CALENDER ANOMALIES IN STOCK RETURNS: EVIDENCE FROM NAIROBI SECURITIES EXCHANGE

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DECLARATION

This research project is my original work and has never been submitted for a degree in any other university or college for examination/academic purposes.

Signed .... Date ....

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Approval by the supervisor

This Research project has been submitted for examination with my approval as the University supervisor.

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DEDICATION

This project is dedicated to my Parents Monica Opondo and Vitalis Opondo. My siblings Moses, Maureen, Chris, Lordvick and Irene. Your support and love is priceless.

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LIST OF ABREVIATIONS

AMEX	American Stock Exchange
DOW	Day of the week
APT	Arbitrage Pricing Theory
CAPM	Capital Asset Pricing Model
CMA	Capital Market Authority
EGARCH	Exponential Generalized autoregressive conditional heteroskedasticity
EMH	Efficient Market Hypothesis
GARCH	Generalized autoregressive conditional heteroskedasticity
N20I	Nairobi 20-Share Index
NASI	Nairobi All-Share Index
NSE	Nairobi Securities Exchange
NYSE	New York Exchange
NYSE	New York Stock Exchange
JSE	Johannesburg stock exchange
OLS	Ordinary least squares

ABSTARCT

The efficient market hypothesis postulates that security markets exhibit efficiency, consequently it is not possible to make abnormal returns by either following fundamental analysis or technical analysis. It assumes stock prices move randomly and therefore forecasting future stock prices using historical stock prices is unfeasible and returns are not significantly different from one day to another or from one month to another. However, based on calendar trading, it is feasible to earn inflated or reduced returns on certain days or in certain months. This research enquires into the subsistence of calendar anomalies, specifically the day of the week and the January effect in stock returns at Nairobi Securities Exchange. Three statistical models, OLS, symmetric GARCH (1, 1) and asymmetric EGARCH (1, 1) models have been employed to answer the objective of the study. The results from GARCH (1, 1) and EGARCH (1, 1) models confirm subsistence of the day of the week and the January effect in stock market returns at NSE.

CHAPTER ONE

INTRODUCTION

1.1 Background of the study

The efficient Market hypothesis (EMH) promulgated by Fama (1970), holds that all securities are efficiently priced and incorporate all the available information in the securities prices and that market participants have access to this information. New information will be spontaneously incorporated into the prices of securities immediately. Stock prices are unpredictable because they follow unsystematic path. This precludes any investor from earning surplus returns on the basis of using historical price trends to trade (Malkiel, 2003).

Since Fama (1970) proclaimed market efficiency hypothesis, the subject has attracted a number of academic researches. A number of researchers have undertaken to test whether indeed the stock prices follow a random walk path (Malkiel, 2003). Market patterns have been observed that can lead to excess or abnormal returns which violates the efficient market hypothesis. These abnormal market patterns are referred to as market anomalies. Anomalies are empirical findings which are not consistent with the established conventional theories of asset pricing behaviour. This implies that either the markets are inefficient and opportunities for earning abnormal profits subsists or underlying asset-pricing model has some shortcomings. Different market anomalies have been documented from previous studies. These include; small firm effect, neglected firm effect, Day of the week effect, January effect, low PE effect, low-priced-stocks.

Different studies have documented seasonal patterns in security returns, also referred to as calendar anomalies. These time patterns imply that returns can be relatively inflated or significantly reduced contingent on certain times or periods (Elton & Gruber, 1995). Market returns have also been documented to exhibit volatility clustering, the tendency for market returns to appear in bunches. Well performing stocks exhibit the same trend over a relatively longer period and in the same manner, poorly performing stocks carry on with the same trend over a relatively longer period. Prudent investors thus can take advantage of the calendar anomalies and volatility clustering of returns to make excess profits. The mostly documented calendar abnormalities are January and Day of the week effect (weekend effect). Several studies have indicated that market returns distribution vary from period to period. Observations have been made that Mondays generally seem to have lower or negative returns compared to other days according to study by French (1980). This was also confirmed by Hess (1981). According to study by Levi and Lakonishok (1982), Friday returns are relatively inflated than other days. Keim & Donald (1983) provided evidence that January returns exceed returns for the other months.

Several explanations have been proffered to explain these market anomalies. Some studies attribute the anomalies to a group of factors including transaction costs, bad news and biases among others. Other researchers are of the opinion that these anomalies are as a result of statistical aberrations. On the other hand, behavioural finance proponents, opine that the anomalies can be explained by psychological factors that are closely linked with eccentricity of investors' and subject on their mood, they affect returns.

1.1.1 Calendar Anomalies

Calendar anomalies sometimes referred to as seasonality in stock returns is the habit of securities to show higher or lower yield during certain periods, a fact that can offer a chance to professional investors and market participants to seize the opportunity and earn excess returns. The existence of seasonality in asset returns has elicited great interest from scholars worldwide keen on ascertaining the validity of the hypothesis of market efficiency and Random walk theory. Subsistence of calendar anomalies in stock markets would imply that the markets are inefficient and opportunities to earn abnormal returns by following the calendar patterns exist. The existence of calendar anomalies violates the weak form of efficient market theory. Studies by Gibbon and Hess (1981) and Levi and Lakonishok (1982) observed that different days had significantly different returns. Fridays seem to havezz significantly higher returns and Mondays tend to have significantly lower returns, a phenomenon known as the Monday effect. They concluded that the Monday effect was manifested in the US securities market. Researches by Kinney and Rozeff (1976) and Keim, Brown, Kleidon and Marsh (1983) examined US security markets for existence of January effect. They observed January returns significantly inflated than other months, a phenomenon known as the January effect.

1.1.2 Stock returns

Stock returns refer to the returns that an investor receives from a stock market. The return could be in form of capital gain got from trading or in kind of dividends paid by the company to the investors from time to time. Stock returns can be calculated from a time series of stock prices e.g. prices of share X taken at 4pm each day for a given period. A sequence of stock prices can be converted to returns using two methods, the simple return or the continuously compounded returns, as shown below:

Simple return $R_t = \left(\frac{P_{t-P_{t-1}}}{P_{t-1}}\right)*100\%$

Where P_t = Stock price at time t

P_{t-1} = Stock price at time t-1

Continuously compounded return $r_t = \ln(\frac{P_t}{P_{t-1}}) *100$

Where P_t = Stock price at time t

P_{t-1} = Stock price at time t-1

ln = Natural logarithm

Total return for holding a stock or portfolio of stocks, is made up the sum of the capital gain and the dividends paid during the holding period. The most common form of generating returns by investors is by buying stocks at diminished prices and selling at inflated prices. The stock market returns are not guaranteed. They highly depend on the market risks, and as such can either be negative returns or positive returns depending on the level of market risks, the level of risk an investor is willing to take and how best he does his market analysis before investing.

1.1.3 Calendar anomalies and stock returns

According to Fama (1970), stock markets efficiently reflect all information on all stocks and incorporate this information in stock prices. In a market that is considered efficient, there are no investment opportunities which may lead to abnormal returns. Any profit opportunity that is unexploited is eliminated by arbitrage (Ajayi et al, 2004).

However, a number of scholars have observed evidence that contradicts the semi-strong and weak type of market efficiency theory. Such findings contradicting the EMH are considered anomalies as they go against the accepted position of EMH. The existence of calendar anomalies in securities markets points out inefficiency in the market, the inadequacy or limitation of the underlying asset pricing model (Scwertz, 1996). A number of empirical studies have pointed out seasonality in stock returns, a phenomenon that has come to be known as calendar anomaly. Seasonality in stock returns implies that investors can use the past stock prices as the basis for predicting future stock prices. There are different forms of calendar abnormalities namely, Day of the week, January, turn of the month and holiday effect just to mention a few.

The day of the week effect is the habit of the stock market yield to fluctuate depending on the day, where returns on Monday usually tends to be diminished or negative, while the returns on Friday tend to be the highest of all the days. This was corroborated by Fields (1931). He used the Dow-Jones index. He made observations that the Monday returns were negative while the Friday returns were positive. French (1980) also studied the day of the week phenomenon. He used quotidian prices for the S&P 500 from 1953 to 1977. He concluded that Monday return was negative and significant while the average yield for the rest of the days were positive.

January effect denote the behaviour for average yield in January to be significantly inflated than the rest of the months. This was corroborated by Kinney and Rozeff (1976). In their study, that covered the interval 1904-1974, they concluded average yield in January was materially inflated than other months.

1.1.4 Nairobi Securities Exchange

Nairobi Securities exchange came into being in 1954 initially as Nairobi Stock exchange registered under the societies Act ("History of NSE," n.d., para. 2). (NSE) is one the largest stock exchanges in Africa and has been a key driver of the economy of Kenya by allowing trading of shares. Investors can buy and sell their shares at NSE and earn a return. NSE uses various market indices to measure the market return. The popular ones are the NSE20 index and the NASI index. NSE20 index is a composite index derived by weighting shares of 20 companies listed at the market chosen by specified criteria during the period of examination. The criteria include: market capitalization, the number of shares bought and sold, liquidity and throughput in the period of examination, awarded weights in the ratio of 4:3:2:1 respectively.

A company is required to have floated at least 20% of its shares: its market capitalization should not be less than 20 million: preferably it should be a blue chip firm. NASI index was introduced in 2008, which measure the market return of all companies listed. This was with a view to providing investors with a comprehensive measure of the stock market performance. In 2011, NSE partnered with FTSE International and introduced FTSE NSE Kenya together with FTSE Kenya 25 indices, which provide investors with a comprehensive, alternative and complimentary indices to measure the performance of the main capital and industry segments of the Kenyan stock market. (History of NSE, n.d.).

NSE has developed by leaps and bounds. To enhance the efficiency of the Capital markets in Kenya and thus ensuring no market anomaly at the NSE, capital market authority (CMA) was formed in March 1990. CMA is tasked with the responsibility of ensuring growth and development of capital markets in Kenya, ensuring fairness and efficiency by developing effective regulations that encourages innovations while safeguarding the integrity of the capital markets. To further enhance the operations of NSE, the Central Depository and settlement Corporation Limited (CDSC) was formed under the companies act in 1999. CDSC is tasked with the responsibility of operating a central depository system to provide centralized clearing, settlement and depository services for all securities listed at the bourse ("History of NSE," n.d., para. 19)

In 2011 NSE improved its settlement cycle. The equity settlement cycle was reduced to T+3 days from the previous T+4 days of settlements. This meant that investors would get their money from sale of shares in three days after the sale.

As at September 2016, NSE had sixty seven stocks actively trading at the bourse.

In the context of this study, two types of seasonalities are investigated namely DOW and the January effect in stock returns employing NSE 20 Index. The research seeks to bring forth evidence of subsistence of the two calendart abnormalities employing linear regression, (GARCH) model and exponential generalized autoregressive conditional heteroskedasticity (EGARCH).

1.2 Research problem

According to Fama's market efficiency theory, it is unfeasible to surpass normal market return in any way whatsoever, because the stock markets are efficient and as such share prices always adjust to factor in all the available information. EMH postulates that shares always trade at their fair value, eliminating the possibility of an investor purchasing undervalued stocks or selling stocks for an inflated price thereby making abnormal return. This consequently obviates the possibility of any investor applying the market timing or expert stock selection to outperform the market. Stock prices movements are random and follow Brownian motion (Kendall, 1953). Many researchers have, however, found evidence that contradict the propositions of EMH. Studies have unearthed evidence pointing out that stock returns vary depending on time, day or month, a phenomenon known as calendar anomaly. This implies that prior share prices can used to foretell upcoming share prices.

A number of international studies on calendar anomalies in stock returns have adduced evidence to the effect that one can follow seasonal patterns and earn excess returns contrary to the arguments of EMH. Field (1931) studied the day of the week phenomenon, using Dow-Jones index, he spotted returns on Monday showing a tendency of significantly diminished returns compared to all the other days, while the Friday returns were relatively higher and positive. French (1980) also studied calendar anomalies in stock returns. He used daily prices of S&P 500 between the intervals 1953 -1977, and noted Monday average yield was materially negative compared to the rest of the days whose average returns were positive. Hess and Gibbons (1981) further investigated S&P 500 index. They found return on Monday was negative. Kinney and Rozeff (1976) and Brown et al (1983) analyzed the presence of January phenomenon in the US security markets. They observed January returns to be materially higher compared to the rest of the months. Studies by Gultekin and Gultekin (1983) also concluded that the January returns was materially higher contrasted with other months. Keim (1983) observed January phenomenon being more evident for small firms and that the excess returns mainly occurred in the first week of January. (Keim, 1983, p.13).

Locally, some studies have been carried out to find out whether calendar anomalies exist at NSE. Kingori (1995) found no January effect at NSE. Mokua (2003) did not find the Monday effect at NSE. Onyuma (2009), Nyamosi (2013) and Allan & George (2013) found January effect at NSE. Sifuna (2012) did not find Monday effect at NSE. However, Oyori (2012) found the presence of Monday effect at NSE. Wachira (2012) using daily values of two major share indices, NSE 20 index and NASI found the presence of January effect at NSE. Kuria (2013) studied day of the week phenomenon, weekend phenomenon and monthly phenomenon and concluded presence of seasonality in market returns at NSE.

From the local studies, there are mixed findings on the subsistence of calendar anomalies at NSE. These studies used descriptive statistics and linear regression to arrive at their conclusions. However, Connolly (1989, 1991) claims that these approaches have some limitations and consequently some specific problems are bound to arise. The yields are possibly serially correlated, yield residuals probably do not exhibit normal distribution, and the residuals are possibly heteroskedastic. Connolly (1989) therefore suggested the use of standard GARCH on dummy variables, to handle ARCH effects, autocorrelation and heteroskedasticity in the return distribution. This study seeks to use GARCH, and EGARCH models in addition to OLS and descriptive statistics to answer the objective of the study. GARCH and EGARCH models are considered superior to OLS in that they can model volatility clustering of stock returns. In the wake of mixed findings on the subsistence of calendar anomalies at NSE, are stock returns at NSE affected by seasonality?

1.3 Research Objective

This enquiry seeks to examine subsistence of calendar anomalies in stock yields at Nairobi securities Exchange.

1.4 Value of the study

Enquiry of calendar anomalies in stock returns is of great importance to financial analysts, investment analysts, stock brokers, and all stock market players interested in devising profitable trading strategies. Investors can use the day of the week phenomenon and January phenomenon to buy stocks on days or months which exhibit relatively lower returns and dispose the stocks on days or months exhibiting higher return. It will also assist investors in making objective decisions when investing on stocks by understanding the relationship between returns and risks (volatility). It is important for investor considering investing in stocks to understand the relationship between yields and risk, and whether low yields can be associated with low risks and high returns can be linked to high risks. Such patterns would help investors to make investments decisions not only based on the returns but the risks as well and thus chose or adjust their portfolio accordingly. Engel & Ng (1993) offers that risk averse investors can adjust their portfolio by reducing the amount of investments in securities whose risks is anticipated to increase. Identifying the risk pattern could also be of use to investors in hedging purposes and risk management generally.

This enquiry will also benefit government policy makers like the CMA which is tasked with ensuring growth and development of an efficient capital markets in Kenya. The presence of calendar anomalies at NSE will indicate inefficiency at NSE. Thus it will point out to the policy makers the need to device appropriate strategies to bring about operational and informational efficiency in the market. Islam and Gomes (1999) offers that the positive weekend effect is as a result of factors such as insufficient financial knowledge, intermittent trading and using price fluctuations as the basis for buying or selling of stocks. Thus CMA should devise appropriate measures to deal with such factors so as to bring about efficiency in the market.

The enquiry will enrich literature on market efficiency theory, with respect to day of the week phenomenon and January phenomenon. It seeks to verify the validity efficient market hypothesis at NSE by using GARCH models which cures some of the limitations linear regression and descriptive statistics approaches to studying calendar anomalies.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

The chapter discusses both conceptual and experimental literature on calendar anomalies in stock returns. It covers theoretical literature focusing on market efficiency theory, Random walk theory and behavioural finance. It also covers review of experimental literature on DOW and January phenomenon done locally and internationally and summary to conclude the chapter.

2.2 Theoretical Review

This segments provides a concise discussion of the efficient market hypothesis, and discusses some of the subtleties involved in defining an efficient market. It also looks at the Random walk theory and theory of behavioural finance and how it contributes to market anomalies.

2.2.1 Efficient Market Hypothesis

Fama (1970) defines market efficiency situation as a security market in which assets costs fully manifest all accessible news in the market. New information e.g. earnings, dividends announcement, macroeconomic news, is quickly factored into asset prices, therefore it is not possible to make excess returns by predicting price movements as the assets prices follow a random walk pattern (Malkiel, 2003). Asset prices are always at levels consistent with 'fundamentals'

EMH exists in various types, the weak type, semi-strong type and the strong type ((Levy & Post 2005).

Weak forms contends prevailing security costs factors in all the historical information of stock prices. It furthers argues that the past security prices do not have correlation with the expected direction of share prices, and therefore, investors cannot make excess returns by using technical analysis (Fama, 1970). Technical analysts, however, believe that historical fluctuations of a stock prices can foretell future price fluctuations. Thus using charting tool, technical analysts will examine the rise and fall in stock prices and develop a pattern of stock prices movements. On the basis of these patterns, technical analysts then chart what they believe would be the likely future price movements in the stock being examined.

The semi-strong type of market efficiency theory holds the prevailing share costs alter fast to the release of any new universal information- historical share costs, financial news, earnings news, etc. This information is factored in security prices (Fama, 1970). Consequently, it is not possible to make excess returns by applying fundamental evaluation; the investigation of a firm's business environment, a firm's market share and the general economy at large to guess expected price fluctuations. Fundamental analysts believe the price of an asset is a function of its intrinsic value which is determined by fundamental factors such future earning potential of the firm, industry trends, company's earnings per share and economic news. Thus careful analysis of the fundamental factors would help determine whether a stock is undervalued or overvalued. Bettman, Sault & Welch (2006) observe that comparing a stock's price to its intrinsic value would consequently enable fundamental analysts to predict the future price movements.

The strong form of EMH assumes that security prices have already factored in both universal and confidential knowledge. Confidential knowledge encompasses all news accessible to market participants, insider knowledge accessible to investment and institutional fund managers. It assumes a perfect market, with perfect information for all the market players and thus it is not possible to achieve excess returns consistently.

The EMH is the underpinning of the theory that share prices trail a random path.

2.2.2 The Random walk theory

Unsystematic movements of share prices holds that past fluctuations of share prices have no bearing at all in influencing future prices movements, implying that a series of stock price movements is memoryless and historical prices have no bearing whatsoever on the future prices of stocks. Fama (1965) argues that expected share price is just as unpredictable as a series of random numbers. Kendall (1953) studied regularities in price fluctuations in the US stock market. He discovered price fluctuations were not regular but instead followed unsystematic path. He stated stock prices fluctuations are altogether autonomous of each other. The theory assumes that securities prices follow a random and unpredictable path and therefore it is not possible to outperform the market either by using fundamental or technical analysis. Poshakwale (1996) describes random path (walk) as consecutive prices variations autonomous of each other, thus today's stock prices have no bearing on tomorrow's stock prices. Thus prices changes do not exhibit any trend. Poshakwale (1996) further states, random path theory for security prices changes represent a security market where any recent news is immediately factored in the share prices which obviates the possibility of making abnormal returns by following trends or banking on new information to trade.

2.2.3 Behavioural finance theory

The traditional finance models assumes that people are rational. However, this proposition has been challenged by various researchers who are of the view that people often suffer from cognitive, psychological and emotional biases which predispose them to sometimes act irrationally (Kahneman & Tversky, 1979; Shefrin & Statman, 1994; Shiller, 1995; Shleifer, 2000). Consequently, people err in the way they process information and think, they focus on the recent happenings and experiences and as a result, they sometimes become overconfident or pessimistic. Their preferred choices may also create some distortions (Olsen, 1998). Behavioural finance uses people's behaviours to explain some of the inefficiencies in the markets that are not explained by the traditional finance theory. Behavioural finance comes in handy in explaining the occurrence of inefficiencies in the market. The wide acceptance of behavioural finance in explaining some of the market inefficiencies has been as a result of the inability of the traditional finance models to offer explanations on some empirical evidences that have been witnessed like stock market bubbles which occurred in the USA, Japan and Taiwan.

Behavioural finance theory has been used to explain stock prices anomalies related to overreaction, under reaction and herding behaviour. These anomalies violate market efficiency theory and thus render traditional models for pricing assets, like CAPM and APT inappropriate when relating risk and return.

2.3 Determinants of stock returns

This part ventilate the various factors that determine stock returns.

2.3.1 Day of the week effect

The DOW phenomenon stands out as one of the most canvassed calendar anomalies, where stock returns exhibit materially higher returns on particular days while on others days, the returns are significantly diminished. It has been observed by a number of researchers that

Mondays generally tend to have relatively lower returns than other days, a phenomenon commonly referred to as the Monday effect. Fridays have also shown the tendency to have relatively higher returns. Cross (1973) studied the DOW occurrence. He used S&P 500 index in the 1953-1970 interval. He observed typical return on Friday to be significantly higher in comparison to the return on Monday. Kelly (1930) also studied the same phenomenon. He made observation that Monday recorded the lowest returns of all days and thus Monday was not the best day to dispose stocks. He further stated that the possible explanations for the low return on Mondays maybe as a result of investors processing information and making decisions over the weekend. Fields (1931) also concluded that the US markets exhibited significant negative effects during Mondays and highly positive on Fridays, respectively. Osborne (1962), with an extensive research on S&P 500 index, observed that the Friday's yields dominate Monday's, where the results were consistent with Cross (1973). The Monday effect arise as a results of factors such as: Statistical aberrations, Micro market structures, information flow and behavioural impact among others.

2.3.1.1 Measurement Errors

Some scholars have argued that the apparent Monday effect phenomenon may be as a result of of applying statistical tools and models wrongly. According to Timmermann, Sullivan, and White (2001), seasonal effects are the consequence of data mining. They did not identify weekend effect or any seasonal anomaly using a new bootstrap procedure. Most of the statistical tests make the assumption that stock returns are normally distributed contrary to empirical evidence that returns are not normal. This brings about the issue of heteroscedasticity, which according Chen, Lee & Wang (2002), reduce the weekday effect.

Gibbson & Hess (1981), however, argue that varying residuals of returns (heteroscedasticity) does not have any significant impact on the weekday phenomenon. Connolly (1989) tests for robustness and consistency to investigate manifestation of the DOW phenomenon. When testing with a normal OLS regression he found that there was an effect in 28 of the 32 cases. However, after increasing the size of the sample, and using the F-statistic to draw conclusion, he observed that null hypothesis was bound to be rejected unless the level of significance was revised downwards, a scenario he called Lindley Paradox. Again, When Connolly (1989) adjusted for his sample size with help of the Bayesian statistical tool, he only found evidence in 4 out of the 32 cases. In the research paper from Chang, Pinegar and Ravichandran (1993) they investigate 23 markets on the day of the week phenomenon. They found proof using normal regression for 13 markets and when they corrected in the same manner as Connolly (1989) did the total of significant markets declined to only 9 markets.

2.3.1.2 Micro Market Effects

Another possible explanation for the Monday effect is the micro market effects, market operations that causes variances in stock prices across the week such as settlement procedures. According to Levi and Lakonishok (1982) suggested that yields on Monday should be relatively lower on Monday and relatively higher on Friday. They argue this is because of the interval of days from day of trading and settlement. In USA, settlement takes five business days after trading which has the effect of making the stock returns to be relatively higher on Fridays and significantly lower on Mondays. Buyers should prepare to pay more when they buy stocks on Friday. The sellers of stocks should ask for higher prices for their stocks they dispose on Friday because of the extra days that lapses payment is received making the return higher on Friday than other days. Similarly Monday return relatively lower by two days of interest than the return expected from either a trading day or calendar time view (Lakonishok and Levi, 1982). However, Settlement procedures are different in each country. According Board and Sutcliffe (1988), the settlement procedures in the United Kingdom markets somewhat tends to moderate the Monday effect phenomenon. According Branch and Echevarria (1991), tax matters have an impact on how prices of shares respond to ex-dividend and this may have an impact on the weekend effect particularly on the condition that date of ex-dividend fail to follow methodological pattern across the days of the week. However, they did not note any significant difference between samples without dividend and ex-dividend stocks. They concluded that explanations based on micro market structures for the weekend effect was not emphatically supported in the US equity markets.

2.3.1.3 Information Flow Effects

The Monday effect phenomenon could also be explained by the different rates of flow of micro and macro information. French (1980) suggests most firms usually defer releasing any negative information towards the end of the week to avoid disrupting the market, a proposition that has been supported by Kross & Schroeder (1984). However, subsequent studies have found that the delay of bad news events only give part explanation to the weekend effect. According to Damodaran (1989), the annoucements of earnings and dividends only offer part explanation for the weekend effect, a position that has been supported by Fishe, Lasser and Gosnell (1993) when they studied the US equity markets and similarly Choi and O'Hanlon (1989) when they studied the equity markets in the UK. However, study by Schatzberg and Datta (1992) which considered a larger number of dividend announcements concluded that dividend announcements in fact increases the returns on Monday.

According to Steeley (2001), in his examination of the stock market in UK, concluded that Monday phenomenon is related to the systematic pattern of market wide news arrivals that concentrates between Tuesdays and Thursdays. This however, only offers part explanation.

2.3.1.4 Behavioural Impact

According to Benson and Rystrom (1989), the day of the week occurrence can be accounted for by the 'blue Monday' psychological effect. They say that people are generally optimistic on Friday due to the fact that the weekend is beginning and less optimistic on Monday. If a large number of investors are pessimistic on Monday, they are likely to dispose their stocks causing prices to plummet. The opposite is true on Friday. The Blue Monday Hypothesis was confirmed by Pettengill and Buster (1994). They observed that people tend to invest in risky assets on Friday as opposed to Monday when they are less optimistic. According to Pettengill (2003), investors tend to avoid buying securities on Mondays to avoid potential loses that might arise from trading with well-informed traders selling their stock as a result of bad news received over the weekend. Singal and Chen (2003) state the weekend effect is explainable partly in the manner short sellers behave. Since short sellers are unable to trade during weekend, they prefer closing on their stock on Friday and in a bid to mitigate risk exposure, re-establish new short position on Mondays by borrowing and disposing securities. This has the effect of resulting to relatively inflated yields on Friday and diminished yields on Monday.

2.3.2 January effect

January phenomenon refers to the habit of Stocks to exhibit both inflated yield and inflated risk premiums in January vis-à-vis other months. It is the habit prices of shares to rise from the end of the final week December to about the last day of the first seven days of January. The January effect phenomenon has been corroborated by a slew of previous research studies. Wachtel (1942) studied the January effect. He used Dow Jones Industrial average between 1927 and 1942 and concluded presence of seasonality trends in stock returns. This finding was further supported by the study by Rozeff and Kinney (1976). They observed materially higher January returns in comparison to other months. Keim (1983) observes January effect and further finds a relationship between January phenomenon and the largeness of the firm.

The January effect phenomenon may explained by various factors, viz: tax-loss selling hypothesis, window dressing, data mining and performance hedging.

2.3.2.1 Tax-loss selling

It has been argued by many researchers that it is actually the individual investors who are tax sensitive who drive the January effect. .They sell their losing stocks in December to realise capital losses for tax purposes. They then use the funds in January to re-establish their new positions in small capitalisation, and thus drive up prices. The focus of tax-loss hypothesis is primarily on individual investors as institutional money managers tend to focus on large-capitalization equities and are also not particularly concerned with tax issues as opposed to individual investors (Eakins and Sewel, 1993)

Wachtel (1942), argues that the main explanatory factor for January effect phenomenon is the tax-loss selling theory. He observes that investors usually dispose their losing stocks midway in December and the subsequent sustained increase in prices in towards the end of December and early January is merely a response from the low stock market levels experienced early in the month. Ritter (1988) posits that January effect is explained by predictable portfolio rebalancing by individual investors, who are driven by taxes. His findings have been corroborated Johnston & Cox (1996) who equally observes strong correlation between the January effect and the size of ownership. Roll (1983), also argues that small-capitalization stocks become better candidates for tax-loss selling because of their high volatility.

Rettengill (1986) undertook to verify whether January effect existed before enactment of tax law in the USA. He used 1913 as the first taxable year and failed to observe evidence of a post-January phenomenon. He, however, observes a significant January effect between the periods 1918 to 1929 confirming the tax-loss selling hypothesis. Brailsford & Easton (1993), found a much more significant January effect over the post-tax period, however states that the tax-loss selling theory alone cannot wholly calendar anomalies in stock returns.

The recent proponents of tax –loss selling theory causing the January phenomenon are Chen and Singal (2004). They researched on calendar abnormalities in share returns using a sample of shares traded at AMEX, NYSE and NASDAQ. They observed five-day January return is 2.1%, which is higher compared with the five day December return of 1.1%. This implies the continued existence of the January effect.

2.3.2.2 Window dressing

The Window dressing theory was proposed by Haugen and Lakonishok (1987). They argue that institutional managers are normally appraised on three key performance indicators namely: favourable performance of the portfolio, investment philosophy and the outlook of the portfolio in their accounts. As such they tend to have blend relatively more risky stocks i.e. small cap with relatively less risky stocks in their portfolio to improve the returns. However, they dispose the risky stocks before the year end so they don't appear in their end of year holdings. They reverse this process at the start of the following year by disposing less risky stocks i.e. large cap stocks and acquiring more risky stocks i.e. past losers. Thus the year end portfolio holding is expertly managed and window-dressed to look better for the annual reporting. According to Chevalier and Ellison (1997), fund manager behave in this manner in order to attract more funds from new or prospective investors. This is because normally new investors tend to examine the past performance of different mutual funds before making a decision on which one would be the best to invest in. Thus the reason why fund managers window dress their portfolio to look better and attract new investors and in the process causing the January effect (Lakonishok et al. 1991).

2.4 Empirical literature

This part looks at the international and local experimental literature on calendar anomalies in stock yields.

2.4.1 International studies

Cross (1973) looked into subsistence of day of week (DOW) at the New York Stock Exchange. He examined relationship between price changes on Fridays and Mondays as well as the distribution of the price changes. The study sought to determine non-random movements in stock prices. The study population was S&P 500 composite stock index where a representation of 844 data points for Fridays and Mondays from 2nd January 1953 through December 21, 1970 for which the NYSE was open on both days is drawn. The study observed that the index performance on Friday was better than its performance on Monday, confirming subsistence of DOW phenomenon in the New York Stock Exchange.

Hess and Gibbons (1981) enquired into DOW phenomenon in stock markets in US. They studied 1962-1978 interval. They used variances and mean returns for S&P and the CRSP indices. They observed negative Monday returns, confirming subsistence of Monday phenomenon in the US stock markets. They observed significantly inflated returns on Fridays and Wednesdays. Smidt and Lakonishok (1988) who also studied DOW in US stock markets, observed Monday exhibited negative returns. Rivoli and Aggarwal (1989) studied DOW phenomenon in stock returns in developing markets of Hong-Kong, Singapore, Philippines and Malaysia. They observed seasonality in stock returns and also found out manifestation of Monday phenomenon.

Kiymaz and Berument (2001) examined the US stock market for any proof of DOW phenomenon. They used S&P 500 return, specifying the mean and the conditional variance equations that included the dummy variables. They recorded inflated yields on Wednesday and diminished yields on Monday. In terms of risks, the greatest turbulence is recorded on Friday while Wednesday recorded depressed turbulence. Kavetsos and Asteriou (2006) studied January phenomenon in Hungary, Poland, Czech Republic, Russia, Poland, Lithuania, Slovenia, Romania and Slovakia. There was a strong evidence of January in stock markets of Romania, Poland and Hungary.

McGowan and Ibrihim (2009) analysed DOW phenomenon in stock market in Russia. They applied ARCH/GARCH models and observed positive returns in every day with the exception of Wednesday, which recorded the lowest return. Friday recorded the highest return. They failed to observe the Monday occurrence in the Russian stock exchange. Enowbi, Mlambo and Guidi (2009) studied the week occurrence in Morocco, Egypt, Tunisia and South Africa. They used two models including OLS regression in their analysis and observed the subsistence of different material DOW phenomena inclusive of classical negative yield Monday and significantly positive yield Friday.

Ayadi (1998) examined seasonality in share return in some of the African emerging markets. He used market indices for Ghana during the period of 1991 and 1996, market index for Nigeria Nigerian during the periods 1984 and 1995 and the market index for Zimbabwe during the periods 1987 and 1995. He used Friedman test and Kruskal-Wallis in his analysis. He failed to observe seasonality in the returns in Zimbabwe and Nigeria. However, the Ghana stock market exhibited the January phenomenon.

Abdalla (2012) investigated the subsistence of DOW phenomenon at Khartoum Stock Exchange (KSE). There was no DOW phenomenon at KSE, using linear regression and GARCH model. In their study, Chipeta and Mbululu (2012) investigated DOW phenomenon in nine out of the listed indices at stock exchange in Johannesburg. They failed to observe this phenomenon in eight of the indices for the nine sectors. They however, observed Monday phenomenon in one of the sector, the material sector. Paul Alagidede (2012), examined the pre-holiday effects and month of the year effect and, and how they impact efficiency of stock market in some of the comparatively developed markets of Africa. He used monthly market indices for the markets namely: Nigeria's NSE all share index, NSE20 index for Kenya, Tunisia's Tunnindex, Morocco's MASI index, South Africa's FTSE/JSE A index, Egypt's CASE30 Index for Egypt and Zimbabwe's ZSE index. The January effect is evident in Egypt, Nigeria and Zimbabwe. The February effect is observed in Kenya, Nigeria, Morocco and South Africa. In the markets of Morocco, Kenya, South Africa and Tunisia, there is no material variation in the monthly yields, besides not one of them showed January phenomenon. Part of this results contradicts the findings by Claessens et al. (1995), who failed to observe month of the year occurrence in Zimbabwe's market.

Agnani and Aray (2011), using a selection of monthly returns of five portfolio size using US data in the 1940-2006 interval, find January effect in stock returns. They studied January effect in high and low volatility regimes. They found January effect in both volatility periods. They however noted, that the prevalence of January effect is larger during high volatility period. On the other hand, study by Friday and Hoang (2015) on the seasonality of returns in Vietnam stock exchange, shows significant positive April returns and materially July negative returns, showing absence of the January effect in this market.

2.4.2 Local studies

Rutto (2014) examined existence of Monday effect in securities returns at the NSE. She used simple linear regression to test for the Monday effect. She found that daily stock returns fall after Friday with negative returns recorded on Mondays. She verified subsistence of DOW phenomenon at the NSE. Njunguru (2014) explored the subsistence of the DOW in stock yield at the NSE. He found DOW subsist at NSE. Mwinamo (2013) observed DOW at the NSE and greatest turbulence in returns on Monday and depressed turbulence on Thursday. He adopted a descriptive research design. Data used included daily prices and market indexes which was facilitated by the calculation of the daily stock returns of 50 companies listed at NSE from 1st January 2008 to 31st December 2012. Kuria and Riro (2013) studied stock market anomalies effects on average returns at the NSE. The study examined DOW and monthly anomaly at NSE. They observed average negative yield on Monday other days recorded positive returns. Findings of the month effect showed that returns in December are generally lower and relatively greater in January, thus confirming the existence of the January phenomenon at NSE.

Onyuma (2009) studied month of the year effect at NSE from 1980 to 2006. He found that January had the largest positive returns thus confirming a January effect. Nyamosi (2009) also reported similar results. He used regression analysis from which negative coefficients were generated confirming comparatively greater returns in January than other months. Their findings were later supported by Allan and George. In their paper on Stock Market Anomalies in the NSE Allan & George (2013) examined the NASI and N20I for a period of 12 years up to 2011.They employed F-test and t-test in their analysis at 5% level and observed significant July, September and January returns. Therefore, they reported that monthly effect exists in NSE. They further stated that the December returns were comparatively lower and January yield were materially greater compared to other months, concluding January effect was present at NSE.

John (2012) also investigated the presence of seasonal effect in stock returns at NSE. The investigation encompassed fifty listed companies at NSE as at end of December 2011. He applied linear regression, observed absence of relationship between January phenomenon and stock yield at NSE. Wachira (2013) concluded that January effects exist at the NSE. He concluded that January returns differ significantly compared to other months implying that the NSE is not efficient.

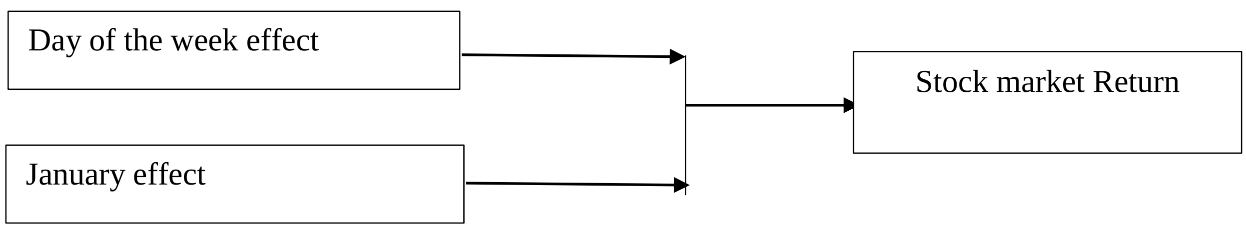
Sifuna (2012) investigated subsistence of DOW phenomenon at NSE. He employed multiple regression and daily market capitalization was used to compute the stock return.

The study excluded all public holidays that fell between Monday and Friday. Findings showed that Tuesday had the most inflated positive yield and Wednesday has the most inflated negative yield. He concluded that Monday effect does not exist at NSE.

2.5 Conceptual Framework

The enquiry seeks find out subsistence of DOW phenomenon and January phenomenon in stock returns at NSE. This conceptualised in the below figure:

Fig 2.1 The conceptual framework



(Source, Author, 2016)

2.6 Summary of literature review

The chapter has reviewed the theories supporting the topic of the study, efficient market theory and random walk theory. It has also reviewed international and local studies on calendar abnormalities in stock yields, particularly DOW phenomenon and January effect in security yields in various stock markets. The factors that these anomalies may be attributed to have been discussed at length, among them are: tax-loss selling theory, window dressing, micro-market effects, information flow effects, statistical aberrations and behavioural impact. The chapter concludes by giving a conceptual framework that shows the relationship between the variables of the study.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

The chapter delves into the design, methods of collecting data for analysis, discussion of the population of interest, selection of the study sample and analytical models adopted for the analysis.

3.2 Research Design

The study chose a descriptive correlational research design, where the existence of calendar anomalies and their effects on returns at NSE was examined. According Mugenda and Mugenda (2003), the choice of descriptive research design provides a methodical and experimental inquiry in which the investigator has no direct control whatsoever over independent variable because they already manifested and consequently the researcher is not in a position to manipulate them. This research design suits the study, because the study seeks to use empirical evidence from the historical data at the NSE.

3.3 Population of the study

The study populace is made up of returns of all the companies which were listed at NSE between 1st January 2008 and 31st December 2015 as captured by the market indices. The major index of interest was the Nairobi 20-Share Index (N20I) which measure the market return of all companies listed.

3.4. Data collection

This enquiry employed already existing data on stock prices. The daily and monthly closing prices of N20I Index between 1st January 2008 and 31st July 2016, was sourced from the official NSE website.

3.5 Data Analysis

This study used Eviews econometrics software package version 7 to analyse the data. Ordinary linear regression model, symmetric GARCH and asymmetric EGARCH models were used to test for subsistence of DOW and January phenomenon.

3.5.1 Analytical Model

To obtain monthly and daily stock yields, we convert daily and monthly closing prices to daily and monthly continuously compounded returns (logarithmic returns) as proposed by Strong (1992). This is worked out as follows:

$$R_t = \ln \left(\frac{P_t}{P_{t-1}}\right)$$

Where R_t denotes the continuously compounded returns at time t, P_t represents index price at period t, P_{t-1} represents index price at period *t-1*.

The logarithm returns are generally considered better than the simple returns, because they are easier to manage especially when linking two sub periods to form returns for a longer period. Again, logarithmic returns tend to be normally distributed compared to simple returns. Normal distribution of returns is important in various statistical models. (Strong, 1992).

The daily stock prices do not arrive in a regular pattern owing to the weekends and holidays in between. The returns have thus to be converted into regular frequentness data.

In testing for DOW and January phenomenon in stock market returns, the following mean equation presented in 1983 by Gultekin and later in 1989 by Jaffe and Westerfield will be adopted.

$$D_{Rt} = X_1D_1 + X_2D_2 + X_3D_3 + X_4D_4 + X_5D_5 + \mu_t \quad (1)$$

$$M_{Rt} = Y_1M_1 + Y_2M_2 + Y_3M_3 + Y_4M_4 + Y_5M_5 + Y_6M_6 + Y_7M_7 + Y_8M_8 + Y_9M_9 + Y_{10}M_{10} + Y_{11}M_{11} + Y_{12}M_{12} + \mu_t \quad (2)$$

In equation (1), X_1, X_2, X_3, X_4, and X_5 are coefficients while D_1, D_2, D_3, D_4 and D_5 are daily dummy variables for Monday, Tuesday, Wednesday, Thursday and Friday. Dummy variable D1=1 if the return is on Monday and Zero if not. In the like manner, dummy variable D2 =1 if the return is on Tuesday and zero if not, dummy D3=1 if the return is on Wednesday and zero if not and so on. Similarly, in equation 2, Y = (1, 2, 3……12) are parameters while M = (1, 2, 3….12) are dummy variables for January to December, where D1 =1 if the return is for January and 0 otherwise, D2 = 1 for February and 0 otherwise and so on. Since five dummy variables have been included in equation 1 and twelve dummy variables in equation 2, the intercept is omitted to avoid perfect co-linearity of the model (dummy trap).

First, the above two models is estimated in Eviews using the OLS model which make the assumptions that: the returns are normally distributed, the returns do not have serial correlation, and the residuals have a stationary variance (Wooldridge, 2003).

The model is examined is examined for ARCH effects (ARCH-LM test). The model is examined for ARCH effects in the residuals, which is not desirable if the model is to be a good fit. Further diagnostics: serial correlation test, normality test, unit root test are carried on the OLS model to determine its suitability. GARCH and EGARCH models are thereafter estimated, and further diagnostics carried out.

This study applies OLS method, symmetric GARCH and asymmetric EGARCH models. The ordinary least squares regression models and the linear models in general, in essence, falls short in accounting for certain stylized features of financial time series yield such clustering of volatility, leverage effect (asymmetry in conditional variance) and the leptokurtosis (due to the long-time interval) for the financial data. GARCH models are superior to OLS because of their ability to model certain stylized features of finacial returns viz: fat tails as a result of volatility varying over time, Skewness caused by mean non-stationarity, nonlinearity and volatility clustering. Again, GARCH models have the ability to reduce the excess skewness and kurtosis if well specified. They can also significantly remove ARCH effect.

The GARCH model created by Bollerslev in (1986) and adopted by Connolly (1989) in his study of calendar effects is considered a good model because of its ability to model the varying variance of the residuals. The standard GARCH model is symmetric in how it responds to news. However, favourable news affect volatility differently from bad news as such, an alternative asymmetric GARCH model, EGARCH is considered. EGARCH has the advantage of being able to explain any leverage effects in stock returns. Leverage effect refers to the tendency for variability of returns to increase more as a result of bad news than good news.

3.5.2 GARCH model

The appropriate equation for the mean and variance for the model have to be specified.

Mean equation:

$R_t = \mu + \varepsilon_t \sim N(0, \sigma_t^2)$ s (3)

The variance equation is given by:

$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2$ (4)

Where in equation 3, the daily or monthly stock return R_t is regressed on a constant μ, ε_t is an error term which is dependent on historical information and σ_t^2 is the conditional variance.

For the conditional variance to meet non-negativity constraints so as to be meaningful, the following conditions must be met: $\omega > 0$; $\alpha_1 \geq 0$; $\alpha_1 + \beta_1 < 1$.

According to Engle and Bolleslev (1986), the enduring of shocks on volatility is dependent on the sum of $\alpha_1 + \beta_1$. If the sum is close to unity, it implies that variability persist over a longer period. On the hand, if the sum is equal to (or greater) than unity, it implies the volatility tends to increase over time.

3.5.3 EGARCH MODEL

The Asymmetric EGARCH (1, 1) model developed by Nelson in 1991 remedies the drawback of the GARCH (1, 1) model of not being able to capture the leverage effect. In this model, conditional Variance of EGARCH (1, 1) model is given by:

$$\ln(\sigma_t^2) = \omega + \beta . log(\sigma_{t-1}^2) + \alpha \left| \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right| + r \frac{\mu_{t-1}}{\sqrt{\sigma_{t-1}^2}}$$

This EGARCH model through its asymmetry does not constrain the effects on volatility in one sign and level. In particular, this can be achieved through the benefits of the EGARCH model, which is based on logarithms and therefore, even if negative values will arise for the coefficients, they will be positive, thus, there is no need for further constraints in those models. Subsistence of leverage effects is investigated by the hypothesis that $r > 0$ and the impact is asymmetric if $r \neq 0$.

CHAPTER FOUR

DATA ANALYSIS, RESULTS AND DISCUSSION

4.1 Introduction

The chapter focuses on in-depth analysis of collected data for the study. It gives preliminary descriptive statistic results for DOW and the January phenomena in stock yields. It also gives OLS model results for the day of the week effect and the January effect. It also provides diagnostic tests results to determine the reliability of the OLS model results. The section further covers the summary statistics for more robust symmetric GARCH (1, 1) and asymmetric EGARCH models to determine the existence of calendar anomalies at the NSE.

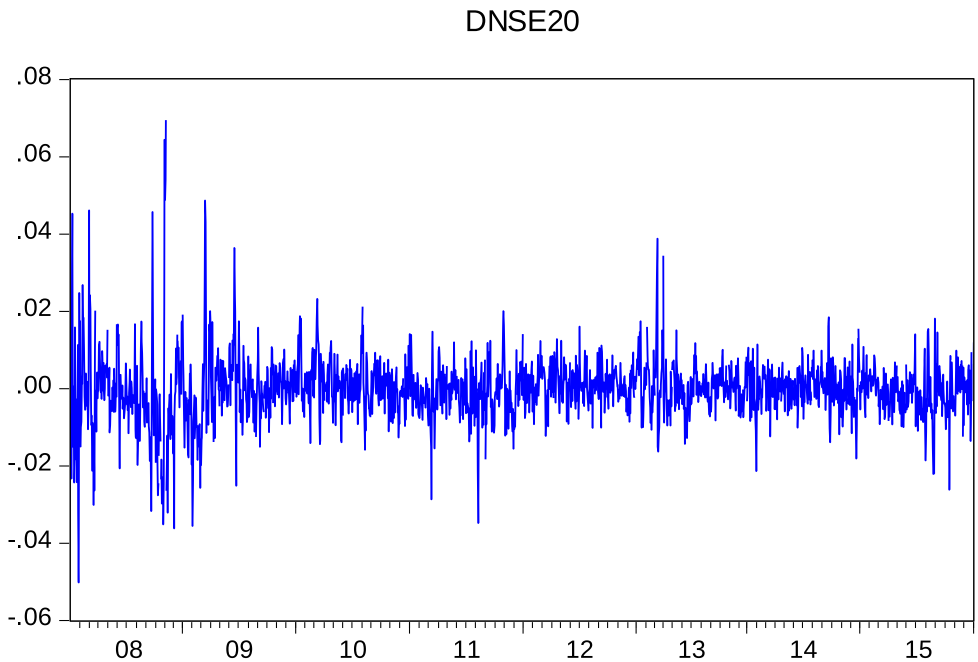
4.2 Day of the Week effect Analysis

Table 1: Descriptive statistics-daily NSE20 returns

Weekday	Mean	Median	Max	Min.	Std. Dev.	Skew.	Kurt.
Monday	-0.000122	-0.000903	0.048803	-0.031923	0.008237	1.150531	9.096695
Tuesday	-0.000641	-0.000291	0.054081	-0.050178	0.009355	0.072741	11.07968
Wednesday	-0.000397	-7.37E-05	0.069477	-0.032138	0.008355	1.051253	15.56131
Thursday	-0.000212	-1.39E-05	0.036393	-0.029772	0.007272	0.039458	6.655420
Friday	0.000782	0.000821	0.064380	-0.030104	0.008546	1.895418	16.60199
All	-0.000123	-0.000140	0.069477	-0.050178	0.008384	0.837880	12.63599

From Table 1, Tuesday recorded diminished returns while Friday recorded inflated returns. The returns for all the days are negative except Friday which has positive return. In terms of turbulence of yields (Risk) as captured by the standard deviation, Thursday has the lowest volatility while Tuesday exhibits the highest volatility. All the days of the week exhibit excess kurtosis (greater than 3), as such ARCH/GARCH models have to be employed to reduce the excess kurtosis.

Figure 1 Daily NSE20 returns from 2nd January 2008 to 31st Dec 2015



4.2.1 Ordinary Least Square (OLS) Regression

Table 2: OLS model results-Daily NSE20 Returns

Day	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
Monday	-0.000122	0.000423	-0.288478	0.7730
Tuesday	-0.000641	0.000416	-1.539120	0.1239
Wednesday	-0.000397	0.000416	-0.954904	0.3397
Thursday	-0.000212	0.000415	-0.509510	0.6105
Friday	0.000782	0.000422	1.854880	0.0638

Results in table 2 above shows yield on Tuesday as being diminished while yield on Friday is inflated. However returns for all the days are insignificant. Coefficients for all the days may be insignificant due to heteroskedasticity in the residuals, the returns may be serially correlated, the residuals may not be normally distributed and there could be ARCH effect.

4.2.2 Diagnostic Tests (OLS)

Unit Root Test (Augmented Dicker-Fuller test)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-27.16511	0.0000
Test critical values:	1% level	-3.433412	
	5% level	-2.862779	
	10% level	-2.567476	

Table 3: Augmented Dicker-Fuller test results-Daily returns (OLS)

Null hypothesis: Daily return have unit root

Alternative hypothesis: Daily return do not have unit root

Decision rule:

If the probability of Augmented Dickey-Fuller statistics is below 5%, we dismiss the null hypothesis and take the alternative.

Should the Probability be more than 5% we take null hypothesis.

From table 3, probability of Augmented Dickey-Fuller test is zero, implying that we dismiss null take alternative hypothesis, returns do not have unit root and so there is no need for differencing. This is a desirable results for the returns to be modelled.

Testing for serial Correlation in the OLS model

Table 4: Serial Correlation test results –Daily returns (OLS)

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	271.1814	Prob. F(2,1999)	0.0000
Obs*R-squared	428.1088	Prob. Chi-Square(2)	0.0000

Null Hypothesis: There is no serial correlation

Alternative Hypothesis: There is serial correlation

Decision rule:

If the probability of Observed R^2 is smaller than five percent, we dismiss null hypothesis and take alternative.

If the probability of Observed R^2 is greater than five percent, null hypothesis cannot be dismissed.

From table 4, probability of Observed R^2 is zero, the null hypothesis is dismissed instead accept the alternative hypothesis, implying existence of serial correlation, which is not desirable.

Testing for heteroskedasticity

To test for heteroskedasticity, Heteroskedasticity Test: Breusch-Pagan-Godfrey test is used. The results are as below.

Heteroskedasticity Test: Breusch-Pagan-Godfrey			
F-statistic	1.091643	Prob. F(4,2001)	0.3590
Obs*R-squared	4.367950	Prob. Chi-Square(4)	0.3585
Scaled explained SS	25.12109	Prob. Chi-Square(4)	0.0000

Table 5: Heteroskedasticity test results- Daily returns (OLS)

Null hypothesis: Homoscedasticity

Alternative hypothesis: Heteroskedasticity

Decision rule:

If the p-value of observed R^2 is smaller than five percent, null hypothesis is dismiss and alternative taken.

If the p-value of observed R^2 is greater than five percent, null hypothesis cannot be dismissed.

From Table 5 probability of observed R^2 is 35.85%, which is more than five percent, we therefore cannot dismiss null hypothesis, implying the residuals are constant (homoscedasticity). This is desirable.

Histogram-Normality Test

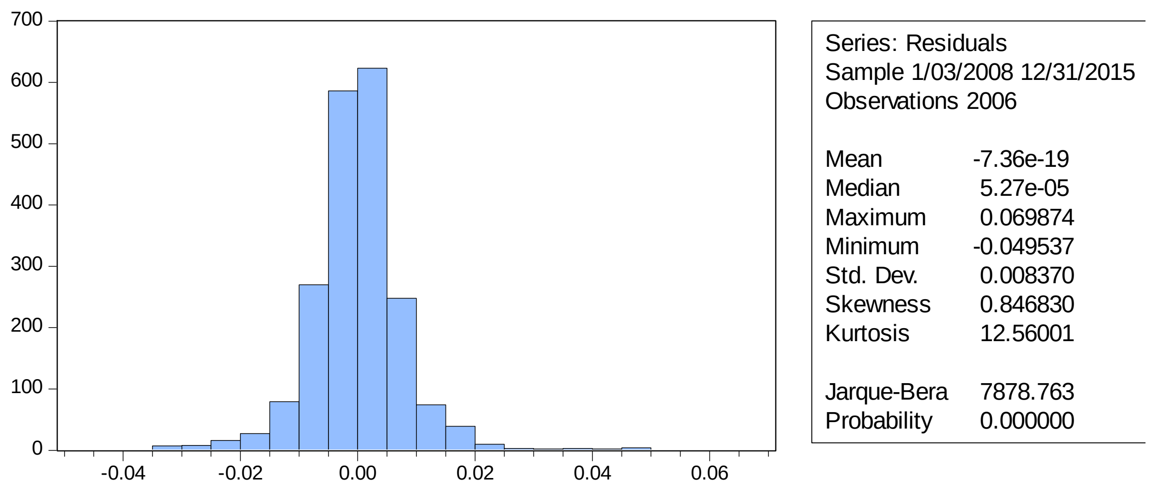


Figure 2: Histogram-Normality test results

Null hypothesis: Normal distribution

Alternative hypothesis: Non-normal distribution

Decision rule:

Should the P-value of Jarque-Bera statistics be smaller than five percent, null hypothesis dismiss alternative taken.

Should the P-value of Jarque-Bera statistics be greater than five percent, null hypothesis cannot be dismissed?

From figure 2, the p-value of Jarque-Bera statistics is zero, so null hypothesis is dismissed, implying the residuals are not normally distributed. This is not desirable.

Testing for ARCH effect

To test for ARCH effect, Heteroskedasticity ARCH test is used. The results are as follows.

Heteroskedasticity Test: ARCH			
F-statistic	820.5383	Prob. F(1,2003)	0.0000
Obs*R-squared	582.6658	Prob. Chi-Square(1)	0.0000

Table 6: ARCH effect test results-Daily returns (OLS)

Null hypothesis: ARCH effect is absent (Desirable)

Alternative hypothesis: ARCH effect is present (Not Desirable)

Decision Rule:

If p-value of observed R^2 is smaller than five percent, null hypothesis is dismissed and alternative taken.

If p-value of observed R^2 is greater than five percent, null hypothesis cannot be dismissed.

From table 6: probability of Obs*R-squared is zero, we dismiss alternative hypothesis and take alternative, signifying ACRH effect is present residuals. This is not desirable.

From the diagnostic tests conducted on the OLS model to determine its reliability, the model falls short. The residuals are serially correlated, are not normally distributed and there is the presence of ARCH effect, thus the need to use GARCH and EGARCH models.

4.2.3 GARCH (1, 1) Model

Table 7: GARCH (1, 1) Estimation of the mean and Variance equation

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Monday	-0.000535	0.000272	-1.962821	0.0497
Tuesday	-0.000170	0.000269	-0.629835	0.5288
Wednesday	0.000279	0.000267	1.043821	0.2966
Thursday	0.000225	0.000259	0.871384	0.3835
Friday	0.000912	0.000274	3.326531	0.0009
		Variance Equation		
C	6.91E-06	2.71E-06	2.552674	0.0107
RESID(-1)^2	0.310251	0.034244	9.059880	0.0000
GARCH(-1)	0.602392	0.030713	19.61350	0.0000
Monday	-1.54E-06	4.61E-06	-0.333671	0.7386
Tuesday	-4.84E-07	4.10E-06	-0.117903	0.9061
Wednesday	2.57E-07	4.11E-06	0.062513	0.9502
Thursday	-4.15E-06	4.73E-06	-0.877177	0.3804

The Friday Dummy variable has been dropped in conditional variance equation to prevent perfect co-linearity. C in the variance equation thus becomes the coefficient for the Friday Dummy upon which other coefficients are compared against.

The results from table 7, mean equation shows that return on Monday is the lowest (negative) and significant. This confirms the presence of Monday effect. The results also reveal Friday has significantly most inflated returns. The returns for the other days are insignificant.

The variance equation reveals the highest variability is exhibited on Wednesday, though it is not significant. The lowest volatility is observed on Tuesday which is also not significant. Friday has the second highest volatility which is significant. The ARCH term and the GARCH term are both material, implying that the model is suitable. The total ARCH and GARCH parameters is near unity (0.9126), implying persistence in shocks to the conditional variance.

4.2.4 Diagnostic tests-GARCH model

Testing for ARCH effect in the GARCH (1, 1) model

Heteroskedasticity Test: ARCH			
F-statistic	1.795492	Prob. F(1,2003)	0.1804
Obs*R-squared	1.795675	Prob. Chi-Square(1)	0.1802

Table 8: ARCH test results GARCH (1, 1)

Null hypothesis: ARCH effect is absent

Alternative hypothesis: ARCH effect is present

Since the p-value of observed R^2 is greater than 5%, null hypothesis cannot be dismissed. (ACRH effect is absent). This is desirable.

4.2.5 EGARCH (1, 1) Model

Table 9: EGARCH (1, 1) Estimation of the mean equation for the day of the week effect

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Monday	-0.000668	0.000264	-2.528415	0.0115
Tuesday	-0.000215	0.000253	-0.847353	0.3968
Wednesday	0.000195	0.000254	0.769675	0.4415
Thursday	0.000193	0.000261	0.738230	0.4604
Friday	0.000760	0.000264	2.879214	0.0040
Variance Equation				
C(6)	-1.634141	0.182823	-8.938374	0.0000
C(7)	0.522952	0.039436	13.26085	0.0000
C(8)	-0.021789	0.020452	-1.065344	0.2867
C(9)	0.877336	0.017026	51.52781	0.0000

From table 8, Monday has the lowest return which is significant, confirming the presence of Monday effect. Friday has the highest returns which is also significant. From the variance equation C8 used for testing the leverage effect is negative confirming the presence of leverage effect though it is not significant.

4.2.6 Diagnostic test-EGARCH model

Testing for ACRH effect

Heteroskedasticity Test: ARCH			
F-statistic	4.510874	Prob. F(1,2003)	0.0338
Obs*R-squared	4.505232	Prob. Chi-Square(1)	0.0538

Table 10: ARCH effect test results

Null hypothesis: ARCH effect is absent

Alternative Hypothesis: ARCH effect is present

Since the probability of Obs*R-squared is 5.38%, more than 5%, the null hypothesis is not rejected, thus ARCH effect is absent, which is desirable.

4.3 January effect Analysis

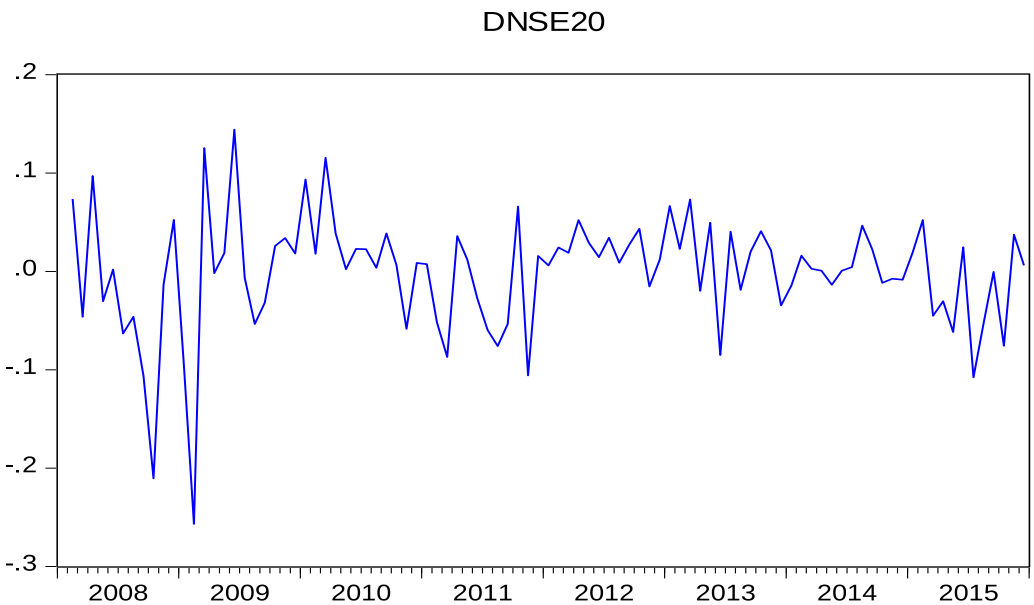
Table 11: Descriptive statistics for the Monthly NSE20 returns

MONTH	Mean	Max	Min.	Std. Dev.	Skew.	Kurt.	Obs.
January	0.011680	0.093377	-0.095987	0.060623	-0.450113	2.711406	7
February	-0.012718	0.073553	-0.256671	0.104928	-1.786501	4.878626	8
March	0.019564	0.125277	-0.086951	0.078713	0.137736	1.625853	8
April	0.021519	0.096912	-0.030318	0.042242	0.472078	2.252998	8
May	0.000647	0.049484	-0.061708	0.035260	-0.450042	2.381765	8
June	0.011989	0.144052	-0.085173	0.064296	0.761878	3.780804	8
July	-0.016963	0.040365	-0.107795	0.053751	-0.522390	1.881631	8
August	-0.023620	0.046458	-0.075955	0.040930	0.425090	2.040070	8
September	-0.010532	0.038578	-0.106199	0.049874	-0.896526	2.567910	8
October	-0.014516	0.065777	-0.210565	0.090310	-1.412461	3.819562	8
November	-0.013495	0.037378	-0.105723	0.048704	-0.786776	2.599832	8
December	0.008673	0.052383	-0.034690	0.024607	-0.019923	3.243037	8
All	-0.001619	0.144052	-0.256671	0.060251	-1.089537	6.592098	95

From table 11, April and August recorded the highest and lowest returns respectively. The months of August, July, October, November, February and September have negative returns, while the months of May, December, January, June, March and April have positive returns. In terms of the variance (volatility) as captured by standard deviation, December has the lowest volatility while the month of February has the highest volatility.

The results in table 11, however has some drawbacks. It ignores some features of financial time series that may be present. There is a likelihood that financials returns may be serially correlated, residuals may not be normally distributed, residuals may not be homoscedastic and there could be ARCH effect in residuals. We thus employ GARCH and EGARCH models to deal with some of these features.

Figure 3 Monthly NSE20 returns from January 2008 December 2015



4.3.1 Ordinary Least Square (OLS) Regression

Month	Coefficient	Std. Error	t-Statistic	Prob.
January	0.011680	0.023466	0.497760	0.6200
February	-0.012718	0.021950	-0.579415	0.5639
March	0.019564	0.021950	0.891310	0.3753
April	0.021519	0.021950	0.980373	0.3298
May	0.000647	0.021950	0.029495	0.9765
June	0.011989	0.021950	0.546189	0.5864
July	-0.016963	0.021950	-0.772779	0.4418
August	-0.023620	0.021950	-1.076067	0.2850
September	-0.010532	0.021950	-0.479795	0.6326
October	-0.014516	0.021950	-0.661316	0.5102
November	-0.013495	0.021950	-0.614788	0.5404
December	0.008673	0.021950	0.395145	0.6937

Table 12: Results of OLS for Monthly returns

From Table 12, April recorded inflated yield while August recorded diminished yield. The returns for all the months are insignificant.

4.3.2 Diagnostic Tests (OLS)

Unit Root Test (Augmented Dicker-Fuller test)

Table 12: Unit root test results

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.048031	0.0000
Test critical values:	1% level	-3.501445	
	5% level	-2.892536	
	10% level	-2.583371	

Null hypothesis: Monthly returns have unit root

Alternative hypothesis: Monthly returns do not have unit root

Decision rule:

If the probability is less than five percent then the null hypothesis is dismissed.

If the Probability is greater than five percent, null hypothesis cannot be dismissed, implying returns have got unit root.

Since p-value is zero, we dismiss null hypothesis. Yields do not have unit root.

Testing for serial Correlation in the OLS model

Table 13: Serial Correlation test results

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	28.405684	Prob. F(1,381)	0.0000
Obs*R-squared	17.776185	Prob. Chi-Square(2)	0.0000

Null hypothesis: There is no serial correlation

Alternative Hypothesis: There is serial correlation

Decision rule:

If p-value of observed R^2 is smaller than five percent, we dismiss null hypothesis and take alternative.

If p-value of observed R^2 is greater than five percent, we fail to dismiss the null hypothesis.

From table 13, probability of observed R^2 is zero, which implies we dismiss the null hypothesis and take alternative hypothesis. The returns thus have serial correlation, this is not desirable.

Testing for heteroskedasticity

Table 14: heteroskedasticity test results

Heteroskedasticity Test: Breusch-Pagan-Godfrey			
F-statistic	1.026373	Prob. F(11,83)	0.4311
Obs*R-squared	11.37510	Prob. Chi-Square(11)	0.4124
Scaled explained SS	21.99991	Prob. Chi-Square(11)	0.0244

Null hypothesis: Homoskedasticity

Alternative hypothesis: Heteroskedasticity

Decision Rule:

If p-value of observed R^2 is smaller than five percent, null hypothesis is dismissed, instead alternative is taken.

If p-value of observed R^2 is greater than five percent, null hypothesis cannot be dismissed.

P-value observed R^2 is 41.24% which is more than 5%. We fail to dismiss null hypothesis and conclude residuals are homoskedastic (constant) which is desirable.

Histogram-Normality test

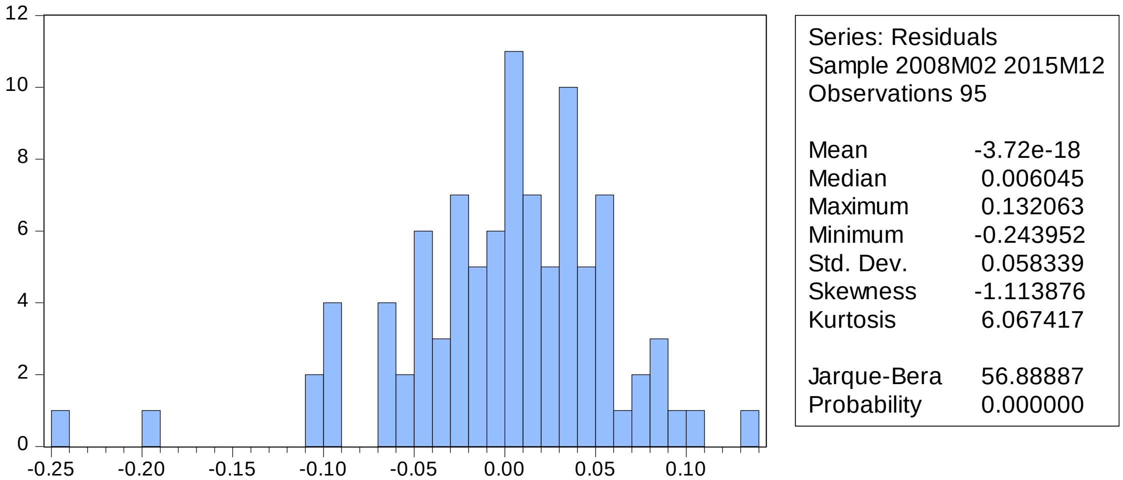


Figure 4: Histogram-normality test results

Null hypothesis: Normal distribution of residuals

Alternative hypothesis: Non normal distribution of residuals

Decision Rule:

If p-value of Jarque-Bera statistics is smaller than five percent, null hypothesis is rejected and instead accept the alternative hypothesis.

If the p-value of the Jarque-Bera statistics is more than five percent, null hypothesis cannot be dismissed.

From figure 4, the p-value of the Jarque-Bera statistics is zero. We decline the null hypothesis and take the alternative. The residuals are non-normally distributed.

Testing for ARCH effect

Table 15: ARCH effect results

Heteroskedasticity Test: ARCH			
F-statistic	3.436277	Prob. F(1,92)	0.0670
Obs*R-squared	3.384562	Prob. Chi-Square(1)	0.0458

Null hypothesis: ARCH effect is absent

Alternative hypothesis: ARCH effect is present

Decision rule:

If p-value of observed R^2 is smaller than five percent, null is dismissed and alternative is accepted.

If p-value of observed R^2 is greater than five percent, we fail to dismiss the null.

From the results in table 15, p-value of observed R^2 is 4.58% which is smaller than 5%. We therefore decline the null and take the alternative, implying ARCH effect is present in the residuals. From the diagnostic tests of the OLS model, it is evident that the residuals are serially correlated, non-normal and have ARCH effect. Thus the need to use GARCH and EGARCH models to deal with the ARCH effect present in the residuals.

4.3.3 GARCH (1, 1) Model

Table 16: GARCH (1, 1) estimation of the mean and Variance equation.

Month	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
January	0.034365	0.010650	3.226768	0.0013
February	0.011418	0.009419	1.212201	0.2254
March	0.023933	0.011456	2.089214	0.0367
April	0.027428	0.018469	1.485048	0.1375
May	0.006112	0.018228	0.335307	0.7374
June	0.004281	0.019654	0.217796	0.8276
July	0.007134	0.013708	0.520457	0.6027
August	0.014278	0.013423	1.063734	0.2874
September	0.020066	0.020189	0.993898	0.3203
October	0.012833	0.013167	0.974666	0.3297
November	-0.021159	0.012571	-1.683130	0.0923
December	-0.004035	0.029425	-0.137117	0.8909
		Variance Equation		
C	0.000207	0.000207	0.999078	0.3178

RESID(-1)^2	0.569043	0.238022	2.390717	0.0168
GARCH(-1)	0.401338	0.166575	2.829588	0.0047

From table 16 results, in the mean equation, January recorded significantly higher yield than other months, confirming subsistence of January effect. April yield is the second highest and is also material. The month of November exhibit the lowest negative returns, though it is not significant.

From the variance equation, ARCH and GARCH parameters are material confirming suitability of the model. Total of the coefficients of the ARCH and GARCH parameters is very near to unity (approximately 0.97), implying shocks to the conditional variance equation is persistent.

4.3.4 Diagnostic Tests- GARCH model

Testing for ARCH effect in the GARCH model

Heteroskedasticity Test: ARCH			
F-statistic	0.012858	Prob. F(1,92)	0.9100
Obs*R-squared	0.013136	Prob. Chi-Square(1)	0.9088

Table 17: ARCH effect test results

Null hypothesis: ARCH effect is absent

Alternative hypothesis: ARCH effect is present

Decision Rule:

If p-value of observed R^2 is smaller than five percent, we dismiss null and instead take alternative.

If p-value of observed R^2 is greater than five percent, we fail to dismiss null.

From table 17, p-value of observed R^2 is 90.88%, this is greater than 5%. The null cannot be dismissed. ARCH effect is absent in the residuals.

Testing for Serial Correlation in the GARCH model

Table 18: Correlogram of Standardized Residiuals Squared results

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |. |	. |. |	1	0.012	0.012	0.0137	0.907
.*|. |	.*|. |	2	-0.099	-0.100	0.9937	0.608
. |. |	. |. |	3	-0.027	-0.025	1.0670	0.785
. |* |	. |* |	4	0.140	0.132	3.0561	0.548
. |* |	. |* |	5	0.088	0.081	3.8422	0.572
.*|. |	.*|. |	6	-0.099	-0.078	4.8511	0.563
.*|. |	. |. |	7	-0.079	-0.058	5.5010	0.599
. |. |	. |. |	8	-0.022	-0.051	5.5508	0.697
. |. |	. |. |	9	-0.021	-0.060	5.5969	0.779
.*|. |	.*|. |	10	-0.152	-0.151	8.1076	0.618
. |. |	. |* |	11	0.048	0.078	8.3629	0.680
.*|. |	.*|. |	12	-0.082	-0.101	9.1138	0.693
. |. |	. |. |	13	-0.033	-0.025	9.2381	0.755
. |. |	. |. |	14	-0.013	0.010	9.2563	0.814
.*|. |	.*|. |	15	-0.112	-0.134	10.696	0.774
. |. |	.*|. |	16	-0.044	-0.073	10.920	0.814
. |. |	. |. |	17	0.057	0.052	11.309	0.840
. |. |	. |. |	18	0.001	-0.036	11.309	0.881
. |. |	. |. |	19	-0.058	-0.054	11.713	0.898
. |* |	. |* |	20	0.091	0.111	12.729	0.889
. |. |	. |. |	21	0.005	-0.027	12.732	0.918
.*|. |	.*|. |	22	-0.098	-0.180	13.941	0.904
. |. |	. |. |	23	-0.043	-0.024	14.172	0.922
. |. |	. |. |	24	0.037	-0.012	14.349	0.938
. |** |	. |* |	25	0.231	0.159	21.349	0.673
. |. |	. |* |	26	0.022	0.085	21.415	0.720
.*|. |	. |. |	27	-0.074	0.000	22.159	0.729
. |** |	. |** |	28	0.217	0.218	28.661	0.430
. |* |	. |. |	29	0.107	0.033	30.259	0.401
. |. |	. |. |	30	0.012	0.002	30.278	0.451
. |. |	. |. |	31	0.013	0.037	30.302	0.502
.*|. |	.*|. |	32	-0.128	-0.178	32.682	0.433
. |. |	. |. |	33	-0.001	-0.016	32.682	0.483
. |. |	. |. |	34	0.009	0.011	32.696	0.531
.*|. |	. |. |	35	-0.073	-0.004	33.503	0.540
. |. |	. |* |	36	0.031	0.120	33.652	0.581

Null hypothesis: There is no serial correlation

Alternative hypothesis: There is serial correlation

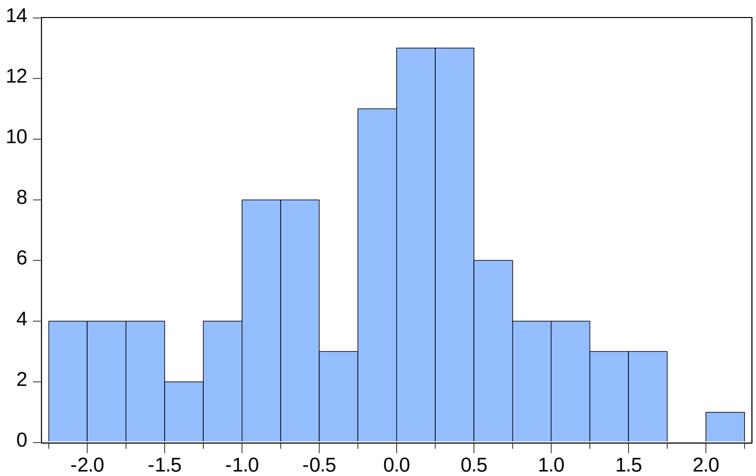
Decision Rule:

If the probabilities of Q-statistics are smaller than 5%, we dismiss null hypothesis and accept alternative.

If the probabilities of Q-statistics are more than 5%, we fail to decline the null hypothesis.

From table 18, the probabilities of Q-statistics (36 lags) are all more than 5%. Null cannot be dismissed. Residuals are not serially correlated.

Histogram-Normality test



Series: Standardized Residuals
Sample 2008M02 2015M12
Observations 95

Mean	-0.159252
Median	-0.040274
Maximum	2.219780
Minimum	-2.245731
Std. Dev.	0.991620
Skewness	-0.153760
Kurtosis	2.564145
Jarque-Bera	1.126295
Probability	0.569414

Figure 5: Histogram-Normality test results

Null hypothesis: Normal distribution

Alternative Hypothesis: Non-normal distribution

Decision rule:

If p-value of Jarque-Bera statistic is smaller than five percent, null is dismissed and alternative taken.

If p-value of Jarque-Bera statistic is greater than five percent, the null hypothesis is not dismissed.

Since the p-value of Jarque-Bera statistic is greater than 5%, null cannot be dismissed. Residuals are normally distributed, which is desirable.

From the diagnostic tests conducted on the GARCH (1, 1) model, there is no ARCH effect, the residuals are not serially correlated and the residuals are normally distributed. Thus GARCH (1, 1) results are reliable.

4.3.5 EGARCH (1, 1) Model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
January	0.036441	0.013198	2.761196	0.0058
February	0.010929	0.024401	0.447882	0.6542
March	0.028630	0.019667	1.455741	0.1455
April	0.023415	0.012525	1.869444	0.0616
May	0.002023	0.009161	0.220846	0.8252
June	0.014440	0.024194	0.596863	0.5506
July	0.012221	0.021477	0.569018	0.5693
August	0.005639	0.014067	0.400847	0.6885
September	0.022590	0.011587	1.949680	0.0512
October	0.012227	0.014070	0.869004	0.3848
November	-0.030557	0.012295	-2.485456	0.0129
December	-0.000990	0.007549	-0.131156	0.8957
Variance Equation				
C(13)	-3.328399	1.377878	-2.415598	0.0157
C(14)	0.737557	0.490051	1.505061	0.1323
C(15)	-0.279284	0.255379	-1.093607	0.2741
C(16)	0.800825	0.161785	4.949939	0.0000

Table 19: EGARCH (1, 1) Estimation of the mean equation and variance equation

From table 19, January recorded significantly higher returns than other months confirming the subsistence of January effect. November recorded lowest return.. There is leverage effect as evidenced by the Coefficient C (15), though it is not significant at 5% level of significance.

4.3.6 Diagnostic tests-EGARCH Model

Testing for ARCH effect

Heteroskedasticity Test: ARCH			
F-statistic	0.040054	Prob. F(1,92)	0.8418
Obs*R-squared	0.040907	Prob. Chi-Square(1)	0.8397

Table 20: Test results for ARCH effect

Null hypothesis: ARCH effect is absent

Alternative hypothesis: ARCH effect is present

Since the probability of observed R^2 is higher than five percent, null cannot be dismissed. ARCH effect is absent in the residuals. This is desirable.

Histogram-Normality test

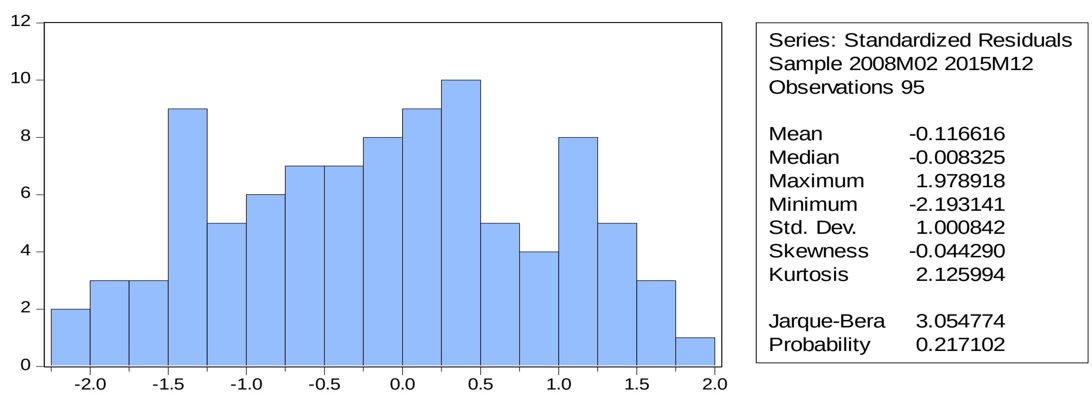


Figure 6: Histogram-normality test results

Null hypothesis: Normal distribution

Alternative hypothesis: Non-normal distribution

Since the probability of Jarque-Bera statistic in figure 6 is 21.71%. This is higher than 5%. Null cannot be dismissed. Residuals are normally distributed.

Testing for serial correlation

Table 21: Correlogram of Standardized Residuals Squared

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |. |	. |. |	1	0.021	0.021	0.0424	0.837
. |. |	. |. |	2	-0.014	-0.015	0.0632	0.969
.*|. |	.*|. |	3	-0.126	-0.126	1.6639	0.645
. |. |	. |. |	4	-0.012	-0.008	1.6795	0.794
. |* |	. |* |	5	0.136	0.135	3.5768	0.612
. |. |	. |. |	6	0.051	0.031	3.8442	0.698
. |. |	. |. |	7	-0.032	-0.037	3.9541	0.785
. |. |	. |* |	8	0.038	0.075	4.1039	0.848
. |* |	. |* |	9	0.095	0.111	5.0668	0.828
.*|. |	.*|. |	10	-0.140	-0.179	7.1930	0.707
. |* |	. |* |	11	0.081	0.096	7.9147	0.721
.*|. |	.*|. |	12	-0.162	-0.139	10.833	0.543
.*|. |	.*|. |	13	-0.116	-0.175	12.354	0.499
. |. |	. |. |	14	0.029	0.030	12.452	0.570
.*|. |	.*|. |	15	-0.069	-0.076	13.005	0.602
. |. |	.*|. |	16	-0.030	-0.092	13.112	0.665
. |. |	. |. |	17	-0.012	0.018	13.130	0.727
. |. |	. |. |	18	-0.011	0.047	13.144	0.783
. |. |	. |. |	19	0.030	0.025	13.255	0.825
. |. |	. |. |	20	0.045	0.041	13.508	0.855
. |. |	. |. |	21	-0.065	0.049	14.031	0.868
. |. |	.*|. |	22	-0.032	-0.068	14.158	0.896
. |. |	. |. |	23	-0.008	-0.015	14.166	0.922
.*|. |	. |. |	24	-0.070	-0.059	14.811	0.926
. |* |	. |. |	25	0.104	0.014	16.226	0.908
. |. |	. |. |	26	0.058	0.040	16.675	0.919
. |. |	. |. |	27	0.027	0.010	16.770	0.937
. |. |	. |. |	28	0.067	0.056	17.382	0.941
. |. |	. |* |	29	0.057	0.101	17.839	0.947

. |. |	. |. |	30	-0.022	-0.018	17.907	0.960
. |. |	. |. |	31	-0.035	-0.046	18.087	0.968
**|. |	**|. |	32	-0.233	-0.234	26.000	0.764
. |. |	. |. |	33	0.044	0.046	26.284	0.790
. |. |	.*|. |	34	0.031	-0.094	26.427	0.820
. |. |	.*|. |	35	-0.006	-0.073	26.433	0.851
.*|. |	. |. |	36	-0.066	-0.065	27.118	0.857

Null hypothesis: There is no serial correlation

Alternative hypothesis: There is serial correlation

Since the probability of Q-statistic (36 lags) are more than 5%, the null hypothesis is not rejected. Residuals are not serially correlated.

From the diagnostic tests conducted on the EGARCH model, there is no ARCH effect, the residuals are not serially correlated and the residuals are normally distributed, all of which are desirable characteristics for a model to be best fit. Thus the results from the EGARCH model are reliable.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

The chapter describes findings of the study, inferences arrived at from the findings and suggestions. In addition, it discusses the limitations of the study and proffers proposal for further enquiry.

5.2 Summary

The objective of the enquiry was to investigate subsistence of calendar anomalies, specifically, DOW phenomenon and January phenomenon in stock returns at Nairobi securities exchange using the NSE20 index for interval between 2nd January 2008 and 31st December 2015. The study employed three models, the OLS, symmetric GARCH (1, 1) and asymmetric EGARCH (1, 1) models. The ARCH-family models were chosen because of their robustness in capturing the various features of financial returns e.g. volatility clustering, leptokurtosis, heteroskedasticity, serial correlation and the leverage effect that cannot be modelled using the OLS model. The three models were estimated for DOW and January phenomenon, and diagnostic tests conducted to determine the suitability of the models and the reliability of the results thereof. The OLS estimation of the mean for DOW and January phenomenon evidenced the presence of serial correlation, ARCH effect and the residuals not being normally distributed, which were not desirable and thus made the results of the model not reliable. Diagnostics conducted on GARCH and EGARCH model, however, showed absence of ARCH effect and serial correlation which is desirable for a model to a good fit. Thus the results of the GARCH and EGARCH model were reliable.

5.3 Conclusions

The first part of the analysis on the DOW confirms subsistence DOW effect at the NSE. GARCH estimation results in table 7 and EGARCH estimation results in table 9, shows Monday return as negative and significant. Friday exhibited significantly highest return. The GARCH and ARCH term in the GARCH variance equation show that the volatility of returns at NSE is persistent.

The second part of the analysis on the January effect also confirms the presence of January effect at the NSE. GARCH estimation results in table 16 and EGARCH estimation results in table 19 show January recorded significantly highest return. Persistence of volatility is also observed in the GARCH variance equation.

5.4 Limitation of the study

The study covered the period between 2nd January 2008 and 31st December 2015 because of the cost of sourcing for the data from NSE. A relatively longer period would have required more resources. Conducting the research for a longer period would have provide better results on whether the calendar anomalies on stock returns really exist at NSE.

The stock market return used in the study did not factor transaction cost that might have provided different results were it considered. Caporale and Zakirova (2016) studied calendar anomalies at the Russian stock market. They found day of the week effect and the January effect at the Russian stock market using OLS, GARCH (1,1), TGARCH (1,1), EGARCH (1,1) models. However, after factoring in the transaction cost using bid-ask spreads as a proxy for transaction costs, the anomalies disappears.

5.5 Recommendation for policy

The study finds the presence of calendar anomalies at NSE and as such point out that NSE is not efficient. The CMA which is tasked with facilitating the growth of fair and efficient and orderly capital markets in Kenya through effectual regulation that promotes innovation and safeguards market integrity, should device appropriate strategies, regulations and policies to bring about operational and informational efficiency in the market and ensure fair and efficient market.

5.6 Suggestion for further research

The study did not factor in transaction cost in the market returns. Gregoriou et al. (2004) observed that when the returns are adjusted by using bid-ask spreads as a proxy for transaction costs, then the apparent calendar anomalies seem to disappear. This was corroborated by Caporale and Zakirova (2016) studying calendar anomalies at the Russian stock market. They observed the DOW and the January phenomenon when they didn't adjust the returns for the transactional cost. However upon adjusting the returns for the transactional cost, they observed the calendar anomalies disappear. Thus it would be interesting to find out whether calendar anomalies will still be present in the NSE market returns after adjusting for the transactional cost.

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