=1}^{12} \theta_y M_y + \varepsilon_2$$

$R_{mt} = \sum_{y=1}^{4} \lambda_y Q_y + \varepsilon_3$ Where R_{mt} is continuously compounded average daily returns on index, D_w- is a dummy representing each of the trading day of the week, D_y - is a dummy representing each of the 12 months of the year, and Q_y- is a dummy representing each of the four quarters of the year .

3.2.2 GARCH models

GARCH models can be used when volatility clustering, asymmetry and leptokurtosis characterize the data generation process. The models have both mean and variance equations. While the mean equation (formulated as in 3.2.1) gives the average returns similar to the OLS results, the variance equation acts as a test for volatility persistence. Three versions of the model namely, GARCH (1,1), TGARCH, and EGARCH are estimated to give insight into volatility clustering, asymmetry and leverage effects.

GARCH (1,1)

GARCH (1,1) is the most popular model in the GARCH class of models. Unlike the generalized GARCH with many lags, it has only one lag. As stated in equation 2.13, the GARCH specification is:

$$\sigma^2_t = \omega + \alpha_1 \mu^2_{t-1} + \beta_1 \sigma^2_{t-1}$$

TGARCH

TGARCH is a modification of the GARCH model that takes into account the possibility of asymmetry in the data generating process. Among the coefficients to be estimated is the tabulated results shown in the appendix. The second part summarizes results from OLS and GARCH models.

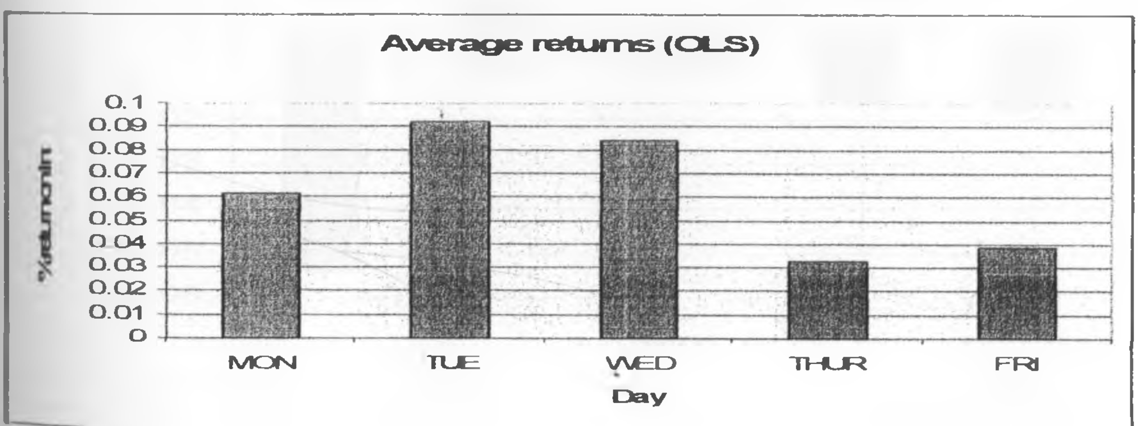
3.3.2 Graphical representation of results

3.3.2a Day-of-the-week effects

Day-of-the-week effects under classical assumptions

The results in Figure 3.1a *show that average returns for all days are* positive and generally low. Tuesdays and Wednesdays seem to have comparatively higher returns than other days while Thursdays have the lowest. However by showing positive returns in all days, the OLS model presents a very unlikely scenario that the index is always gaining, and that on average positive returns will be certain. In addition the OLS results fail to reveal any volatility clustering, asymmetry and non-normal distribution in the data. It is however important to note that the graph demonstrates a trend that returns seems to peak on Tuesday, but continually decline towards the end of the week.

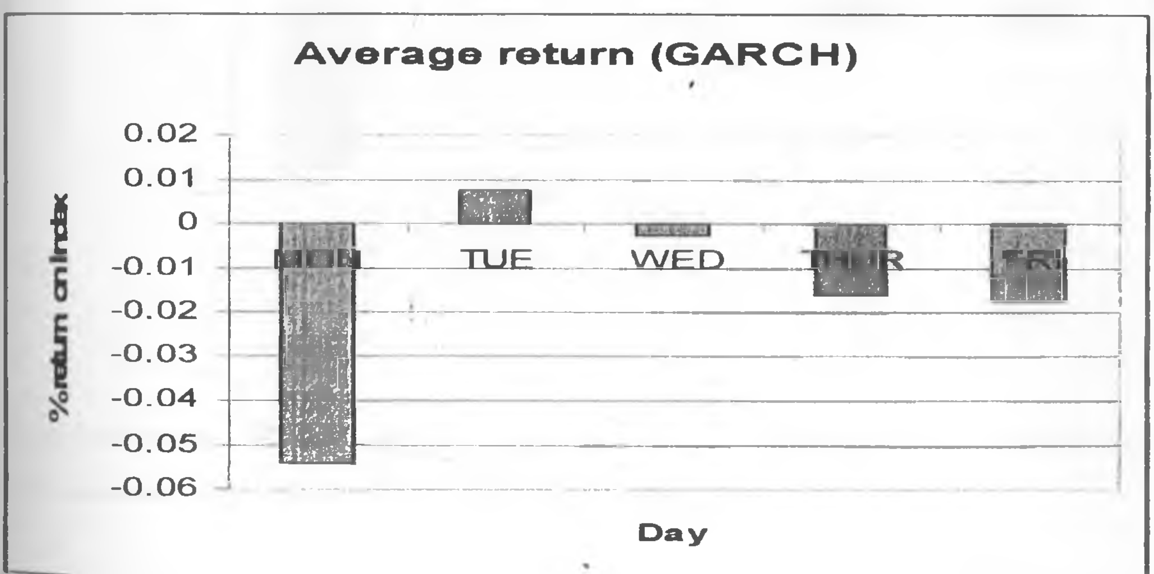
Figure 3.1a Average returns for each day of the week under classical assumptions



Day-of-the-week effects under assumption of generalized autoregressive conditional heteroskedasticity

Figure 3.1b shows Generalized Autoregressive Conditional Heteroskedasticity (GARCH) results for day-of-the-week returns. These results consider volatility clustering in the data. Returns on Tuesday are highest and positive, while all other trading days show negative returns. Monday on the other hand has the lowest returns. Though the absolute values reported are small, the graph demonstrates a similar pattern to that of the OLS model; that from the all week high return on Tuesday, there is a decline in returns towards the end of the week. In addition, Friday and Monday returns have the same sign and direction, suggesting that the momentum of return on Friday extends to Monday.

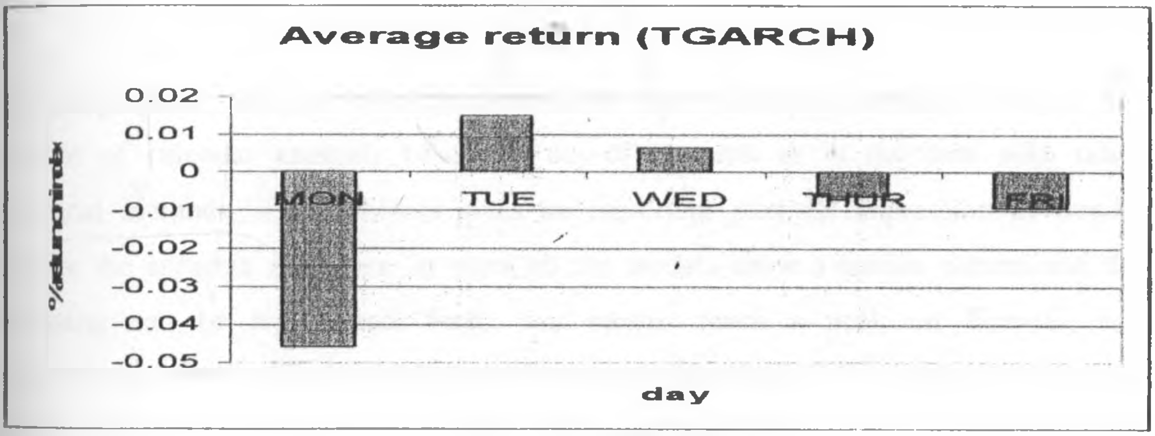
Figure 3.1b Average returns for each day under assumption of generalized autoregressive conditional heteroskedasticity



Day-of-the-week effects under assumption of generalized autoregressive conditional heteroskedasticity with asymmetry and leverage effects

Figure 3.1c shows TGARCH results. Unlike the GARCH, the TGARCH in addition takes into consideration asymmetry and regime switching. The graph shows positive returns on Tuesdays and Wednesdays with the former comparatively higher. Monday, Thursday and Friday have negative returns with absolute sizes increasing in the same order, but he trend is similar to that of GARCH.

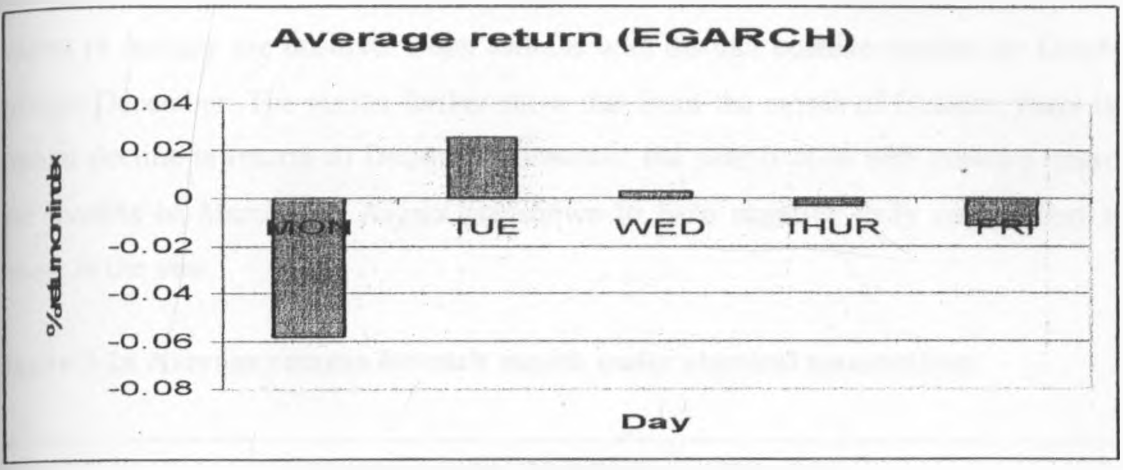
Figure 3.1c Average returns for each day under assumption of generalized autoregressive conditional heteroskedasticity with asymmetry and leverage effects



Day-of-the-week effects under assumption of autoregressive conditional heteroskedasticity with asymmetry but no leverage effect

Figure 3.1d shows EGARCH results. Like the TGARCH, this model takes asymmetry into consideration and ensures that the variance is never negative. The graph demonstrates that Monday and Friday returns are negative while for the rest of the trading days they are positive.

Figure 3.1d Average returns for each day under assumption of generalized autoregressive conditional heteroskedasticity with asymmetry but no leverage effect



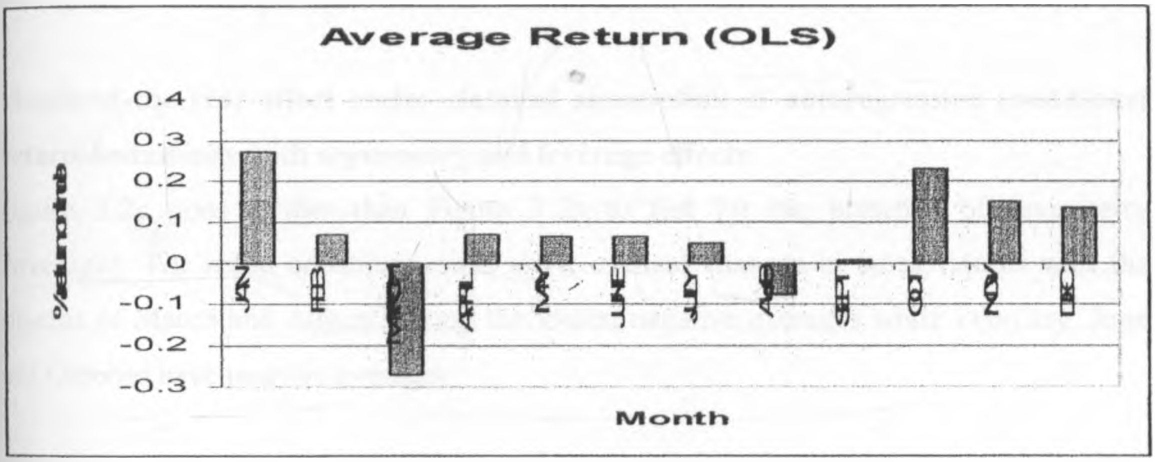
Though graphical analysis lacks the hypothesis tests which can confirm or reject the concept of calendar anomaly based on day-of-the-week as in the case with other statistical methods, it nonetheless gives an important pictorial impression of trends. Despite the apparent difference in signs all the models show a similar pattern and the following can be highlighted. First, that returns reach a peak on Tuesday and progressively decline as you approach the last trading day of the week. Second, that Friday and Monday returns have the same sign and that the latter have a larger absolute value. From the two it can be deduced that the momentum of returns at the last trading day is continued to the first day through the non-trading days meaning that investors carry over their attitudes through the non-trading days. The relatively large size for the Monday returns can be seen as cumulative effect of the two non-trading days. It can be further deduced that investors view end of the week with pessimism. All in all, the graphical results suggest that anomalies are persistent on Mondays and Tuesdays and that investors can make profits by buying on Mondays and selling on any other day but more on Tuesdays.

3.3.2b Month-of-the-year effects

Month-of-the-year effect under classical assumptions

The results in Figure 3.2a (the OLS regression results) show that daily compounded returns in January are positive. Other months with distinct positive returns are October through December. The results further show that from the month of October, there is a gradual decline in returns to December; however, the year is open with positive returns. The months of March and August are shown to have negative daily returns that are lowest in the year.

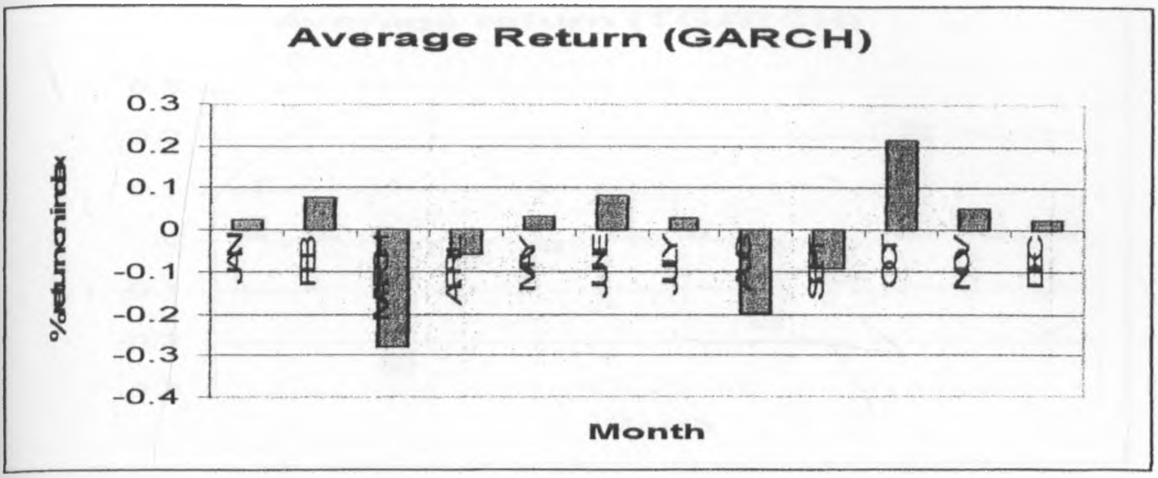
Figure 3.2a Average returns for each month under classical assumptions



Month-of-the-year effect under assumption of autoregressive conditional heteroskedasticity

Results in Figure 3.2b shows that after taking into consideration volatility clustering and heteroskedasticity, daily compounded returns for the months of March, April, August, and September are negative. The returns for March, August and September seem to be distinctly lower than those of other months.

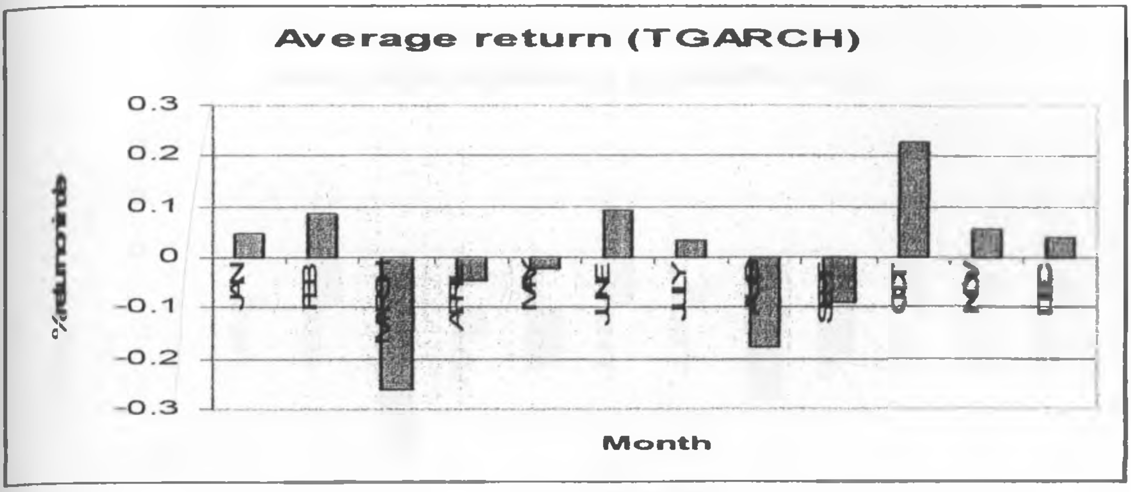
Figure 3.2b Average returns for each month under assumption of generalized autoregressive conditional heteroskedasticity



Month-of-the-year effect under classical assumption of autoregressive conditional heteroskedasticity with asymmetry and leverage effects

Figure 3.2c goes further than Figure 3.2b to test for the presence of asymmetry (leverage). The mean equation results show cyclical changes in stock returns with the months of March and August having the lowest negative averages while February, June and October have positive averages.

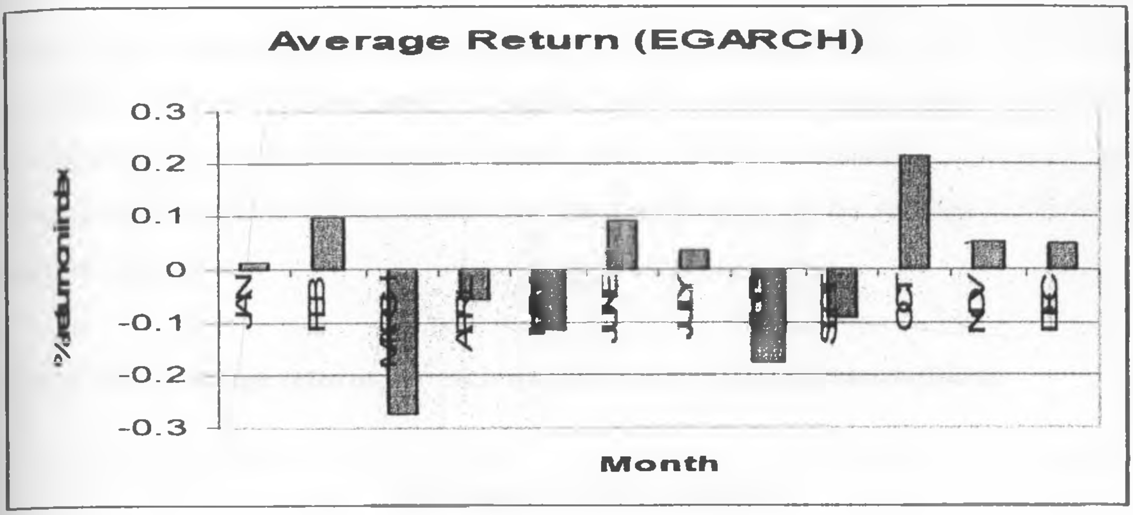
Figure 3.2c Average returns for each month under assumption of generalized autoregressive conditional heteroskedasticity with asymmetry and leverage effects



Month-of-the-year effect under classical assumptions of generalized autoregressive conditional heteroskedasticity with asymmetry but no leverage effect

Like 3.2b and 3.2c, Figure 3.2d which present results for the mean equations for the EGARCH models give mean equation results which are similar though not identical. They all concur that daily returns for the month of March is lowest and that a cyclical pattern is observed if the whole year is considered. There is a tendency for the returns to swing within -0.3 and + 0. 3 % limits. This implies that compounded monthly, stocks can gain or lose up to 9%.

Figure 3.2d Average returns for each month under assumption of generalized autoregressive conditional heteroskedasticity *with asymmetry but no leverage effect*



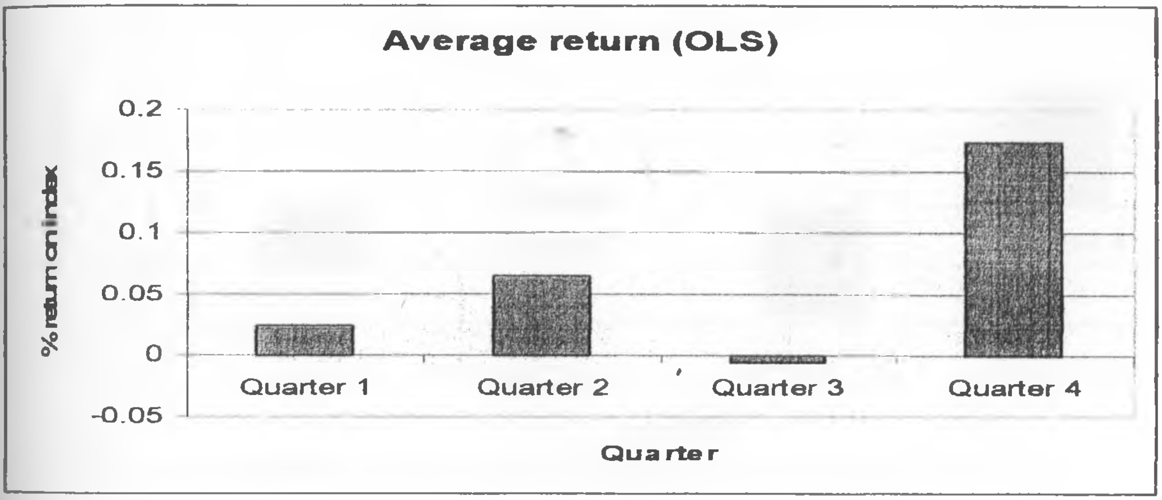
All the models point to the following. First, that there is strong evidence of March and October effects with negative and positive returns, respectively. Second, that there is evidence of consistently cyclical pattern hinging about the months of March, June, August and October. Third, that the year begins with positive and rising returns and close with declining returns. The end year returns are however higher than at the beginning implying that end of the year is viewed with optimism by investors. Fourth, that between the months of June and August is characterized by gradual and uninterrupted decline in returns which climax with the negative return in August. This means that a month is long enough for investors to digest information on the stock market and that on the average investors are cautious speculators. For example, low returns imply that there are opportunities to make profit in the future. Investors therefore buy but mass buying puts pressure on prices. However the investors are cautious to bid beyond two percent on either side.

3.3.2c Quarter-of-the-year effects

Quarter-of-the-year effects under classical assumptions

Figure 3.3a presents the OLS model results and shows that daily compounded return during first, second and fourth quarters are positive and that only the third quarter is an exception. The fourth quarter posts the highest returns while the third one has the least. It is important to note that OLS model does not take volatility clustering and heteroskedasticity into consideration thus the results seem to be skewed in favour of positive returns.

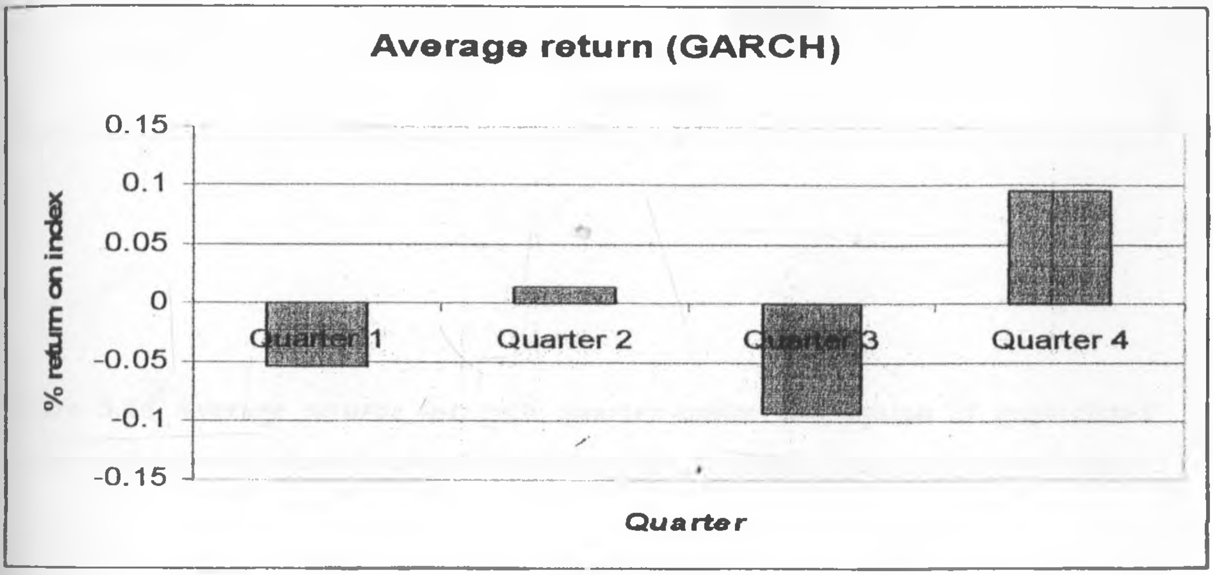
Figure 3.3a Average returns for each quarter under classical assumptions



Quarter-of-the-year effects under assumptions of generalized autoregressive conditional heteroskedasticity

Figure 3.3b show similar pattern to results got using the OLS model but differ in the size of coefficients. The year starts with negative returns, picks up during the second quarter, then slumps massively in the third quarter and finally registers a positive return during the last quarter

Figure 3.3b Average returns for each quarter under assumption of generalized autoregressive conditional heteroskedasticity



Quarter-of-the-year effects under assumptions of generalized autoregressive conditional heteroskedasticity with asymmetry and leverage effects

The results summarized by Figures 3.3c and 3.3d are similar in sign and trend, but differ in magnitude. The fourth and third quarters' returns are highest and lowest, respectively, due perhaps to the fact that the mean equations for the ARCH family of models are actually similar.

Figure 3.3c Average returns for each quarter under assumption of generalized autoregressive conditional heteroskedasticity with asymmetry and leverage effects

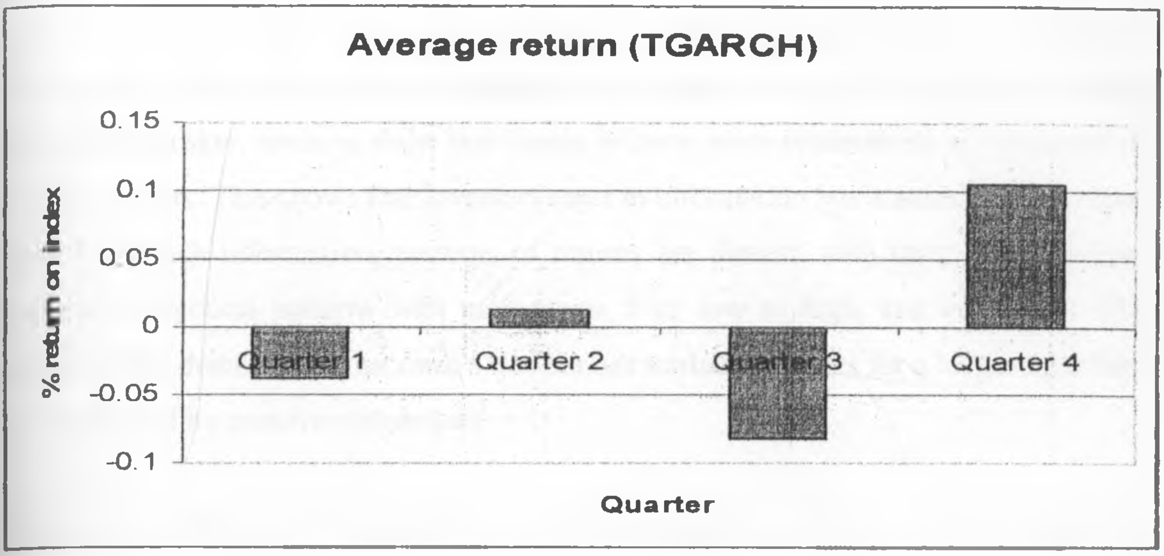
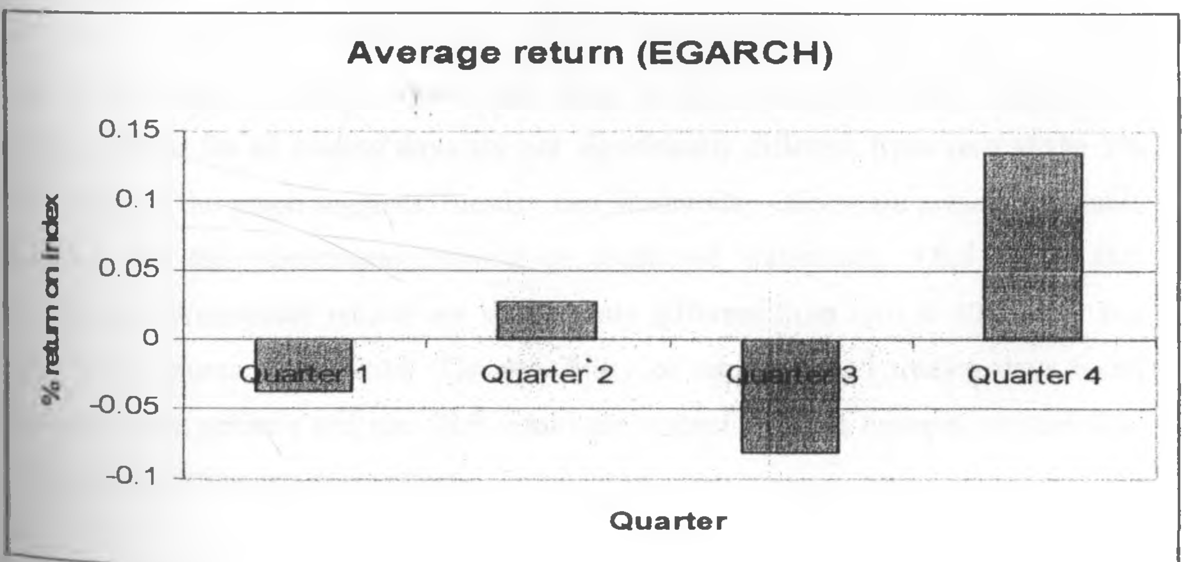


Figure 3.3d Average returns for each quarter under assumption of generalized autoregressive conditional heteroskedasticity with asymmetry but no leverage effect



Unlike the ARCH family of models, analysis by the OLS model shows that returns on stock is on the average positive for most of the calendar periods under consideration. OLS model results thus seem to exaggerate the returns. The graphical analysis though statistically weaker, tends to show that trends become more pronounced as the period of analysis widens. This shows that investors react to information but it takes long to digest and act on such information, patterns of returns are distinct with time. There is also evidence of cyclical patterns with movements from low to high, and vice versa. The graphs further demonstrate that once a decline has started it persists for a longer time than the duration of its positive counterpart.

Despite the difference in magnitude and sometimes sign, all the models show the following. First, that the fourth quarter has the highest return compared to other quarters. Second, that there is a cyclical or alternating pattern of returns where the year starts with low returns, picks up in the second quarter, declines significantly in the third quarter, before finally picking up in the final quarter. This again confirms that investors view the end of the year with optimism.

3.3.3 Estimation results

3.3.3a Day-of-the-week effects

In Table 3.1, daily compounded return on stock market index is regressed against trading days of the week. The tables shows that using all the models, the daily compounded average returns for all trading days are not significantly different from zero at the 5% level. Though the graph suggests Tuesday and Wednesday effects are present, the table indicates that this phenomenon cannot be confirmed statistically. OLS shows that Tuesday and Wednesday returns are significantly different from zero at 10% level and that all the returns are positive. The possibility of returns on all trading days being positive is most unlikely and also OLS results are suspect. There is however no statistical evidence supporting any day's effect.

All GARCH family of models show evidence of auto regressive conditional heteroskedasticity (ARCH) effect implying that volatility is persistent such that big shocks are followed by big volatility and vice versa. GARCH however assumes that volatility depends on magnitude only, and is independent of sign, but this may not be true in the data. TGARCH model confirms the presence of asymmetry and that the leverage effect is negative. The latter model shows that negative returns persist more than the positive returns. EGARCH results like TGARCH also confirm asymmetry and give the same verdict on test of the null hypothesis as the latter, though it is not possible to point out which particular returns are more persistent.

The table further reveals that OLS averages are largest in absolute terms followed by GARCH and EGARCH results which are close. TGARCH results are smaller in absolute terms. Although the OLS and the various GARCH methods show different signs for the average daily returns on the market index, they have the following in common. One, the daily returns are very small. This can be attributed to the fact that the index is a four figure value and any two figure change though reasonable by literal standards translates into a very small percentage. Also, with information easily available and more players joining the stock market transactions, there is a possibility that profits are shared out among many firms thus reducing the expected gains. Two, all the methods concur that returns on Tuesday are comparatively higher than all the returns for other days of the week and that there seems to be a prolonged decline in returns from Wednesday through to Friday, and all the way to Monday. This can possibly be due to investor pessimism towards the end of the week coupled by asymmetric volatility nature of the stock market return. Three, at 5% level, there is no evidence of day-of-the- week effect using either the OLS, GARCH, TGARCH or EGARCH methods. However at the 10% level, OLS method shows that there is evidence of Tuesday's and Wednesday's effect. It can also be pointed out that there is some inconsistency on the signs of coefficients among the stated models. The above results suggest that the verdict on null hypothesis is dependent on the method of analysis used. GARCH methods however are better than OLS. Overall, there seems to be evidence from the graphs that profit can be made if portfolios are bought towards the end of the week and on Monday and then sold on Tuesday. The gain may however be small in terms of percentage earnings and statistically negligible. Moreover the lack of evidence on the day-of-the-week effect suggests that abnormal profits on investment that are made on the basis of day-of-the-week will only be by chance. It is important to note that average return on Monday is between 2.5 and 5 times that for Friday, showing that the return for Monday takes into account cumulative information on the two non-trading days.

Table 3.1 Average daily compounded return on market index for each day (61695 observations)

Dependent variable: **Return on market index**

DAY	OLS	GARCH	TGARCH	EGARCH
MON	0.061 (1.21)	-0.054 (-1.48)	-0.046 (-1.14)	-0.058 (-1.54)
TUE	0.092 **(1.88)****	0.007 (0.23)	0.0148 (0.424)	0.025 (0.763)
WED	0.084 **(1.71)****	-0.003 (-.075)	0.006 (0.18)	0.003 (0.08)
THUR	0.032 (0.65)	-0.016 (-0.492)	-0.006 (-0.184)	-0.003 (-0.10)
FRI	0.039 (0.77)	-0.017 (-0.46)	-0.009 (-0.24)	-0.011 (-0.32)

(*t*-statistics in parenthesis)

** Significant at 10% level

3.3.3b Month-of-the year effects

In Table 3.2, daily compounded returns on the stock market index are regressed on all months of the year. From the table, the OLS regression results show that daily compounded returns in January are positive and significantly different from zero at 5% level. A comparison between daily returns in January and all other months of the year show that except for October through to December, returns are different. Other months with positive results are October and September. The results further show that from the month of October there is a gradual decline of returns up to December; however, the year opens with positive returns. The months of March and August have negative daily returns that are lowest in the year. On the basis of this method, there is evidence of January, March and August effects. However since OLS does not consider volatility clustering, heteroskedasticity and asymmetry, the estimation results need to be subjected to further tests. The mean equations for GARCH, TGARCH and EGARCH models all confirm March, August and October effects, but differ from the OLS results for January, November and December.

The results from variance equations for all the GARCH models confirm the presence of the ARCH effect implying that volatility between months persists. In addition to being consistent with the GARCH results, the TGARCH results confirm leverage effect with a negative sign, showing that negative returns tend to persist more than positive ones. While the months of March and August still show negative daily returns, October has the highest positive returns. EGARCH results are closer to GARCH ones in magnitudes and signs.

Though there is a difference between OLS and GARCH results, all the results drawn from the four models confirm that March and October effects exist and that they exhibit negative and positive daily returns on index, respectively. The models also show that daily returns for the months of January, November and December are not statistically different. This may imply that investors close and begin the year with optimism. The comparatively lower January returns could be explained by the decreased liquidity due to heavy spending in December and commitments in January. The results also point out that there is a possibility of making profit on portfolios bought in March and August and sold at the close of the year or at the beginning of the year. This is a further confirmation that the choice of methodology may lead to different conclusions about the anomaly of returns.

Table 3.2 Average daily compounded return on market index for each month

(61695 observations)

Dependent variable: **Return on market index**

MONTH	OLS	GARCH	TGARCH	EGARCH
January	0.27 (3.6)*	0.025 (0.39)	0.047 (0.72)	0.011 (0.232)
February	0.07 (0.92)	0.077 (1.47)	0.085 (1.57)	0.096 (1.80)**
March	-0.27 (-3.58)*	-0.28 (-6.18)*	-0.261 (-5.68)*	-0.27 (-6.1)*
April	0.068 (0.88)	-0.058 (-0.92)	-0.05 (-0.75)	-0.058 (-094)
May	0.065 (0.87)	0.031 (0.61)	-0.024 (-0.46)	-0.12 (-2.38)*
June	0.064 (0.84)	0.082 (1.24)	0.09 (1.32)	0.09 (1.3)
July	0.048 (0.66)	0.03 (0.658)	0.03 (0.73)	0.034 (0.7)
August	-0.076 (-1.03)	-0.197 (-4.63)*	-0.179 (-3.88)*	-0.177 (-3.89)*
September	0.01 (0.13)	-0.093 (-1.89)**	-0.087 (-1.75)**	-0.09 (-1.68)**
October	0.232 (3.04)*	0.213 (4.61)*	0.23 (4.806)*	0.213 (4.609)*
November	0.149 (1.94)**	0.05 (0.79)	0.056 (0.853)	0.051 (0.826)
December	0.135 (1.69)**	0.025 (0.37)	0.04 (059)	0.048 (0.69)

(t-statistics in parentheses)

* Significant at the 5% level

** Significant at the 10% level

3.3.3c Quarter-of-the-year effects

In Table 3.3, daily compounded returns on stock market index are regressed against all the quarters of the year. The table shows that using OLS model, only the fourth quarter returns are significantly different from zero. The first and second quarter results are onthe average positive while the third quarter is associated with negative returns. GARCH, TGARCH and EGARCH models on the other hand show that third and fourth quarter average returns are significantly different from zero though they are negative and positive, respectively. However at the 10% level, the GARCH model shows that the first quarter average returns are different from zero. Though the OLS results for first and second quarters like the GARCH ones are not statistically significant, their signs differ. OLS and all GARCH models show that daily returns in the 4th quarter of the year are positive, significantly different from zero at the 5% level, and higher than daily returns for all other quarters. They also show that daily returns for the third quarter are negative and are the lowest. The implication is that there is a good chance of making profit if portfolios are bought in any other quarter and sold during the last quarter of the year. However, the largest profit is to be expected between the third and the last quarters. Though all methods confirm fourth quarter effect, the GARCH, TGARCH and EGARCH methods, in addition confirm third quarter effect, thus reconfirming that methodology matters in accounting for period effects revealed in the data

Table 3.3 Average daily compounded return on market index for each quarter (61695 observations)

Dependent variable: **Return on market index**

	OLS	GARCH	TGARCH	EGARCH
QUARTER				
Quarter 1	0.023 (0.52)	-0.053 (-1.65)**	-0.038 (-1.14)	-0.038 (-1.25)
Quarter 2	0.066 (1.49)	0.014 (0.39)	0.013 (0.35)	0.027 (0.78)
Quarter 3	-0.006 (-0.141)	-0.093 (-3.38)*	-0.081 (-2.85)*	-0.08 (-2.70)*
Quarter 4	0.173 (3.83)*	0.095 (2.78)*	0.106 (3.00)*	0.135 (4 42)*

(t-statistics in parenthesis)

* Significant at 5% level

** Significant at 10% level

3.4 Conclusion

In this chapter the market efficiency model has been applied on daily compounded returns on NSE-20 share index using data covering the years 2001 to 2005. Two estimation models have been explored to unravel day-of-the-week, month-of-the-year and quarter-of-the-year effects as major calendar effects. The following conclusions have been derived.

One, that methodology plays a crucial role in the test of hypotheses about the calendar anomalies in the stock market. In particular, the OLS does not give similar conclusions as its GARCH counterparts. In fact, there is evidence to suggest that the coefficients obtained using the OLS models are exaggerated and inconsistent. Since financial data is prone to heteroskedasticity and volatility clustering, changes in share prices cannot be effectively represented by OLS modeling. The GARCH model improves on the OLS to take into consideration volatility clustering and heterosckedasticity but at the cost of assuming symmetry. Both TGARCH and EGARCH models address the problem of asymmetry and in our results these models actually confirm its presence. The EGARCH model however fails to address the direction of asymmetry thus giving results almost similar to the GARCH results. All the models exhibit similar trends and their tests of hypothesis converge as the calendar period increases. This,convergence is demonstrated by the fact that the results are different when the day is considered as the calendar period, but the results become almost similar when month and quarter of the year are taken as the calendar periods. Also, it is noted that all the models show that daily compounded returns on index follow a cyclical pattern.

Two, there is strong evidence of volatility-clustering and of leverage effect. More specifically, negative returns seem to be more persistent than positive ones. This shows that when the market seems to be appreciating, investors do not rush to buy in a bid of making huge profits, but they rush to sell when there is a price decline.

Three, GARCH models are more appropriate for the test of market anomaly since they are more adaptable to the characteristics of the data and generate more definitive results.

In particular, the TGARCH model stands out as the most appropriate model, since its mean equation addresses all the issues that both GARCH and EGARCH do also address, but in addition it shows the direction of the leverage effect.

Four, that averages for daily compounded returns tend to be generally low, and in some cases not significantly different from zero.

Five, though the daily average return on index is negative on Mondays and positive on Tuesday there is no confirmation of day-of-the-week effect. However, we can confirm that the trend shows a gradual decline in returns towards the end of the week, and only picks up on Tuesday. This shows that investors end the week with pessimism.

Six, that there is evidence that market information is cumulated over the non-trading days such that the Monday's return which is between 2.5 to 5 times larger (in absolute terms) than that of Friday reflects the cumulative returns for the two non-trading days of Saturday and Sunday.

Seven, investments made on the basis of day-of-the-week will only earn abnormal profit by chance since there is no evidence of day-of-the-week effect.

Eight, daily compounded returns at the Nairobi Stock Exchange show March and October effects though there is further evidence that average compounded daily returns are positive in January and negative in March. Unlike in many studies, the January effect however cannot be confirmed. This shows that investors can make abnormal profits from their portfolios by designing rules based on month-of-the-year effects. There is also a possibility that such investors may not beat the market all the time since when such information is known, others may follow suit, thus reversing the trend of expected gains.

Nine, there is evidence of quarter-of-the-year effect. Though investors view end of the week and of year with pessimism, the optimism of the month of October gives the impression that on the average, the last quarter of the year is viewed more favourably.

Ten, the calendar anomaly becomes more evident when a larger period is considered. This shows that investment in the stock exchange is more profitable in the long run, and that quick fix investments may earn profits only by chance.

Overall, there is strong evidence of calendar anomaly so the hypothesis of weak efficient market is supported by the Nairobi Stock Exchange data. That is, there is a possibility of making profit at the NSE using rules based on calendar effects. This anomaly becomes more pronounced as the period under consideration increases, so that it may be entertained that it takes time for the information to be assimilated by the market. Though profits on portfolios look small with a mean of 0.062% and may be wiped out as more information enters the market, it should be noted that these are daily compounded effects, and actually translate to a minimum of 22.6% annually, which is much higher than earnings from savings accounts. This finding provides evidence that it is more lucrative investing in portfolios at the Nairobi Stock Exchange than saving in a savings account. Lastly, non-rejection of anomaly cannot be an irrevocable confirmation of irrelevance of the Efficient Market Hypothesis, or a confirmation of expectation of profits. In the former case, i.e., failure to reject EMH may be a pointer at model inefficiency, while the latter case may be evidence of inability to expect profits as, transaction costs must be playing an independent role. Investments in the stock market therefore should be based on long-term consideration and not on daily expediencies, as short-term investments will beat the market only by chance.

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APPENDIX 3.1

OLS results for day-of-the-week effect

(61695 observations)

Dependent Variable: GROWTHINDEX

Variable	Coefficient	Std. Error	*t*-statistic	*P*-value
MON	0.061076	0.050417	1.211402	0.2260
TUE	0.092129	0.048918	1.883336	0.0599
WED	0.084124	0.049110	1.712960	0.0870
THUR	0.032266	0.049305	0.654428	0.5130
FRI	0.038672	0.050004	0.773367	0.4395

APPENDIX 3.2

GARCH results for day-of-the-week effect
(61695 observations)

Dependent Variable: GROWTHINDEX

	Coefficient	Std. Error	*z*-statistic	*P*-value
MON	-0.054234	0.036667	-1.479117	0.1391
TUE	0.007589	0.033484	0.226653	0.8207
WED	-0.002593	0.034346	-0.075485	0.9398
THUR	-0.016099	0.032719	-0.492053	0.6227
FRI	-0.017220	0.037483	-0.459421	0.6459
		Variance Equation		
Constant	0.026610	0.003680	7.232049	0.0000
ARCH(1)	0.196083	0.016641	11.78324	0.0000
GARCH(1)	0.769447	0.012119	63.49094	0.0000

APPENDIX 3.3

TGARCH results for day-of-the-week effect (61695 observations)

Dependent Variable: GROWTHINDEX

	Coefficient	Std. Error	*z*-statistic	*P*-value
MON	-0.045733	0.040149	-1.139075	0.2547
TUE	0.014810	0.034900	0.424354	0.6713
WED	0.006230	0.034465	0.180751	0.8566
THUR	-0.005967	0.032443	-0.183932	0.8541
FRI	-0.009162	0.038564	-0.237582	0.8122
Variance Equation				
Constant	0.028318	0.003658	7.741673	0.0000
ARCH(1)	0.223596	0.022129	10.10398	0.0000
(RESID<0)*ARCH(1)	-0.097827	0.022547	-4.338856	0.0000
GARCH(1)	0.777613	0.012795	60.77400	0.0000

APPENDIX 3.4

EGARCH results for day-of-the-week effect (61695 observations)

Dependent Variable: GROWTHINDEX

	Coefficient	Std. Error	*z*-statistic	*P*-value
MON	-0.058017	0.037747	-1.536989	0.1243
TUE	0.025269	0.033123	0.762878	0.4455
WED	0.002624	0.033429	0.078484	0.9374
THUR	-0.003180	0.030728	-0.103478	0.9176
FRI	-0.011447	0.035848	-0.319327	0.7495
Variance Equation				
Constant	-0.302920	0.017770	-17.04631	0.0000
|RES|/SQR[GARCH](1)	0.334878	0.022937	14.60000	0.0000
RES/SQR[GARCH](1)	0.051646	0.012319	4.192546	0.0000
EGARCH(1)	0.932862	0.008230	113.3455	0.0000

APPENDIX 3.5

OLS results for month-of-the-year effect (61695 observations)

Dependent Variable: GROWTHINDEX

Variable	Coefficient	Std. Error	*t*-statistic	*P*-value
JAN	0.274743	0.075466	3.640630	0.0003
FEB	0.071044	0.077329	0.918722	0.3584
MARCH	-0.267905	0.074757	-3.583670	0.0004
APRIL	0.068267	0.077329	0.882812	0.3775
MAY	0.065188	0.074757	0.871996	0.3834
JUNE	0.064399	0.076567	0.841075	0.4005
JULY	0.048385	0.073398	0.659210	0.5099
AUG	-0.075580	0.073398	-1.029725	0.3033
SEPT	0.009508	0.074757	0.127187	0.8988
OCT	0.232623	0.076567	3.038140	0.0024
NOV	0.148755	0.076567	1.942794	0.0523
DEC	0.135331	0.079759	1.696745	0.0900

APPENDIX 3.6

GARCH results for month-of-the-year effect (61695 observations)

Dependent Variable: GROWTHINDEX

	Coefficient	Std. Error	*z*-statistic	*P*-value
JAN	0.025602	0.065252	0.392354	0.6948
FEB	0.077211	0.052405	1.473353	0.1407
MARCH	-0.280498	0.045375	-6.181747	0.0000
APRIL	-0.058262	0.063379	-0.919272	0.3580
MAY	0.031331	0.050998	0.614367	0.5390
JUNE	0.081923	0.065843	1.244225	0.2134
JULY	0.029244	0.044423	0.658308	0.5103
AUG	-0.197185	0.042567	-4.632346	0.0000
SEPT	-0.093419	0.049531	-1.886078	0.0593
OCT	0.212838	0.046172	4.609671	0.0000
NOV	0.052253	0.065458	0.798270	0.4247
DEC	0.025414	0.068471	0.371169	0.7105
		Variance Equation		
Constant	0.022935	0.003727	6.154216	0.0000
ARCH(1)	0.220023	0.018712	11.75807	0.0000
GARCH(1)	0.758155	0.013879	54.62510	0.0000

APPENDIX 3.7

TGARCH results for month-of-the-year effect (61695 observations)

Dependent Variable: GROWTHINDEX

	Coefficient	Std. Error	*z*-statistic	*P*-value
JAN	0.046586	0.064453	0.722785	0.4698
FEB	0.085356	0.054234	1.573856	0.1155
MARCH	-0.261737	0.046056	-5.683032	0.0000
APRIL	-0.047155	0.062423	-0.755402	0.4500
MAY	-0.024540	0.052962	-0.463351	0.6431
JUNE	0.090662	0.068621	1.321207	0.1864
JULY	0.033042	0.045327	0.728968	0.4660
AUG	-0.178830	0.046096	-3.879483	0.0001
SEPT	-0.087549	0.049985	-1.751495	0.0799
OCT	0.226562	0.047135	4.806701	0.0000
NOV	0.056187	0.065864	0.853080	0.3936
DEC	0.040154	0.068068	0.589904	0.5553

Variance Equation

Constant	0.024591	0.003621	6.790993	0.0000
ARCH(1)	0.243295	0.023480	10.36164	0.0000
(RESID<0)*ARCH(1)	-0.101022	0.024116	-4.189077	0.0000
GARCH(1)	0.770735	0.014218	54.20853	0.0000

APPENDIX 3.8

EGARCH results for month-of-the-year effect
(61695 observations)

Dependent Variable: GROWTHINDEX

	Coefficient	Std. Error	*z*-statistic	*P*-value
JAN	0.011396	0.049061	0.232275	0.8163
FEB	0.096227	0.053389	1.802378	0.0715
MARCH	-0.274018	0.044932	-6.098543	0.0000
APRIL	-0.057973	0.061879	-0.936874	0.3488
MAY	-0.115973	0.048773	-2.377826	0.0174
JUNE	0.092372	0.070305	1.313868	0.1889
JULY	0.033925	0.048147	0.704600	0.4811
AUG	-0.177233	0.045652	-3.882252	0.0001
SEPT	-0.090475	0.053773	-1.682539	0.0925
OCT	0.212879	0.046186	4.609161	0.0000
NOV	0.051410	0.062251	0.825840	0.4089
DEC	0.048106	0.069732	0.689869	0.4903

Variance Equation

Constant	-0.319893	0.022121	-14.46078	0.0000
|RES|/SQR[GARCH](1)	0.350507	0.025097	13.96587	0.0000
RES/SQR[GARCH](1)	0.060514	0.013575	4.457791	0.0000
EGARCH(1)	0.932605	0.009317	100.0928	0.0000

APPENDIX 3.9

OLS results quarter-of-the-year effect
(61695 observations)

Dependent Variable: GROWTHINDEX

Variable	Coefficient	Std. Error	*t*-statistic	*P*-value
Quarter 1	0.023355	0.044148	0.528999	0.5969
Quarter 2	0.065924	0.044362	1.486039	0.1375
Quarter 3	-0.006083	0.042993	-0.141487	0.8875
Quarter 4	0.173227	0.045174	3.834693	0.0001

APPENDIX 3.10

GARCH results quarter-of-the-year effect (61695 observations)

Dependent Variable: GROWTHINDEX

	Coefficient	Std. Error	*z*-statistic	*P*-value
Quarter 1	-0.052857	0.032057	-1.648862	0.0992
Quarter 2	0.014045	0.036017	0.389949	0.6966
Quarter 3	-0.092703	0.027412	-3.381792	0.0007
Quarter 4	0.094637	0.034101	2.775220	0.0055

Variance Equation

Constant	0.025271	0.003822	6.611700	0.0000
ARCH(1)	0.205480	0.017347	11.84511	0.0000
GARCH(1)	0.765383	0.013061	58.60281	0.0000

APPENDIX 3.11

TGARCH results for quarter-of-the-year effect (61695 observations)

Dependent Variable: GROWTHINDEX

	Coefficient	Std. Error	*z*-statistic	*P*-value
Quarter 1	-0.037626	0.032990	-1.140513	0.2541
Quarter 2	0.012830	0.036590	0.350652	0.7258
Quarter 3	-0.081478	0.028570	-2.851843	0.0043
Quarter 4	0.105503	0.035174	2.999448	0.0027

Variance Equation

Constant	0.026701	0.003728	7.161657	0.0000
ARCH(1)	0.234776	0.022735	10.32651	0.0000
(RESID<0)*ARCH(1)	-0.100505	0.022292	-4.508575	0.0000
GARCH(1)	0.773922	0.013665	56.63718	0.0000

APPENDIX 3.12
EGARCH results for Quarter-of-the-year effect
(61695 observations)

Dependent Variable: GROWTHINDEX

	Coefficient	Std. Error	*z*-statistic	*P*-value
Quarter 1	-0.037606	0.030091	-1.249741	0.2114
Quarter 2	0.027123	0.034879	0.777639	0.4368
Quarter 3	-0.080344	0.029723	-2.703046	0.0069
Quarter 4	0.134526	0.030469	4.415200	0.0000

Variance Equation

Constant	-0.311653	0.019096	-16.32030	0.0000
|RES|/SQR[GARCH](1)	0.349587	0.024090	14.51181	0.0000
RES/SQR[GARCH](1)	0.050608	0.012258	4.128614	0.0000
EGARCH(1)	0.934624	0.008712	107.2752	0.0000

CHAPTER FOUR

Ordinary Share Prices and Dividend Announcements

4.0 Introduction

This essay attempts to document the impact of publicly available information in general and dividend announcements in particular on stock returns in emerging markets. It uses the methodologies of event studies to document the impact of new market information on the stock prices and returns.

Dividends are payments to shareholders for the risk position they take in holding ordinary shares in a firm. It is in all cases drawn from excess cash flows above what a firm needs to plough back for expansion or modernization. Dividends are one way of increasing the shareholders wealth, the other being capital gain due to an increase in the share price in the stock market. It is often viewed as a barometer for performance in that a firm that declares dividends portrays a healthy position in the eyes of the public and is likely to be viewed keenly by both long-term investors and short-time speculators. Knowledge on how investors react to dividend announcement can help explain generally whether a particular market incorporates information and more specifrcally whether dividends have a unique impact on share holders' wealth.

An event may be defined as any announcement, which may have an impact on the assets of a firm. In this regard an event may be within the control of the firm like stock splits and earnings announcement or may be outside the control of firms like announcement of the commencement of legislation.

An event study is an analysis whether there is a statistically significant reaction in financial markets to a past occurrence of an event which is hypothesized to affect the market value of a firm. In finance, event studies provide a test for market efficiency since it accounts for the extent in which the security price performs around the time of the event. In essence, it tests the hypothesis that the security price adjusts quickly to fully reflect new information or rather that there is zero abnormal returns. Event Studies is the use of asset prices observed over a relatively short period of time to measure an events economic impact. It measures the impact of an event on the wealth of share holders (Brown and Warner1980; Aggarwal *et al.*, 2002; Ritter and Welch, 2002).

4.1 Literature Review

This part reviews existing theoretical literature in the areas of event studies in general and examines empirical works by scholars highlighting various estimation techniques that have been used and results attained in different markets and situations.

In his pioneering work in event studies, Dolley (1933) used an unsophisticated model to study 95 splits from 1921 to 1931. He found that there was a price increase, decline and no change in 57, 26 and 12 cases respectively. However the methodology of analysis was limited, hence results were not subjected to thorough statistical tests. In the 1940s and 1950s, the issue was revisited by, among others Myers and Bakay (1948), Barker (1958) and Ashey (1962), but this time with improvement in analytical tools. The major improvement was the removal of general price movements and separation of confounding events (Campbell *et al.* 1997). Modern theorists in this field have improved on the methodology further to include handling of violation of statistical assumptions, accommodating more hypotheses and disaggregated data (see Poon and Granger, 2003).

LeRoy (1973), Rubinstein (1976) and Lucas (1978) brought a new angle to the discourse and clarified that market efficiency is different from non-predictability; hence stock returns will be non-predictable only if market efficiency is combined with risk neutrality. From their works, they made it clear that the case of risk aversion test for predictability could not confirm or falsify Efficient Market Hypothesis. This is to say that if the assumption of risk aversion is allowed, the predictability can coexist with market efficiency (see Pesaran and Timmermann, 1994 & 1995;Schwert, 1993; Tse, 1995).

Grossman and Stiglitz (1980) pointed out that while criticizing EMH, there must be sufficient profit opportunities to compensate investors for cost of trading and information gathering. These are often in the form of inefficiencies. This shows that the prices will fully reflect all available information under the unreasonable assumption that the cost of trading and gathering information is zero (see Brooks, 1996, & 2004).

DeBondt and Thaler (1985) in their study of long-term return anomalies found that when stocks are ranked on three – to- five year past returns, there tends to be a reversal such that past winners become future losers and vice versa. They attribute this reversal to investor overreaction. The possible explanation is that in forming expectations, invertors put more weight to past performance of firms and too little on the present. They thus suggest that overreaction is an alternative to market efficiency, the fact that performance tends to mean revert (see Corrado and Zivney, 1992; Fama, 1965, 1970 & 1968).

Liu *et al.* (1990) studied whether securities recommendations have an impact on common stock prices. They specifically examined Wall Street Journal's HOTS column reputed to be one of the most read features. Using daily data, they concluded that HOTS column seems to have an impact on stock prices on the publication day. The impact was found to be symmetrical to 'buy' or 'sell' recommendation. A smaller but significant impact two days preceding the publication was also detected implying that two days after publication, the market was still reacting to information contained in the HOTS column. This however was attributed to high trade volume (see Hess, 1983; Lee, 1994; Pesaran, 2005, Ritter, 1994).

Salinger (1992) discusses the appropriate methodology for measuring the effect of an event in the value of a firm's equity. He concluded that cumulative abnormal returns do not measure the effect of an event on the firm value if there are dividends doing the event window. He further admits that the traditional methodology (Fama, Fisher, Jensen and Roll 1969) was actually meant as a test for semi-strong form of efficiency and only later was it applied on specific firms (see; Kothari and Warner, Engel, 2002 2004; Granger, 1992).

Lakonishok *et al.* (1994) argued that using ratios involving stock prices as proxy for past performance there is evidence that high past performers have low future returns and vice versa. They demonstrated this by showing that firms with high ratios of earnings to price

(E/P), cost flow to price (C/P) and book – to- market equity (BE/ME) tend to have poor past earnings growth and firms with low (E/P), (C/P), (BE/ME) tend to have strong past performance (see Kritzman, 1994; Lakonishok, 1994; Hsieh, 1989).

Odabusi (1998) studied stock returns reaction to earnings announcement on the Istanbul stock exchange. The research was on equally weighted portfolios of 92 securities between 1992 and 1995. Even after dividing the samples into 'good' 'and bad', he found that abnormal returns on announcement days are significantly different from zero for each sub sample. In addition, he found out that the behaviour of cumulative average abnormal returns do not give full support to the hypothesis that security prices come to new equilibrium level after price announcement of earnings (see Glosten *et al.*, 1993; Ho, 2004).

Binder (1998) reviewed several methodologies on event studies. He identified heteroskedasticity and dependence as among major problems encountered when testing for market reaction to publicly available information. However he concluded that many of these problems are minor when event periods are randomly dispersed through calendar time.

Reynolds (2006) investigated the degree to which event studies can be used to analyze the impact of new law. He concluded that though event studies results were a poor prediction of the actual returns, the findings showed that investors anticipated correctly only that they overestimated the returns. This shows that with modifications in analytical tools to suit each problem, event studies is a useful tool (see Samuelson, 1965).

4.2 Methodology

This section highlights and justifies the various techniques used to accomplish the fourth objective of the study. It reviews techniques for gauging the impact of information on stock prices and returns.

4.2.1 Detecting impact of a market event

Fama and French (1992) define the impact of an event as the test for the semi-strong form efficiency. That is, it provides the test if or not the current prices reflect all information on past prices and any other public information. The tests for this impact of information are collectively referred to as 'Event Studies". Such tests therefore examine the stock market's response to a well-defined event (stock split, initial public offering, regulations, dividend announcements or mergers and acquisition announcements) through the observation of security prices around the event. The basic assumption behind event studies is rationality in the market. Assuming that market players are rational, the effect of an event can be immediately reflected in asset prices. This allows the event's impact to be measured using asset prices over a short period. Though it has commonly been applied to stock prices, Event Studies can be generalized to include debt securities (see Schwert, 1990; Pynnonen and Pape, 2005; Brav and Gompers, 1997).

Any event study can be said to test the following null hypothesis:

$H_0 : E(AR_t | \Phi_{t-1}) = 0$

$H_a : E(AR_t | \Phi_{t-1}) \neq 0$

Where, $AR_t = R_t - E(R_t)$ **(4.1)**

Where E is an expectation operator, Φ_{t-1} is information set in the previous period, AR_t is abnormal returns, R_t is ex-post security return subject to the occurrence of the event being studied and $E(R_t)$ is expected return in the absence of the event; t is time.

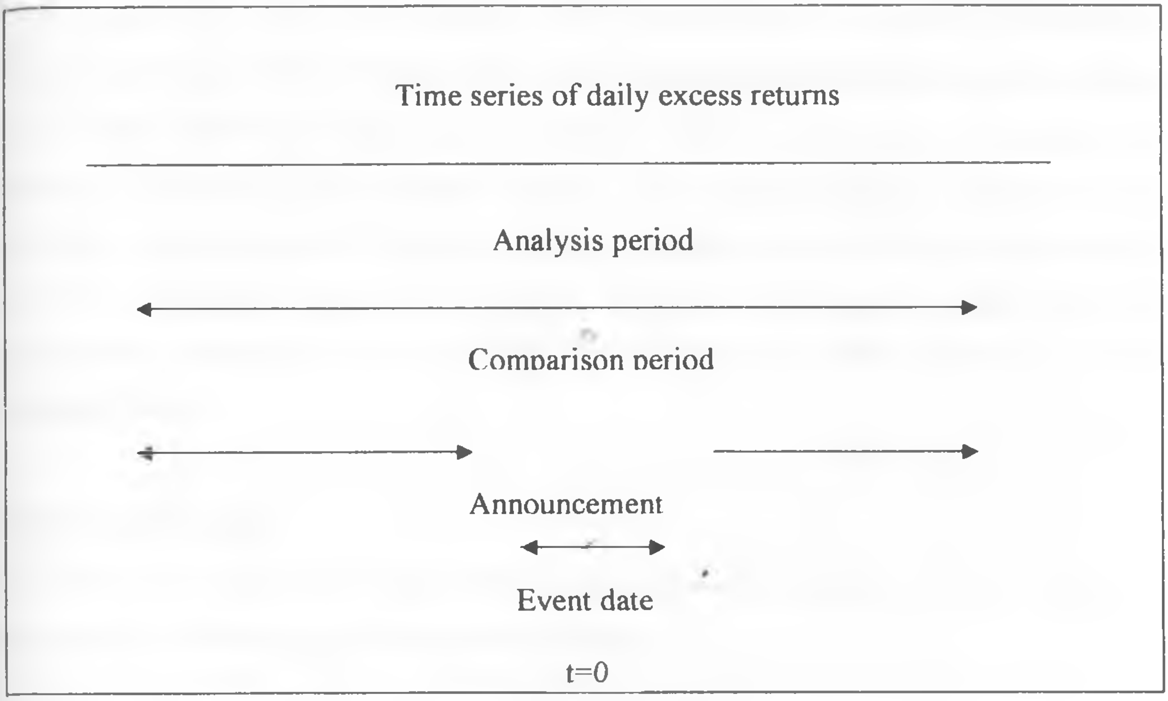
An event study can be outlined to include: defining event of interest, determining event window (period over which securities will be examined), selecting the frequency of the sample, determining the method of measurement of normal returns, defining the estimation window and choosing benchmarks to calculate price responses (See Ngugi *et al.*, 2005; Mackinlay 1997; Lakonishok *et al.*, 1994; Laughran and Ritter., 1995; Ibbotson, 1975; Ibbotson and Jaffe, 1973; Koulakiotis *et. al.*, 2006; Figlewski, 2004).

Defining event of interest

The choice of event depends on the researcher's interest and characteristics and/or limitation of the particular market including availability of data. In many emerging markets, certain events may not have happened with reasonable frequencies to warrant statistical analysis. In some cases the post event period is very short

Event Window

Event period is normally one day though an extra day can be given to allow information to filter to all. It can be summarized by the diagram as follows:



Event Horizon

Event horizon (N) is the period before an event and an equal period after the same event in which the event is expected to have a major impact. There are no strict theoretical rules for choice except that the pre-event and post-event periods should not coincide; however, characteristic of the data especially its distribution must be considered. Though daily stock data provide ideal numbers for estimation, they are often associated with the following problems: non-normality, non-synchronous trading and variance estimation. Though these problems may lead to biased and inconsistent results, the Central Limit

Theorem stipulates that with large sample size, distribution will tend towards normality. Brown and Warner (1985) concluded that these problems might not have any impact on the accuracy of results from daily data. The study will consider 20 days before and after an event. This horizon is large enough to provide numbers for regression analysis for measurement of returns, but not too large to cause event overlap. Daily stock prices are used to compute returns.

4.2.2 Normal Returns

Security price can only be considered abnormal relative to a particular benchmark (Brown and Warner1980). Normal returns thus constitute a benchmark. It refers to that return which would have been expected had the event not occurred. It is basically the measure of returns in the estimation window. Two broad categories; statistical and economic models have been used to measure normal returns. While the former uses statistical assumptions and do not include economic arguments, the latter rely on assumptions concerning investor behaviour. Several methods exist for computing normal returns as follows:

Statistical Models

Statistical models include Constant Mean-Return and Market models. They are basically mechanical models devoid of economic arguments.

Constant-Mean-Return Model

This is the simplest model and can be applied to both nominal, real and returns depending on the frequency of data and takes the form:

$$R_{it} = \mu_i + \zeta_{it}, \quad \zeta_{it} \sim N(0, \sigma^2_{it}) \qquad \textbf{(4.2)}$$

Where R_{it} is the period-t return of security i, ζ_{it} is the disturbance term. The weakness of this model is the assumption that the mean return does not vary over time. However despite this, some authors maintain that it gives results not so different from those of the more sophisticated models (Campbell *et al.*, 1997).

Market Model

This model improves on the constant-mean model and relates returns of any security to returns on market portfolio. This in effect removes the part of returns attributed to market variation. The main impact is that it reduces the variance of the error term. It is a linear model stated as follows:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it},\ \varepsilon_{it} \sim N\left(0, \sigma^2{}_{it}\right) \qquad \textbf{(4.3)}$$

where R_{it} and R_{mt} are returns on security i and market portfolio in period t respectively measured by a market index.

The advantage of this model is that it has a smaller variance, is simple and studies have shown that its results are similar to those more sophisticated models.

Economic Models

Generally, these models take into consideration economic arguments. The two most common are Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT).

CAPM

Capital Asset Pricing Model (CAPM) is one of the popular models for measuring returns. Though the foundation was Markowitz's work, CAPM was developed independently by Sharpe (1964) and Lintner (1965). It is based on the assumption that an investor will hold a mean-variance efficient portfolio. In its original form, CAPM assumes the existence of risk free borrowing and lending rate. This original version is given as:

$$E[R_i] = R_f + \beta_{im}\left(E[R_{im}] - R_f\right),\ \beta_{im} = \frac{\sigma_{im}}{\sigma^2{}_m} \qquad \textbf{(4.4)}$$

Where R_{im} is the return on market portfolio of assets, and R_f the return on the risk free asset. This model can be extended to include the absence of risk free asset (see Black 1972). However after 1970s, use of CAPM in event studies has almost ceased due to a discovery that cast doubt on its validity (Campbell et al 1997).

Arbitrage Pricing Theory (APT)

This is a multifactor model. It does not impose the restrictions on mean return. Under this model return is modeled as:

$$R_i = \alpha_i + \sum_{i=1}^{n} \beta_i F_i + \varepsilon_i \tag{4.5}$$

where F_i is i the covariate and ε_i the error term.

This model does not seem to have any advantages over the other simpler models (Campbell et al 1997).

Market model will be used to predict normal returns as:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}, \operatorname{var}(\varepsilon_{it}) = h_t \tag{4.6}$$

where h_t is the variance (measure of volatility), R_{it} is return on security i and R_{mt} is return on market portfolio in period t.. NSE 20 share index is used as a proxy for the market portfolio.

4.2.3 Abnormal returns

Abnormal return can be interpreted as a measure of impact of the event on the value of an asset. It is the measure of the unexpected change in security holders worth associated with the event. It can be measured as the component of return which is unexpected. It is important that pre-event and post-event periods should not overlap so that the event remains exogenous with respect to market value of security.

$$R_{it} = k_{it} + \varepsilon_{it} \tag{4.7}$$

Where k_{it} is the predicted return for ith security at day t given a particular model and ε_{it} the component of the return which is unexpected which in turn can be expressed as:

$$\varepsilon_{it} = R_{it} - k_{it} \tag{4.8}$$

For a sample of K securities, the cross-sectional mean abnormal return (AR) for a particular event at day t can be expressed as:

$$AR_t = \frac{1}{K}\sum_{i}^{N}\varepsilon_{it} \tag{4.9}$$

This average is for a single return and to draw inference must be aggregated across securities and through time to give cumulated average return (CAR) as follows:

$$CAR = \sum_{t=T_1}^{T_2} AR_t \tag{4.10}$$

And for the two periods; before (t<0) and after (t>0) an event the expression can be modified respectively as follows:

$$CAR_{(t<0)} = \sum_{t=-N}^{-1} AR_t \tag{4.11}$$

$$CAR_{(t>0)} = \sum_{t=0}^{N} AR_t \tag{4.12}$$

The item on the left hand side gives the return to investment in a portfolio of K projects at the start of the event horizon till event. The item on the right on the other hand shows the return from the same portfolio from the date of the event to the end of the horizon.

4.2.4 Hypothesis to be tested

The general objective is to test EMH. If a market is efficient, it reacts fast to each of the events. The null hypothesis for each case is that there are no abnormal returns; hence the event has no impact on returns. This can be given in statistical notation as:

$$H_0 = \frac{1}{N}\sum_{i=1}^{N}\Gamma_{it} = 0$$

$$H_a = \frac{1}{N}\sum_{i=1}^{N}\Gamma_{it} \neq 0$$

where Γ are the cumulative abnormal returns over the stated period.

nce the distribution of returns is unknown and there is evidence that it is not normally tributed (see Ngugi *et al* 2005), a non-parametric test is appropriate. Essentially the propriate test should be to test the difference between measures of location and persion on returns before and after dividend announcement. Sign test and Wilcoxon ık test are two alternative tests that can be used.

gn test

gn test is used to test the hypothesis that there is no difference between the two column tributions. The basis of the sign test is that if there is efficiency it should be equally obable that CAR will be negative or positive. It requires that returns be independent ross securities and that expected proportion of positive abnormal returns be 50% of all normal returns. The null and alternative hypotheses are stated, respectively as:

$_0 : \rho \leq 0.5$

$_0 : \rho \geq 0.5$

here ρ is the probability that CAR has a positive sign. This hypothesis implies that ven a random pair of measured (x,y), then both x and y are equally likely to be larger an the other. In this respect, accepting the null hypothesis implies that there is no idence of difference between daily returns on ordinary shares before and after dividend nouncement.

e test statistic is

$$S = \frac{|\rho_0 - \rho|}{\sqrt{\rho(1-\rho)/N}} \qquad \textbf{(4.13)}$$

here ρ_0 is observed fraction of positive values.

4.2.5 An alternative model for computing abnormal returns

Izan (1978) and De Jong *et al.*, (1992) provide an alternative model to compute abnormal returns. This a regression model that adds dummy variables into the normal returns model as follows:

$$R_{it} = \alpha_i + \beta_{mt} + \sum_{k=T_1}^{T_2} \gamma_{ik}\delta_{ikt} + \varepsilon_{it}, \text{var}(\varepsilon_{it}) = h_t \qquad \textbf{(4.14)}$$

Where γ_{ik} captures abnormal return for firm i and day k, δ_{ikt} is the dummy variable representing the event. It takes a value of 1 when t=k and 0 otherwise. T_1, T_2 is the beginning and end of the event window respectively.

To capture the cumulated abnormal returns, the equation can be modified as:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \Gamma_i \delta_{(T_1 T_2)} + \varepsilon_{it} \qquad \textbf{(4.15)}$$

Where $\delta_{(TT_{21})}$ is the dummy variable representing the event period. It takes a value of 1 when $t \in [T_1 T_2]$ and 0 otherwise.

This model can be extended to test whether the abnormal returns differ between days after the event and between firms. This is done by regressing the error term on days to event and firms as follows;

$$\varepsilon = \delta_0 + \sum_{i=-20}^{20+1} \delta_i DAY_i + \sum_{j=1}^{15} \theta_j FIRM_J + v \qquad \textbf{(4.16)}$$

Where ε is error, DAY_i is the dummy for the *i*th day to or after the event and $FIRM_j$ is the dummy for the *jth* firm

4.2.6 Sampling strategy

The population of study is all firms listed in Nairobi Stock Exchange market. A sample consisting of all the 20 firms used in the computation of NSE index was considered. Four firms were dropped either because they had not declared dividends during the period of study or if they had, it was less than three times in the same period. A fifth firm was dropped because of outliers. A total of fifteen (15) firms were considered.

4.2.7 Empirical models

Two sets of models are used in this chapter to study the stock market reaction to information, particularly to dividend announcement. The first is the traditional CAR method. The second is that popularized by De Jong *et al.*, (1992).

4.2.8 Data

The study employs secondary data from Nairobi stock Exchange archives and yearbooks. The data covers the period between the first trading day in the year 2001 and the last day of 2005. Returns on daily stock prices and indices are computed from the said data.

4.3 Results

This section uses several methodologies to show the results from the attempt to answer the question as to whether ordinary stock prices react to dividend announcements. The first, second and third parts of this section present and discuss CAR, regression and graphical results.

4.3.1 CAR results

The results and are summarized in Tables 4.1 and 4.2. The relevant tests of hypotheses are presented by Tables 4.3 and 4.4; and discussed there after.

Table 4.1 CAR results

BAMBURI		
DAY	AR	CAR
-20	0.9558	0.9558
-19	0.0459	1.00181
-18	0.12867	1.13048
-17	0.67876	1.80924
-16	0.89037	2.699628
-15	-0.64438	2.055249
-14	0.042271	2.097521
-13	-0.31457	1.782946
-12	-0.43683	1.346111
-11	-0.26722	1.078888
-10	0.024091	1.102979
-9	-0.64469	0.458289
-8	0.626104	1.084393
-7	-0.20831	0.876085
-6	-1.02893	-0.15285
-5	0.459208	0.306359
-4	-0.30165	0.004706
-3	-0.16773	-0.16302
-2	0.14636	-0.01666
-1	0.016662	2.13E-12
0	0.474615	
0	-2.94623	
1	2.813902	2.813902
2	0.133471	2.947373
3	-0.20833	2.739043
4	-1.22233	1.516708
5	-0.54666	0.970047
6	0.002827	0.972874
7	0.34283	1.315704
8	-0.48647	0.829233
9	1.590037	2.41927
10	0.199612	2.618882
11	-0.35918	2.2597
12	-0.00648	2.253218
13	-0.0799	2.173318
14	0.389765	2.563083
15	-0.5708	1.992287
16	-0.05072	1.941563
17	0.834951	2.776514
18	0.344944	3.121458
19	-1.65401	1.467445
20	1.004172	2.471618

BARCLAYS		
	AR	CAR
-20	-1.00648908	-1.00649
-19	-0.28093311	-1.28742
-18	-0.342042	-1.62946
-17	-0.43643276	-2.0659
-16	-0.49810508	-2.564
-15	0.256612959	-2.30739
-14	-0.12910531	-2.43649
-13	0.611295076	-1.8252
-12	-0.56511045	-2.39031
-11	-0.06569045	-2.456
-10	0.008010185	-2.44799
-9	-0.37617598	-2.82417
-8	-0.02766727	-2.85183
-7	0.368804851	-2.48303
-6	1.137095817	-1.34593
-5	-0.22338462	-1.56932
-4	0.911548465	-0.65777
-3	0.229387772	-0.42838
-2	1.143783156	0.715402
-1	-0.7154	3.85E-13
0	0.75734031	
0	0.00119408	
1	-0.2361168	-0.2361
2	0.21480254	-0.0213
3	-0.7492145	-0.7705
4	0.25337968	-0.5171
5	-0.3689044	-0.8860
6	0.25667073	-0.6293
7	1.05986824	0.43048
8	0.72033015	1.15081
9	0.64261742	1.79343
10	-0.3423267	1.45110
11	-0.2004762	1.25063
12	0.36833176	1.61896
13	-0.9340475	0.68491
14	-0.8189391	-0.1340
15	-0.3947548	-0.5287
16	0.47657842	-0.0522
17	0.06643849	0.01423
18	0.02089891	0.03513
19	-0.089207	-0.0540
20	-0.704463	-0.7585

Table 4.1 continued

BAT		
DAY	AR	CAR
-20	0.125803	0.125803
-19	-0.16728	-0.04148
-18	-0.01199	-0.05347
-17	-0.41943	-0.47291
-16	0.050465	-0.42244
-15	-0.09815	-0.52059
-14	-0.1702	-0.69079
-13	0.103053	-0.58774
-12	-0.0869	-0.67465
-11	0.464587	-0.21006
-10	-0.13802	-0.34808
-9	0.415494	0.067411
-8	-0.09129	-0.02388
-7	0.61684	0.59296
-6	-0.24071	0.35225
-5	-0.27147	0.080775
-4	-0.23093	-0.15015
-3	0.000309	-0.14984
-2	-0.01833	-0.16817
-1	0.168173	-4E-12
0	0.782602	
0	2.500061	
1	0.749832	0.749832
2	-3.73929	-2.98946
3	3.921382	0.931922
4	-0.13372	0.7982
5	-0.7109	0.087303
6	-0.4576	-0.37029
7	-2.10625	-2.47655
8	-0.30736	-2.78391
9	-0.82632	-3.61023
10	-0.5611	-4.17133
11	0.60272	-3.56861
12	1.086365	-2.48225
13	-0.79395	-3.27619
14	-0.4035	-3.67969
15	-0.35463	-4.03432
16	0.447151	-3.58717
17	-0.55528	-4.14246
18	0.382058	-3.7604
19	0.298187	-3.46221
20	0.179549	-3.28266

BOC		
DAY	AR	CAR
-20	0.096969	0.096969
-19	1.072576	1.169545
-18	0.261207	1.430751
-17	1.023133	2.453884
-16	-0.36948	2.084407
-15	-0.34134	1.743072
-14	0.08851	1.831582
-13	0.850136	2.681718
-12	0.082335	2.764053
-11	0.710226	3.474279
-10	-1.51135	1.96293
-9	-0.33221	1.630719
-8	0.058129	1.688848
-7	-0.31049	1.378355
-6	-0.83345	0.544903
-5	-0.89368	-0.34878
-4	0.028323	-0.32045
-3	0.404273	0.08382
-2	0.818142	0.901962
-1	-0.90196	1.39E-12
0	1.252019	
0	2.026125	
1	0.428509	0.428509
2	0.291994	0.720503
3	-1.53856	-0.81805
4	-0.72379	-1.54185
5	-0.21579	-1.75764
6	0.216225	-1.54141
7	-1.65355	-3.19497
8	0.459863	-2.7351
9	-0.20742	-2.94252
10	0.120585	-2.82194
11	-0.59039	-3.41233
12	0.217651	-3.19468
13	-1.1581	-4.35278
14	-0.97564	-5.32842
15	0.449476	-4.87895
16	0.207655	-4.67129
17	-0.04594	-4.71724
18	0.036157	-4.68108
19	1.325683	-3.3554
20	0.0901	-3.2653

Table 4.1 continued

DTB		
DAY	AR	CAR
-20	-0.3019	-0.3019
-19	-1.44533	-1.74723
-18	-1.0265	-2.77373
-17	0.132238	-2.6415
-16	0.450476	-2.19102
-15	0.112908	-2.07811
-14	0.293086	-1.78503
-13	-0.07498	-1.86001
-12	0.488796	-1.37121
-11	-0.03276	-1.40397
-10	0.004143	-1.39983
-9	-0.55616	-1.95599
-8	-0.25256	-2.20855
-7	0.04851	-2.16004
-6	0.502426	-1.65762
-5	0.772787	-0.88483
-4	-0.23438	-1.11921
-3	0.474714	-0.64449
-2	0.231173	-0.41332
-1	0.413318	1.2E-12
0	0.037003	
0	-2.4748	
1	1.504166	1.504166
2	-1.95363	-0.44946
3	-1.56491	-2.01437
4	-0.91662	-2.93099
5	0.305507	-2.62548
6	-1.42113	-4.04661
7	0.355232	-3.69138
8	0.660669	-3.03071
9	0.727034	-2.30367
10	1.737232	-0.56644
11	-0.75101	-1.31745
12	0.883705	-0.43374
13	0.300737	-0.13301
14	0.054545	-0.07846
15	0.176834	0.098371
16	0.415453	0.513824
17	1.231674	1.745499
18	-0.69994	1.045558
19	0.590649	1.636207
20	0.801592	2.437799

EABL		
DAY	AR	CAR
-20	-0.21813	-0.21813
-19	0.101239	-0.11689
-18	1.533079	1.416192
-17	-0.12937	1.286823
-16	-0.23091	1.055918
-15	1.061108	2.117026
-14	-0.52011	1.596912
-13	0.104374	1.701287
-12	-0.17125	1.530035
-11	0.111848	1.641883
-10	0.18522	1.827102
-9	0.012097	1.839199
-8	-0.30774	1.531455
-7	-0.51764	1.013815
-6	-0.01694	0.996879
-5	-0.25969	0.737188
-4	-0.33484	0.402344
-3	-0.27319	0.129156
-2	0.298897	0.428052
-1	-0.37518	0.052875
0	-0.23007	
0	0.521783	
1	1.932106	1.932106
2	0.711142	2.643248
3	0.341487	2.984735
4	-0.66194	2.32279
5	-0.61178	1.711008
6	0.728399	2.439408
7	-0.47799	1.961419
8	-0.43332	1.528098
9	0.139956	1.668054
10	-0.09234	1.575718
11	0.242644	1.818361
12	-0.15161	1.666751
13	-0.4749	1.191853
14	-0.15891	1.032939
15	-0.47219	0.560751
16	-0.52574	0.035007
17	-0.49772	-0.46272
18	0.106144	-0.35657
19	0.12804	-0.22853
20	-0.02777	-0.2563

Table 4.1 continued

FIRESTONE		
DAY	AR	CAR
-20	0.81927349	0.819273
-19	-0.0785011	0.740772
-18	-2.0402589	-1.29949
-17	-1.3869533	-2.68644
-16	-1.398257	-4.0847
-15	-0.8290045	-4.9137
-14	0.70525926	-4.20844
-13	0.37570399	-3.83274
-12	1.16481448	-2.66792
-11	0.57632543	-2.0916
-10	1.72400996	-0.36759
-9	-0.4167454	-0.78433
-8	1.04247049	0.258137
-7	-1.571225	-1.31309
-6	0.56947779	-0.74361
-5	0.85613306	0.112523
-4	-0.1788126	-0.06629
-3	0.21485967	0.14857
-2	-0.0890935	0.059476
-1	-0.0594764	-1.6E-12
0	0.26008926	
0	0.98294957	
1	-1.077989	-1.07799
2	1.40673032	0.328741
3	1.32189925	1.650641
4	-1.9018653	-0.25122
5	0.49969988	0.248475
6	0.11626859	0.364744
7	-0.4899892	-0.12525
8	-1.1975246	-1.32277
9	-0.918279	-2.24105
10	1.40645765	-0.83459
11	-0.803211	-1.6378
12	1.19995168	-0.43785
13	0.09000528	-0.34785
14	0.62284283	0.274997
15	1.34680338	1.621801
16	-1.2463072	0.375494
17	-0.0560304	0.319463
18	-1.2032962	-0.88383
19	0.30322555	-0.58061
20	-0.6624314	-1.24304

KENYA AIRWAYS		
DAY	AR	CAR
-20	-1.499504229	-1.4995
-19	-0.906217391	-2.40572
-18	0.460818443	-1.9449
-17	0.099632637	-1.84527
-16	1.664265776	-0.181
-15	0.200530071	0.019525
-14	-1.180363478	-1.16084
-13	-0.58520873	-1.74605
-12	0.281369556	-1.46468
-11	0.184289322	-1.28039
-10	-0.44474192	-1.72513
-9	-0.440462114	-2.16559
-8	0.503870547	-1.66172
-7	-1.014603402	-2.67632
-6	0.105336175	-2.57099
-5	-0.456614789	-3.0276
-4	-0.41996212	-3.44757
-3	0.690894576	-2.75667
-2	1.330864725	-1.42581
-1	1.425806344	-2.4E-12
0	1.582527834	
0	1.328037464	
1	2.781112465	2.781112
2	-1.295492757	1.48562
3	-0.435317701	1.050302
4	-0.084477435	0.965825
5	-0.765335112	0.200489
6	-0.876601589	-0.67611
7	-0.560033711	-1.23615
8	0.232739314	-1.00341
9	0.502227847	-0.50118
10	-0.375209967	-0.87639
11	-0.723148378	-1.59954
12	-1.787781789	-3.38732
13	1.011770679	-2.37555
14	-0.165327524	-2.54088
15	0.009629768	-2.53125
16	-0.29365229	-2.8249
17	-0.026123677	-2.85102
18	-0.474875036	-3.3259
19	0.415331595	-2.91057

Table 4.1 continued

NATION		
DAY	AR	CARt9
-20	-0.23169	-0.23169
-19	1.102778	0.871086
-18	0.294486	1.165572
-17	-2.05094	-0.88537
-16	1.782779	0.897412
-15	0.283235	1.180647
-14	1.795296	2.975943
-13	0.993049	3.968992
-12	0.922706	4.891697
-11	-0.25694	4.634753
-10	1.059504	5.694257
-9	-0.72615	4.968105
-8	1.98237	6.950475
-7	0.479538	7.430013
-6	-9.03282	-1.60281
-5	10.40028	8.797473
-4	-0.7141	8.083378
-3	-2.74303	5.340348
-2	-1.23017	4.110178
-1	-3.53747	0.572709
0	1.232532	
0	1.643692	
1	1.215527	1.215527
2	0.543975	1.759502
3	-0.097	1.662498
4	-0.71392	0.948576
5	-1.0363	-0.08772
6	-0.02245	-0.11018
7	-0.12501	-0.23519
8	0.317773	0.082586
9	-0.55282	-0.47023
10	-0.41288	-0.88312
11	-0.14969	-1.03281
12	-1.03123	-2.06404
13	0.548887	-1.51516
14	0.593447	-0.92171
15	-0.65437	-1.57608
16	-0.59822	-2.17431
17	-0.02208	-2.19639
18	0.034116	-2.16227
19	0.011477	-2.1508
20	-1.30628	-3.45707

NIC		
DAY	AR	CAR
-20	0.981406	0.981406
-19	0.575827	1.557232
-18	0.23639	1.793623
-17	-1.11576	0.677859
-16	-0.68062	-0.00276
-15	0.105243	0.102484
-14	0.732667	0.83515
-13	-1.03322	-0.19807
-12	0.281726	0.083655
-11	0.231197	0.314852
-10	0.588539	0.903391
-9	-0.79473	0.10866
-8	-0.4659	-0.35724
-7	1.244228	0.886991
-6	0.821969	1.708959
-5	-0.15304	1.555918
-4	-0.48496	1.070956
-3	-0.59956	0.471396
-2	0.288311	0.759707
-1	-0.75971	4.62E-12
0	2.146068	
0	-0.23817	
1	-0.52371	-0.52371
2	-0.6017	-1.12541
3	-1.05374	-2.17915
4	-0.29526	-2.47441
5	0.586695	-1.88771
6	-0.94137	-2.82908
7	-0.23877	-3.06785
8	-0.83712	-3.90497
9	0.637167	-3.2678
10	-0.07664	-3.34445
11	0.312901	-3.03155
12	0.005016	-3.02653
13	0.059623	-2.96691
14	0.0831	-2.88381
15	-0.83614	-3.71994
16	1.329317	-2.39063
17	0.048825	-2.3418
18	0.385042	-1.95676
19	-0.30826	-2.26502
20	0.357123	-1.90789

Table 4.1 continued

SASINI			STANCHART		
DAY	AR	CAR	DAY	AR	CAR
-20	-0.16954	-0.16954	-20	-0.17421548	-0.17422
-19	0.316113	0.146574	-19	-1.07025933	-1.24447
-18	1.450331	1.596905	-18	0.03931367	-1.20516
-17	-0.49449	1.102412	-17	-0.31422704	-1.51939
-16	0.212943	1.315355	-16	0.890011266	-0.62938
-15	1.275374	2.59073	-15	0.027136303	-0.60224
-14	-0.74359	1.847137	-14	0.59387533	-0.00837
-13	-2.15791	-0.31078	-13	-0.17518325	-0.18355
-12	0.112038	-0.19874	-12	0.83273542	0.649187
-11	-0.47522	-0.67396	-11	0.413973545	1.06316
-10	0.680373	0.006409	-10	-0.62487334	0.438287
-9	-0.18031	-0.1739	-9	0.576936237	1.015223
-8	-0.08565	-0.25956	-8	-0.06119104	0.954032
-7	-0.98818	-1.24774	-7	0.244929849	1.198962
-6	0.543379	-0.70436	-6	-0.43621881	0.762743
-5	-0.02989	-0.73425	-5	-0.54934501	0.213398
-4	-1.33851	-2.07276	-4	0.346649456	0.560048
-3	0.7671	-1.30566	-3	-0.10771142	0.452336
-2	0.605384	-0.70028	-2	-0.30656830	0.145768
-1	0.700276	-8.4E-13	-1	-0.14576801	-5.7E-13
0	-0.90418		0	2.122547887	
0	3.7485		0	0.266507014	
1	-0.0356	-0.0356	1	-0.80635262	-0.80635
2	-0.08378	-0.11938	2	-1.16925954	-1.97561
3	1.759024	1.639641	3	-0.00372008	-1.97933
4	-0.47835	1.161294	4	-0.85553824	-2.83487
5	0.419431	1.580725	5	0.480547714	-2.35432
6	0.211727	1.792452	6	0.082720818	-2.2716
7	-3.29084	-1.49838	7	1.032459139	-1.23914
8	-2.11221	-3.6106	8	0.285010244	-0.95413
9	-0.32328	-3.93388	9	0.545418169	-0.40871
10	1.654953	-2.27892	10	0.040929406	-0.36779
11	-1.30664	-3.58556	11	-1.23668175	-1.60447
12	-3.56131	-7.14687	12	0.717764663	-0.8867
13	0.135229	-7.01164	13	-0.05288616	-0.93959
14	0.390871	-6.62077	14	-0.63387657	-1.57346
15	0.476928	-6.14384	15	-1.24844661	-2.82191
16	-1.91722	-8.06106	16	0.542287137	-2.27962
17	0.881935	-7.17912	17	0.719545955	-1.56008
18	3.332239	-3.84688	18	0.326251139	-1.23383
19	0.948497	-2.89839	19	-1.1660852	-2.39991
20	0.054067	-2.84432	20	-0.226	-2.62591

Table 4.1 continued

TOTAL		
DAY	AR	CAR
-20	3.588646	3.588646
-19	2.82648	6.415125
-18	0.572192	6.987317
-17	0.744908	7.732225
-16	-0.46895	7.26327
-15	0.697142	7.960412
-14	-0.57821	7.3822
-13	-2.30728	5.074924
-12	-0.33424	4.74068
-11	-0.98216	3.758522
-10	2.243716	6.002238
-9	-2.49915	3.503091
-8	0.257986	3.761078
-7	1.786256	5.547334
-6	-0.78158	4.765757
-5	-1.08957	3.676191
-4	0.797335	4.473526
-3	-0.92623	3.547294
-2	-0.44082	3.106479
-1	-3.10648	-6.1E-12
0	2.12231	
0	7.988655	
1	-3.20943	-3.20943
2	-0.01773	-3.22717
3	2.92702	-0.30015
4	-1.47055	-1.77069
5	0.055428	-1.71527
6	-2.7471	-4.46236
7	-2.04731	-6.50968
8	-0.87891	-7.38859
9	0.826929	-6.56166
10	1.93179	-4.62987
11	-1.75483	-6.38469
12	0.202366	-6.18233
13	-0.20712	-6.38945
14	-2.9839	-9.37335
15	1.243121	-8.13023
16	-0.72135	-8.85158
17	0.394641	-8.45694
18	-1.71248	-10.1694
19	-0.74798	-10.9174
20	0.806435	-10.111

TPS		
DAY	AR	CAR
-20	-0.75251	-0.75251
-19	-0.18211	-0.93462
-18	-0.97353	-1.90815
-17	-2.14498	-4.05313
-16	-1.01822	-5.07135
-15	-0.23613	-5.30748
-14	0.150771	-5.15671
-13	0.139374	-5.01734
-12	-1.47868	-6.49601
-11	3.858598	-2.63742
-10	2.348644	-0.28877
-9	1.038582	0.74981
-8	0.36421	1.11402
-7	-4.11166	-2.99764
-6	-1.14998	-4.14762
-5	-0.25486	-4.40248
-4	-1.08293	-5.48541
-3	2.442936	-3.04247
-2	-0.10581	-3.14828
-1	3.148281	-2.7E-12
0	2.530173	
0	-1.50495	
1	-0.00144	-0.00144
2	-1.10632	-1.10776
3	-2.74099	-3.84875
4	-1.50527	-5.35402
5	0.542479	-4.81154
6	0.106123	-4.70542
7	-1.41457	-6.11998
8	0.442219	-5.67776
9	3.010921	-2.66684
10	1.058879	-1.60796
11	1.906213	0.29825
12	0.853988	1.152238
13	-0.6812	0.471034
14	-0.36954	0.101498
15	-0.53923	-0.43773
16	1.445903	1.008173
17	-1.59518	-0.58701
18	-1.51313	-2.10014
19	0.833071	-1.26707
20	0.241846	-1.02522

Table 4.1 continued

UNILEVER		
DAY	AR	CAR
-20	0.3640223	0.364022
-19	0.4366861	0.800708
-18	0.1777523	0.978461
-17	-0.430086	0.548374
-16	0.4480916	0.996466
-15	0.0591307	1.055597
-14	0.1779172	1.233514
-13	-0.775347	0.458166
-12	-1.407757	-0.94959
-11	0.2455857	-0.70401
-10	0.3415738	-0.36243
-9	0.0660143	-0.29642
-8	-0.003389	-0.29981
-7	0.1336845	-0.16612
-6	-1.300782	-1.46691
-5	1.7317658	0.264861
-4	0.0850429	0.349904
-3	-0.078997	0.270907
-2	-0.155070	0.115836
-1	-0.115836	3.98E-12
0	-0.254119	
0	-0.321682	
1	-1.222740	-1.22274
2	-1.094733	-2.31747
3	-1.061301	-3.37878
4	0.1601316	-3.21864
5	0.907912	-2.31073
6	0.1676682	-2.14306
7	-0.012077	-2.15514
8	-0.095401	-2.25054
9	-0.067220	-2.31776
10	0.3523835	-1.96538
11	-0.096024	-2.0614
12	0.5227821	-1.53862
13	0.3799792	-1.15864
14	-0.161738	-1.32038
15	0.0571351	-1.26325
16	1.4372031	0.173957
17	-0.268661	-0.0947
18	-0.101700	-0.1964
19	0.8053104	0.608906
20	-0.033104	0.575801

WILLIAMSON		
DAY	AR	CAR
-20	-0.692732321	-0.69273
-19	1.661621368	0.968889
-18	-1.797760867	-0.82887
-17	5.170925709	4.342054
-16	-0.162987385	4.179067
-15	-0.112406357	4.06666
-14	-4.842650178	-0.77599
-13	-2.304283571	-3.08027
-12	-2.46169528	-5.54197
-11	3.249034044	-2.29293
-10	1.962417838	-0.33052
-9	-3.134933661	-3.46545
-8	0.146258791	-3.31919
-7	-0.156274007	-3.47547
-6	-2.086615833	-5.56208
-5	-7.137168773	-12.6993
-4	3.151513494	-9.54774
-3	6.851515526	-2.69622
-2	-1.358230361	-4.05445
-1	4.054451824	-5.9E-12
0	1.722070797	
0	-6.064719458	
1	-3.931511177	-3.93151
2	1.03331601	-2.8982
3	3.680462439	0.782267
4	-1.161391521	-0.37912
5	-0.174821873	-0.55395
6	6.806000533	6.252054
7	-2.396974464	3.85508
8	5.169980485	9.02506
9	5.156165938	14.18123
10	2.717685634	16.89891
11	-1.355384403	15.54353
12	-0.444134814	15.09939
13	2.956160079	18.05555
14	-0.271934779	17.78362
15	-5.166446364	12.61717
16	-2.106982798	10.51019
17	-2.009045294	8.501144
18	-7.38583844	1.115305
19	2.27673723	3.392042
20	0.95060624	4.342649

Table 4.2 Cumulative abnormal returns

FIRM	BEFORE DIVIDEND	AFTER DIVIDEND
Bamburi	2.13E-12	2.471618
Barclays	3.85E-13	-0.758534
BAT	-4.04E-12	-3.282662
BOC	1.39E-12	-3.265298
DTB	1.20E-12	2.437799
EABL	0.052875	-0.256299
Firestone	-1.55E-12	-1.243039
K.airways	-2.40E-12	-2.910565
Nation	0.572709	-3.457071
NIC	4.62E-12	-1.907895
Sasini	-8.40E-13	-2.844320
Total	-5.73E-13	-2.625912
TPS	-6.10E-12	-10.11097
Unilever	-2.72E-12	-1.025223
G.Williamson	3.98E-12	0.575801

Test of Hypothesis

Sign test

This non-parametric test, tests whether abnormal returns before dividend announcement are different from those after the announcement. The null hypothesis is that the cumulative abnormal returns are equal on both sides of the date of dividend announcement. Both mean and median represent measures of location while variance is used as the measure of dispersion.

Table 4.3Test for Equality of Medians Between Series

Method	df	Value	Probability
Med. Chi-square	1	10.80000	0.0010
Adj. Med. Chi-square	1	8.533333	0.0035
Kruskal-Wallis	1	7.838710	0.0051
van der Waerden	1	5.817290	0.0159

Category Statistics

Variable	Count	Median	Overall Median	Mean Rank	Mean Score
AFTERDIVIDEND	15	-1.907895	3	11.00000	-0.403948
BEFOREDIVIDEND	15	3.85E-13	12	20.00000	0.403948
All	30	-2.56E-12	15	15.50000	-2.96E-17

Based on all the test results in Table 4.3, since the *p*-values are smaller than the generally acceptable 5% level of significance in all non-parametric test performed, the null hypothesis of equality in the medians of cumulative abnormal returns before and after dividend announcement is rejected at the 5% level. This shows that average cumulative abnormal returns before the dividend announcement is not equal to that after the announcement.

All the tests show that the null hypothesis of equality in the medians of cumulative abnormal returns before and after dividend announcement is rejected at the 5% level.

Table 4.4Test for Equality of Variances Between Series

Method	df	Value	Probability
F-test	(14, 14)	411.2649	0.0000
Siegel-Tukey	(1, 28)	12.18861	0.0016
Bartlett	1	62.69027	0.0000
Levene	(1, 28)	13.10096	0.0012
Brown-Forsythe	(1, 28)	13.44106	0.0010

Category Statistics

Variable	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.	Mean Tukey-Siegel Rank
AFTERDIVIDEND	15	2.991810	2.048443	2.046594	10.73333
BEFOREDIVIDEND	15	0.147528	0.072290	0.041706	20.26667
All	30	2.299323	1.060366	1.044150	15.50000

Bartlett weighted standard deviation: 2.118099

The results in Table 4.4 show that the hypothesis of equality of variances before and after dividend announcements is rejected. The category statistics show that the variance before dividend announcement is larger than after thus suggesting that more volatility is expected after dividend announcement than before.

4.3.2 Regression results

Results 1: Impact of dividend announcements on returns

This part presents the regression results for the equation (4.14). It shows the impact of several dividend announcements on returns on ordinary shares. Since only one event is considered this equation takes the form

$$R_{it} = \beta_{it} R_{mt} + \gamma \delta_{it} + \varepsilon_{it}$$

Where δ_{it} is a dummy variable representing dividend announcement date for *ith* firm. It takes the form 1 if it is after the announcement and 0 otherwise.

The estimated regression result is summarized as:

$$R_{it} = 0.87R_{mt} + 0.22\delta_{it}$$
$$\quad\;(3.2)\qquad\;(0.52)$$

t-values in parentheses.

The results show that the coefficient of δ_{it} is positive but not significantly different from zero. This shows that on average dividend announcement tends to lead to an increase in returns on ordinary shares and by extension to an increase in nominal share prices. Since this coefficient is not significantly different from zero, it shows that returns on ordinary shares during pre-dividend announcement and post-dividend announcement periods are not different. This implies that though dividend announcement seems to lead to increased capital gains, this average over three weeks is not significantly different from zero, meaning that within less than three weeks, the market would have factored in the dividend factor, hence no broker can consistently make profits by setting rules based on dividends.

Results 2: Impact of day and firm characteristics on abnormal returns

This section presents regression results for equation (4.16) which shows whether there is a difference between abnormal returns on the day of the event and other days around the event time and between different firms. The exact equation estimated is:

$$\varepsilon = \delta_0 + \sum_{i=-20}^{20+1}\delta_i DAY_i + \sum_{j=1}^{15}\theta_j FIRM_j + v$$

The day of the event, and the first firm are taken as control groups in the estimation. The empirical results are given as follows:

Table 4.5 Impact of Day and Firm Characteristics on Abnormal Returns
Dependent Variable: Abnormal Return (ε)

abnormalreturn	Coef.	Std. Err.	t	P>|t|
eventdate1	.7114174	1.655202	0.43	0.667
daytoevente1	.1455096	1.911263	0.08	0.939
daytoevent2	.016307	1.911263	0.01	0.993
daytoevent3	.1320665	1.911263	0.07	0.945
daytoevent4	-.4738757	1.911263	-0.25	0.804
daytoevent5	.0853218	1.911263	0.04	0.964
daytoevent6	-.0526441	1.911263	-0.03	0.978
daytoevent7	.4832436	1.911263	0.25	0.800
daytoevent8	-.5634899	1.911263	-0.29	0.768
daytoevent9	-.1194248	1.911263	-0.06	0.950
daytoevent10	.1300398	1.911263	0.07	0.946
daytoevent11	.0298832	1.911263	0.02	0.988
daytoevent12	-.1489825	1.911263	-0.08	0.938
daytoevent13	-.0176894	1.911263	-0.01	0.993
daytoevent14	.0651277	1.911263	0.03	0.973
daytoevent15	-.6432393	1.911263	-0.34	0.736
daytoevent16	1.001178	1.911263	0.52	0.600
daytoevent17	.0906769	1.911263	0.05	0.962
daytoevent18	.2766368	1.911263	0.14	0.885
daytoevent19	.3075489	1.911263	0.16	0.872
daytoevent20	(dropped)			
dayafter1	-.4850823	1.655202	-0.29	0.769
dayafter2	-1.380442	1.655202	-0.83	0.404
dayafter3	-.315246	1.655202	-0.19	0.849
dayafter4	-1.183289	1.655202	-0.71	0.475
dayafter5	-.8886457	1.655202	-0.54	0.591
dayafter6	-1.209222	1.660407	-0.73	0.466
daytafter7	-.9876604	1.660407	-0.59	0.552
daytafter8	-.8911283	1.660407	-0.54	0.592
dayafter9	-.5290245	1.655202	-0.32	0.749
dayafter10	-.6533224	1.655202	-0.39	0.693
dayafter11	-1.848395	1.655202	-1.12	0.264
dayafter12	7.68875	1.655202	4.65	0.000
dayafter13	-1.010891	1.655202	-0.61	0.541
dayafter14	-.9942768	1.655202	-0.60	0.548
dayafter15	-1.252009	1.655202	-0.76	0.449

Table 4.5 continued

dayafter16	-.7859245	1.655202	-0.47	0.635
dayafter17	-.7902974	1.655202	-0.48	0.633
dayafter18	-.8084128	1.655202	-0.49	0.625
dayafter19	-1.033155	1.655202	-0.62	0.533
dayafter20	-.7248785	1.655202	-0.44	0.661
firmcode2	-.1242663	.9646898	-0.13	0.898
firmcode3	-.1733518	.8940913	-0.19	0.846
firmcode4	-.1532348	1.063036	-0.14	0.885
firmcode5	-.2977797	1.276165	-0.23	0.816
firmcode6	.0514995	1.023208	0.05	0.960
firmcode8	.242107	1.181499	0.20	0.838
firmcode9	.0327384	.9911246	0.03	0.974
firmcode10	-.2724402	.9911246	-0.27	0.783
firmcode11	-.1184917	1.181499	-0.10	0.920
firmcode12	1.602072	.9425101	1.70	0.089
firmcode13	-.1793203	1.419985	-0.13	0.900
firmcode14	-.0848171	1.419985	-0.06	0.952
firmcode15	-.3599424	1.276165	-0.28	0.778
firmcode16	-.2398564	1.181499	-0.20	0.839
eventdate1	(dropped)			
constant	-.2174207	1.499439	-0.15	0.885

The following can be noted from the regression results:

i. The coefficient for the event date though positive is not significantly different from zero. This show that the abnormal return on the event date is not different from any other day within the range of three weeks before or after the dividend announcement

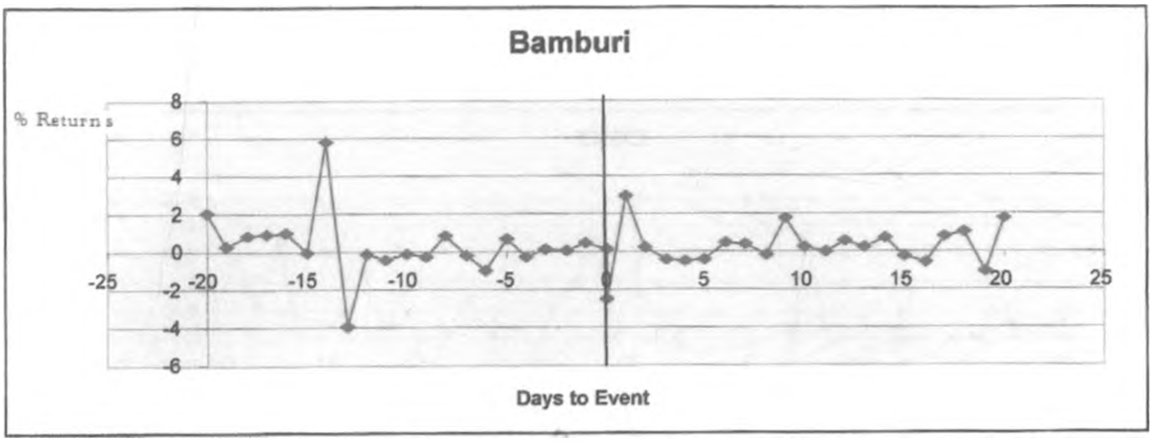
ii. The coefficients for all dummy variables representing various days to the event are all not significantly different from zero. Since the event date was used as the base this imply that there is no significant difference in share prices between the dividend announcement date and all the 20 days before and after the announcement.

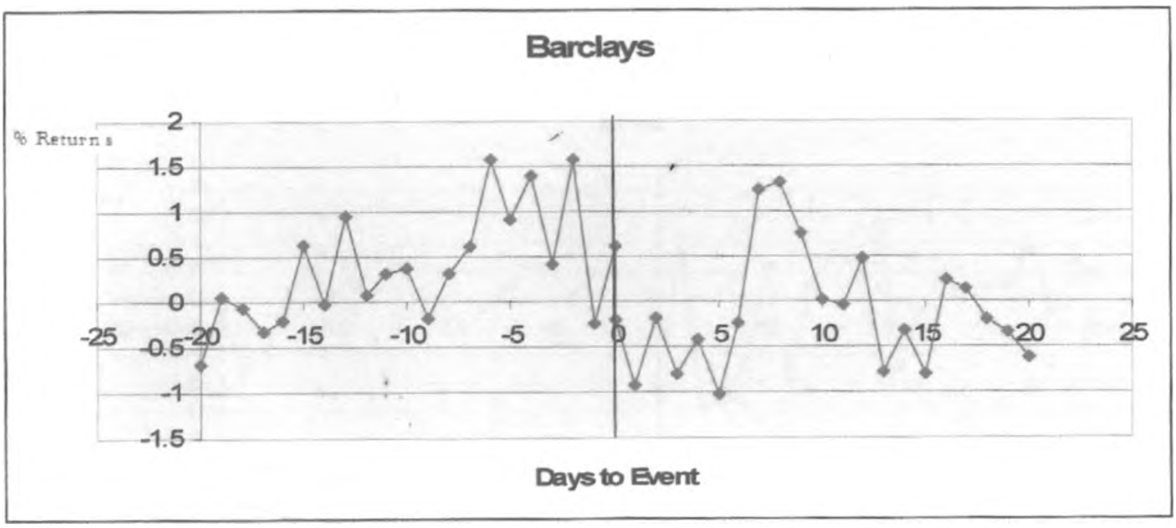
iii. In the 14 out of 16 firms considered, the coefficients representing individual firms are not significantly different from zero implying that on the average investors' decision is not based on firm characteristics.

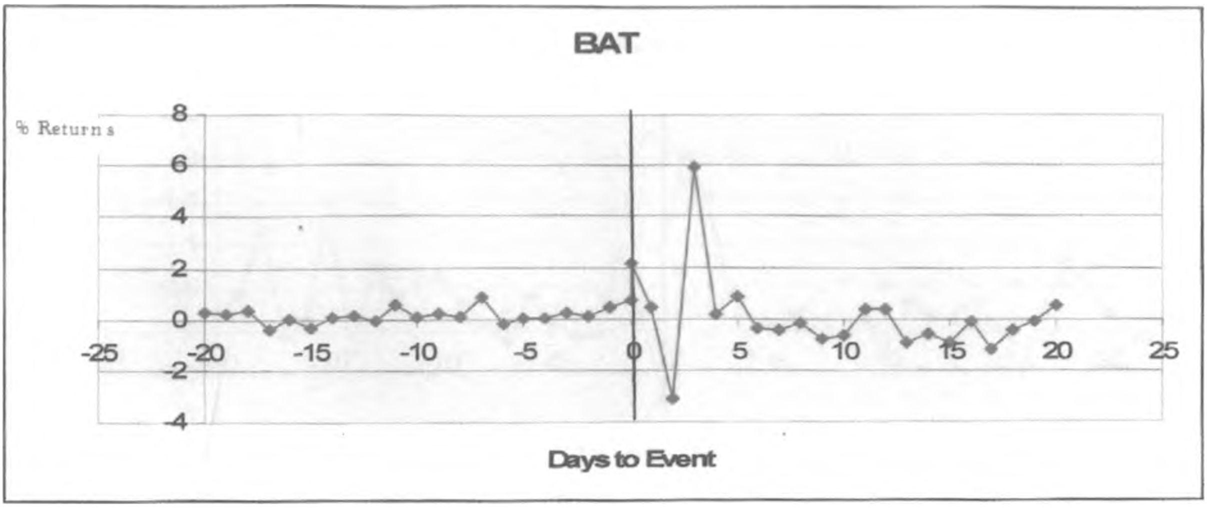
4.3.3 Graphical results

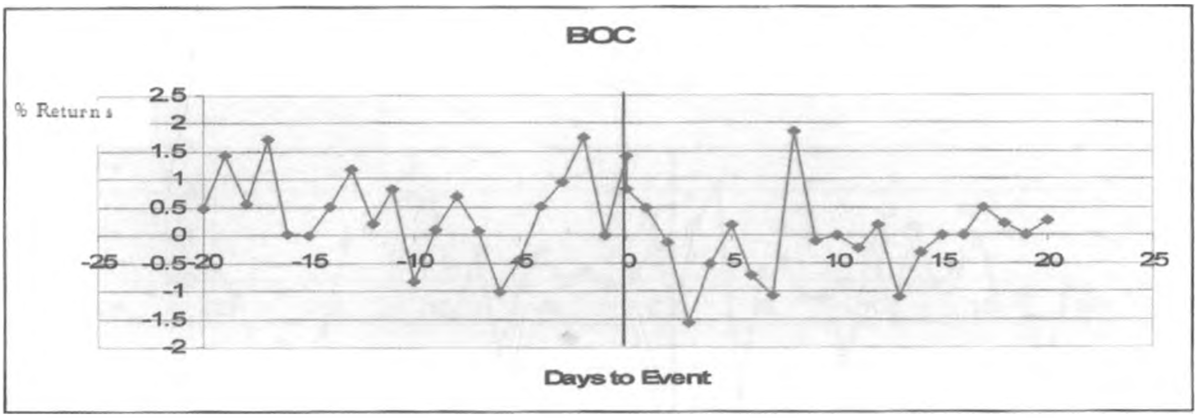
It can be noted that the regression results seem to contradict the cumulative abnormal returns results. As a way of arbitration, average daily compounded ordinary returns computed using the market model are graphed against days to and after dividend announcement for selected firms. The vertical line passing through the zero point shows the day dividend was declared.

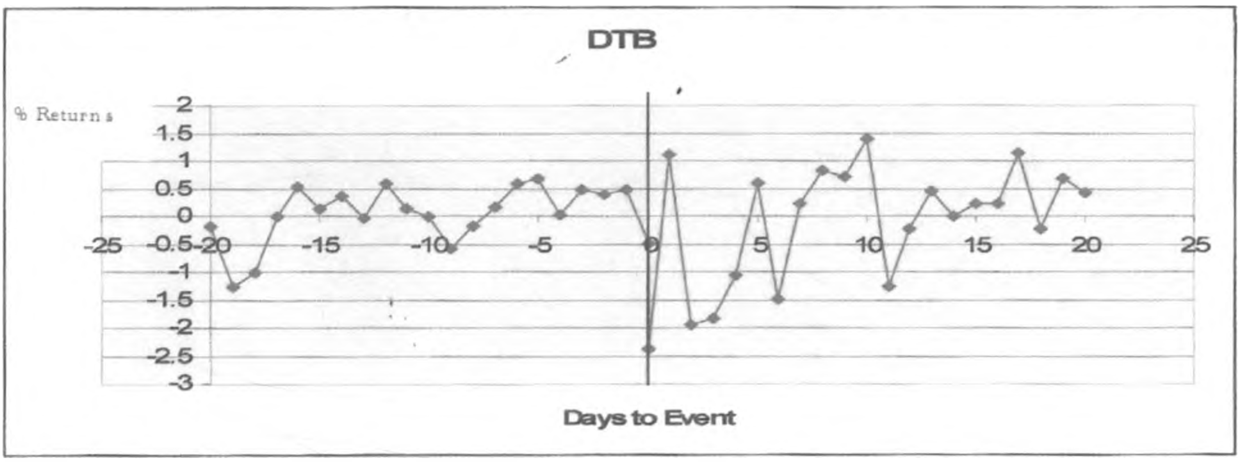
Returns on ordinary shares graphs

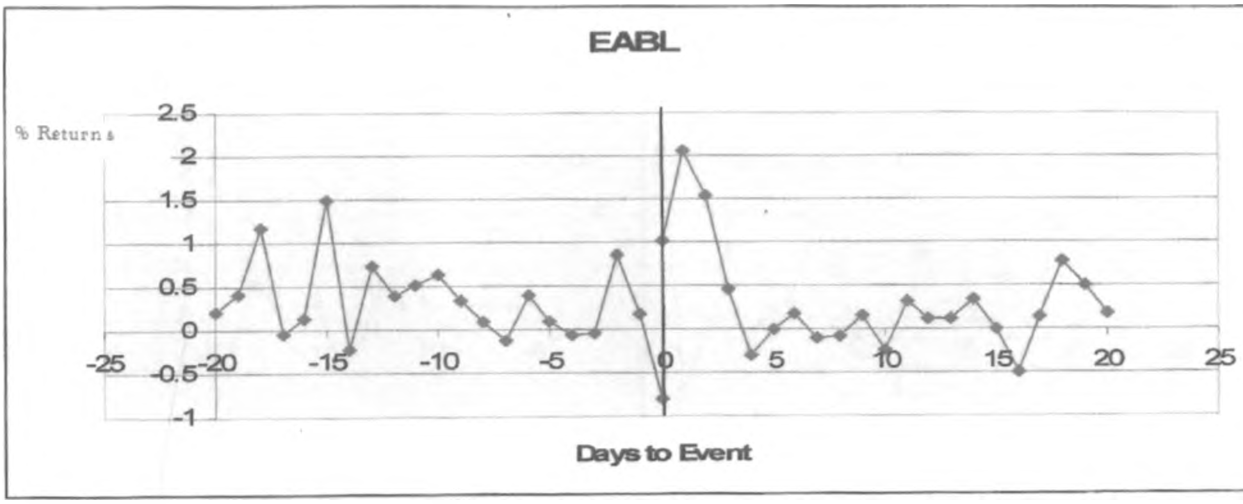


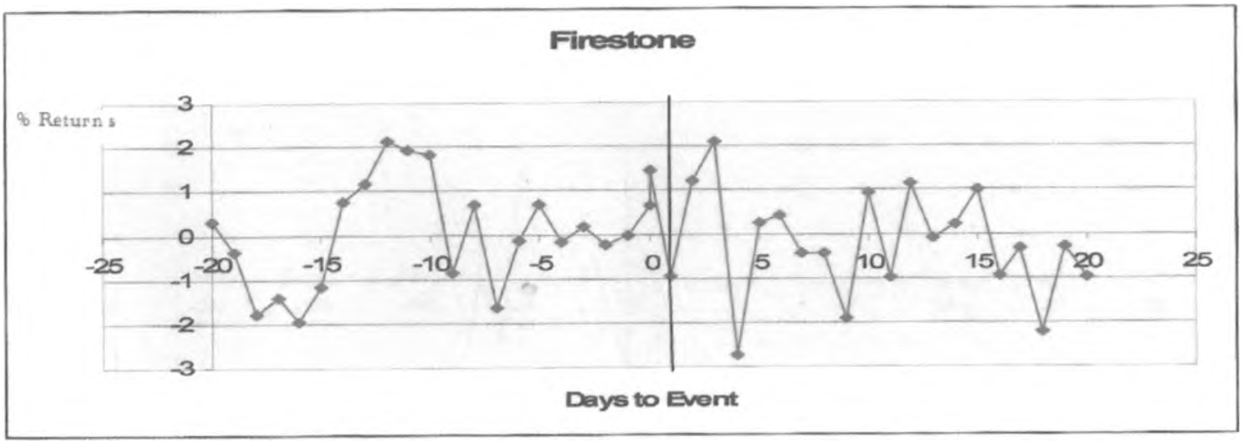


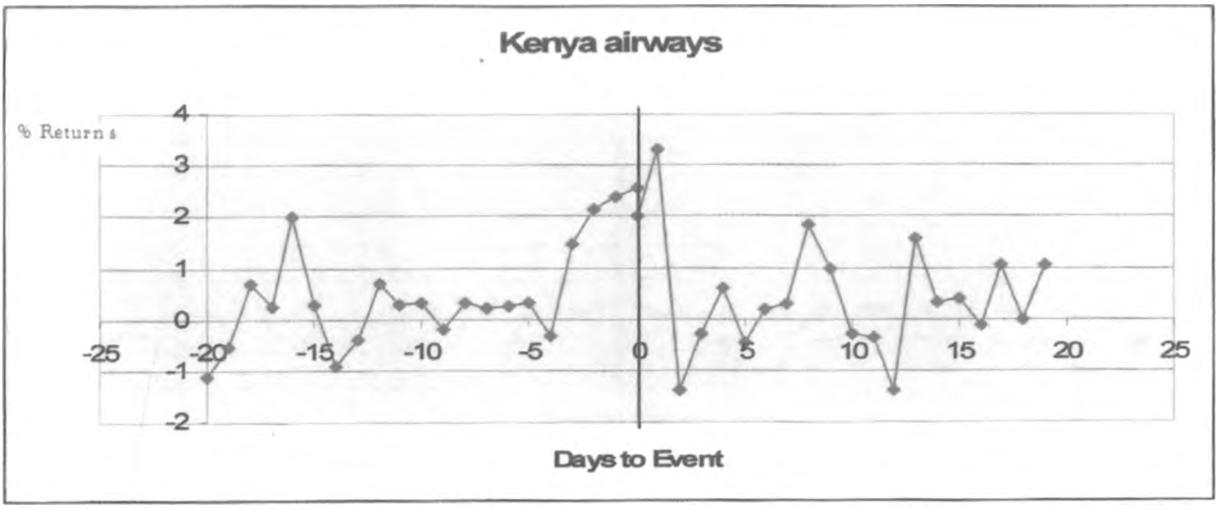

BAT
% Returns
Days to Event

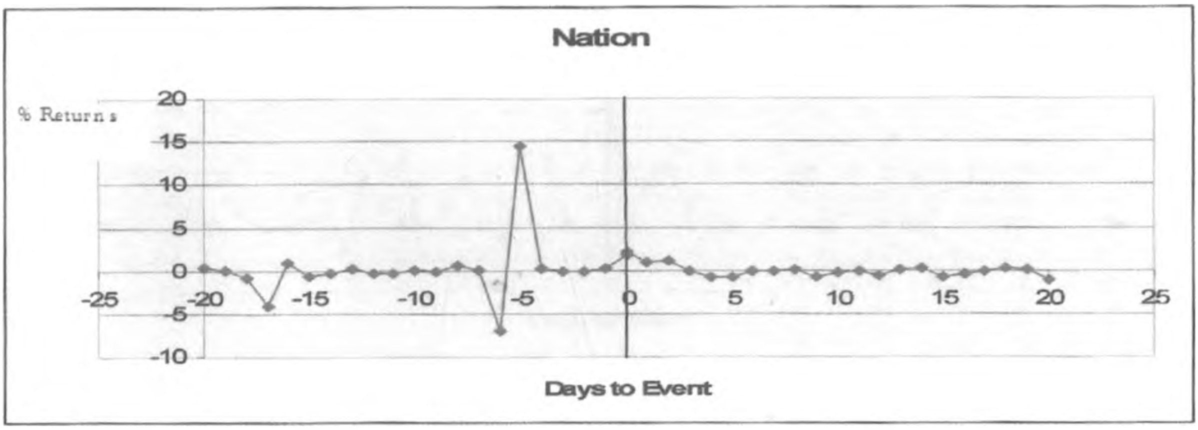

BOC
% Returns
Days to Event

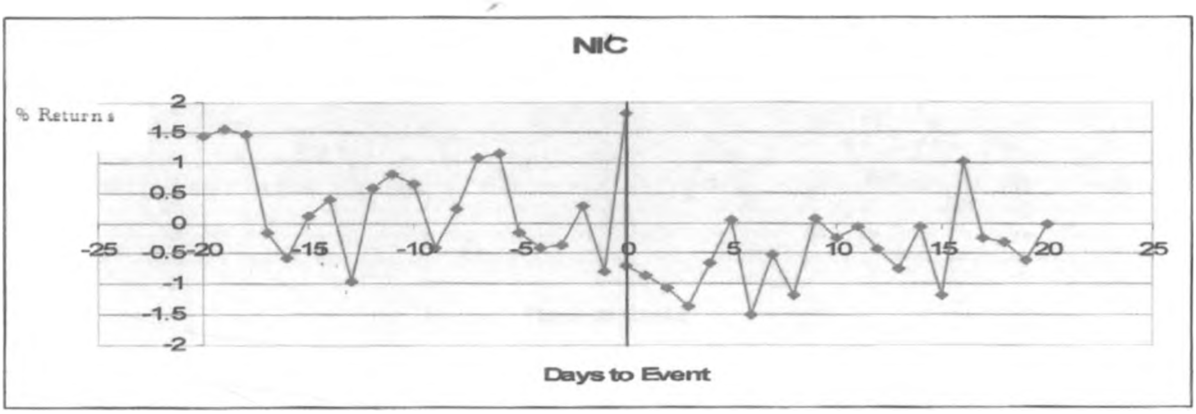

DTB
% Returns
Days to Event

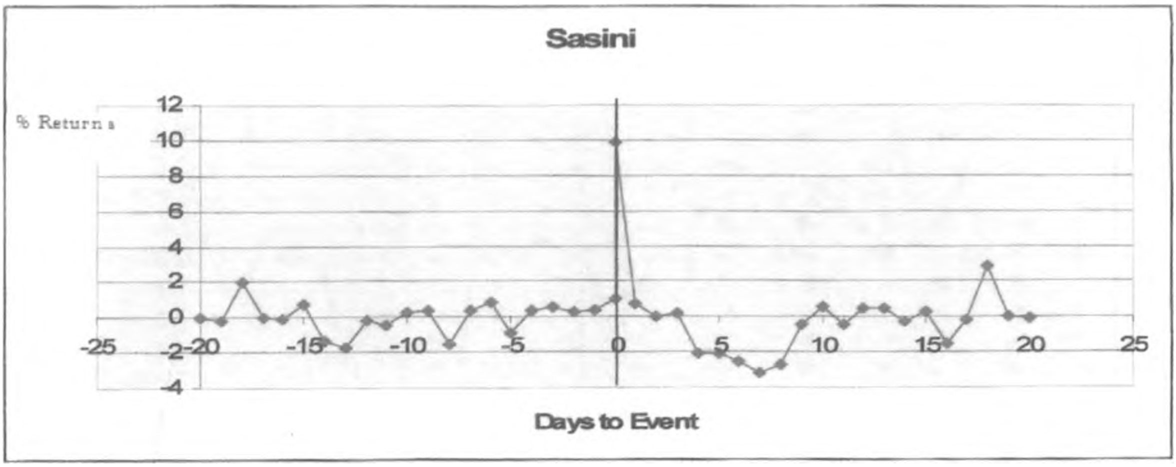

EABL
% Returns
2.5
2
1.5
1
0.5
0
-0.5
-1
-25
-20
-15
-10
-5
0
5
10
15
20
25
Days to Event

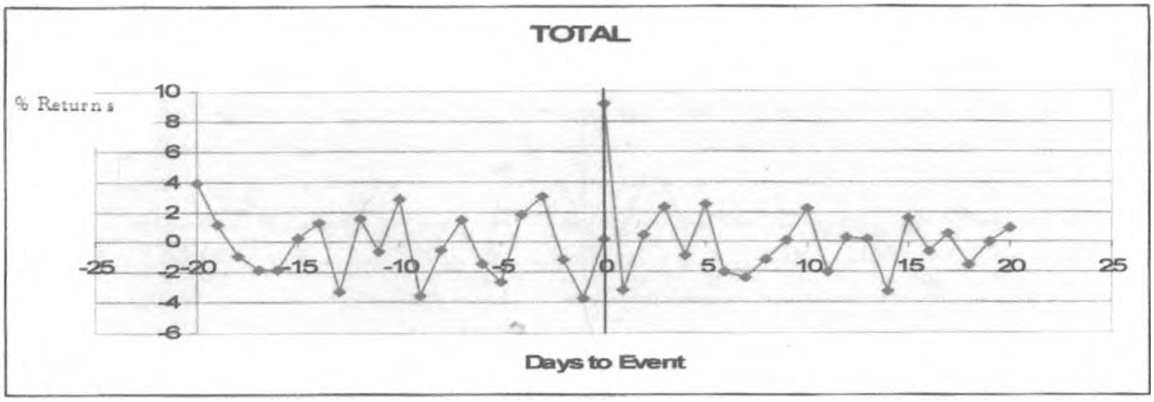

Firestone
% Returns
3
2
1
0
-1
-2
-3
-25
-20
-15
-10
-5
0
5
10
15
20
25
Days to Event

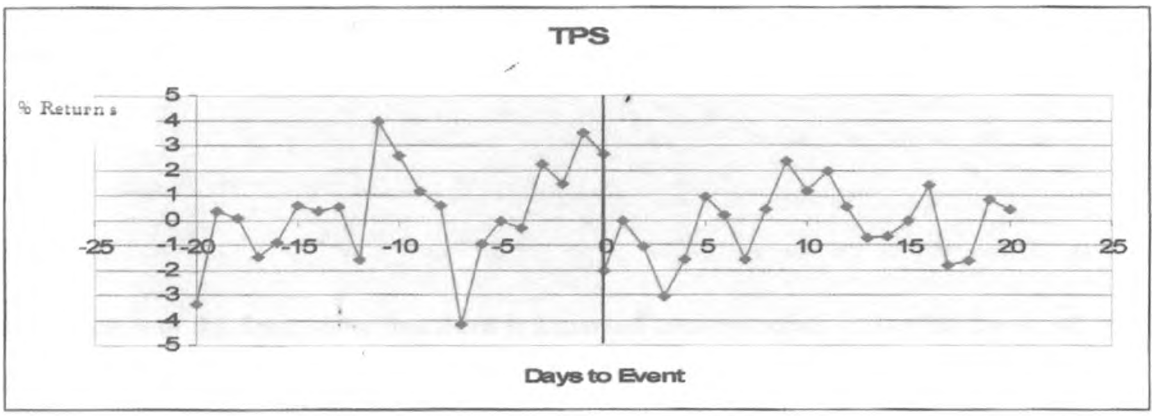

Kenya airways
% Returns
4
3
2
1
0
-1
-2
-25
-20
-15
-10
-5
0
5
10
15
20
25
Days to Event

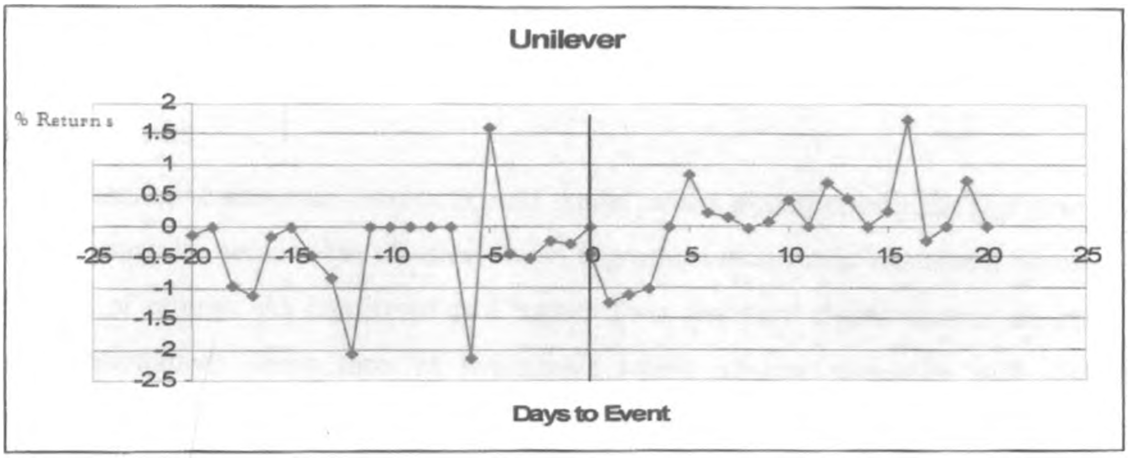

Nation
% Returns
20
15
10
5
0
-5
-10
-25
-20
-15
-10
-5
0
5
10
15
20
25
Days to Event

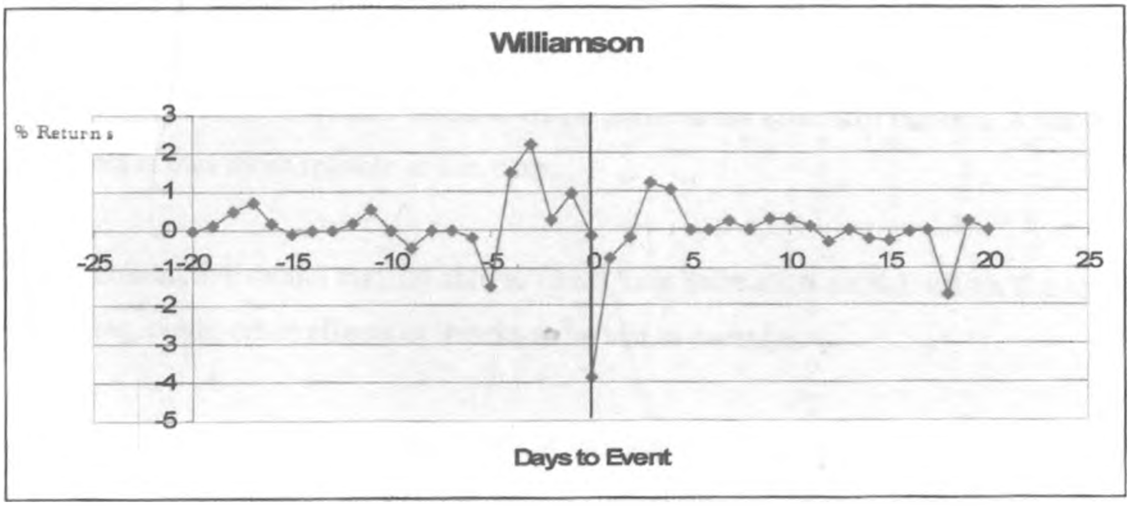

NIC
% Returns
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-25
-20
-15
-10
-5
0
5
10
15
20
25
Days to Event


Sasini
% Returns
12
10
8
6
4
2
0
-2
-4
-25
-20
-15
-10
-5
0
5
10
15
20
25
Days to Event


TOTAL
% Returns
10
8
6
4
2
0
-2
-4
-6
-25
-20
-15
-10
-5
0
5
10
15
20
25
Days to Event


TPS
% Returns
5
4
3
2
1
0
-1
-2
-3
-4
-5
-25
-20
-15
-10
-5
0
5
10
15
20
25
Days to Event





The majority of the firms show that there is a marked positive return on the returns on or around the dividend announcement date. There seems to be a consensus that there is marked variability within the first five days after the dividend announcement. The results obtained from the market average consistent with results associated with period of the dividend announcement.

4.4 Conclusions

First, the cumulative abnormal returns (CAR) model seems to outperform the regression model. This may be because the classical linear regression incorrectly assumes a normal distribution of returns. As confirmed in Chapter Two, ordinary shares returns are not normally distributed; hence tests of hypothesis which assume normality will give misleading results. Also, since an event is a shock giving rise to outliers, regression analysis may not be the best technique for capturing such shocks since by definition its result is an arithmetic mean. Thus, as the sample size increases, the impact of such shocks on returns becomes less and less prominent. The cumulative abnormal returns model uses distribution free tests and is median based so that it is free from effects of outliers. A non-parametric test is thus more reliable in this case.

Second, the cumulative model may be able to avoid long estimation period, which due to data smoothing, could cause effects of shocks to be lost in averages.

Third, the stock market is sensitive to dividend announcement. In particular, returns on ordinary stock and by extension prices of ordinary stock tend to increase after dividend announcement This means that though dividend announcements are considered good news as they enhance shareholders wealth they are a source of market volatility. Further, public information is not received or synthesized uniformly among the participants in the market so that it is possible that some investors can make abnormal profits by setting rules based on dividend dates

Fourth, the market seems to effectively incorporate information within the first week of dividend announcement, implying that after this period, all investors have factored in all the information about public pronouncements in the share prices such that any abnormal profits made on the basis of the public pronouncement can only be arbitrary.

Fifth, more volatility is expected after an event. In the particular case of dividend announcement, the variance is larger after the announcement. This suggests that as more earnings are expected, the risk of losses is also higher for short term investors.

Sixth, dividend announcement that brings good news is an important event in temporarily increasing the wealth of security holders. This suggests that trading in shares within a week of dividend announcement could bring large profits but, this event is also associated with high risks of losses.

Seventh, most investors are speculators with no loyalty to firms i.e., they buy shares for speculation, with no interest in the ownership of particular firms.

Eighth, graphical methods which at first sight seem to be unsophisticated as tools for testing the EMH, have nonetheless provided valuable insights about the behavior of share prices in an emerging market.

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