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Okumu Argan Wekesa
Simiyu Christine Nanjala
Karume Alice Wakarindi

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Effect of Calendar Anomalies on Stock Price Volatility using GARCH Models: Evidence from Nairobi Securities Exchange

By: Okumu Argan Wekesa[1], Simiyu Christine Nanjala[2] & Karume Alice Wakarindi [3]

Abstract
Many researchers have shown that the financial market of the Kenyan economy is weakly inefficient in terms of calendar anomalies. The inefficiency in the market may be explained by the volatility of the stock returns. This study was conducted with the main objective being to establish the effect of calendar anomalies on stock price volatility using the GARCH (1,1) model. The main characteristics of the Kenyan financial market are briefly explained. The empirical analysis is done on the transformed daily returns data of the NSE 20 share index. A comparison between the OLS model and the GARCH model is done on the return equation. The day of the week effect is found to be significant in both models where Friday had the highest returns while Monday had the lowest returns but January effect is only explained in the OLS model while the GARCH model does not show any presence of the January effect. The coefficients of the volatility equation are positive, significant and their summation is less than one indicating that the volatility is persistent and is mean reverting, that is, there is a normal volatility that the volatility should return to no matter what. In conclusion the variance in the calendar anomalies studied is time varying.

Keywords: *GARCH (1,1), EMH, Financial market anomalies, mean reversion*

Introduction

The finance world is one surrounded by a number of hypotheses. Efficient market hypothesis (EMH) is one of the most common hypotheses in the finance world. It was developed by Eugene Fama (1965) and he argued that it is impossible to beat the market prices since it incorporates and reflects all the relevant information. EMH relates to how quickly and rapidly the market responds to new information in the market (William, 2002). EMH takes three forms, In its weakest form prices fully reflect the information contained in the historical sequence of prices therefore the investors cannot profit by analyzing the past pattern of security prices. The semi strong form states that current security prices fully reflect not only past prices of the security but also the available public information. Thus, abnormal large returns cannot be earned consistently by investors using public information. The strong form asserts that all information known to any market participant is fully reflected in its price, thus no individual can benefit from even the most privileged of information as it has already been incorporated. Some of the known sources of this information include economic reports, company announcements, political statements and public surveys. Since

[1] *Senior Lecturer at the Cooperative University*
[2] *Senior Lecturer, KCA University*
[3] *Graduate Student, KCA University*

stock prices incorporate all available information it may sometimes be unnecessary to search for undervalued stocks to try and predict trends in the market through fundamental and technical analysis.

The second is the trading time hypothesis which asserts that the stock returns are generated during a transaction. Each day corresponds to one days adjusting for the effects of risk thus the average returns for a stock should be the same for all days of the week. It assumes that Monday is the first trading day while Friday is the last trading day thus ignores the existence of the weekend that is, a shock to the asset price on Friday influences the asset price on Monday.

A third commonly known hypothesis is the Capital Asset Pricing Model (CAPM) which proves investment therefore the average stock returns should be the same for all days of the week. With CAPM one cannot uniformly achieve a return greater than the average return in a given market and different stocks do have different returns which is brought about by the different betas of the stocks. CAPM argues that by increasing the unsystematic risk of a specified portfolio, investors are able to maximize the returns on that portfolio for a specified amount of variance.

Despite the existence of these hypotheses in the finance world, financial market seasonalities do exists and they violate these hypotheses. This existence of seasonality in the stock prices violates the weak form of market efficiency since stock prices are no longer random and can be predicted based on a historical pattern. This historical pattern has brought about the security price anomalies. According to Trersky and Kahneman (1986) ‘an anomaly is a deviation from presently accepted paradigms that is too wide spread to be ignored, too systematic to be dismissed as random errors and too fundamental to be accommodated by relaxing normative system’. This explains why the security price anomalies have attracted a lot research over the years. Some of the anomalies commonly known are calendar anomalies, fundamental anomalies and technical anomalies. The most researched is the calendar anomalies, which refers to the tendency of securities behaving differently on certain days of the week or month of the year. Some of the most known calendar anomalies include day of the week effect, turn of the month effect, the holiday effect and the January effect. This paper will concentrate on the calendar anomalies with specific reference to the day of the week effect and the January effect.

Studies have effectively and efficiently shown that seasonalities do exist in the stock market, for this reason OLS model cannot be used in predicting patterns. The ARCH and the extension to GARCH models (Bollerslev, 1986) are preferred for several reasons some of these are: one is that most relationships in finance are intrinsically non-linear. Second is the tendency of some financial data to have distributions that exhibit fat tails and excess peakedness at the mean which is known as leptokurtosis (Mandelbrot, 1963). Third is the tendency for volatility in financial markets to appear in bunches or bursts, rather than being evenly spaced over time. This is where large changes in asset prices tend to be followed by large changes and small changes followed by small ones. This is a common feature is time series for financial returns, which classical models may fail to capture; this feature is commonly referred to as volatility clustering (Mandelbrot 1976). Lastly is the tendency for volatility to rise more following a large price rise of the same magnitude. Putting these reasons in mind this study will use these models in the modeling of the data as reported by Bollerslev et al (1992) the GARCH (1,1) model appears to be sufficient to model the seasonality of stock returns.

General Objective

The study endeavors to estimate the effect of calendar anomalies on stock price volatility using the GARCH model.

Specific Objectives

(i) To determine the relationship between the day of the week effect and the stock price volatility at the Nairobi Securities Exchange

(ii) To assess the relationship between the January effect and the stock price volatility at the Nairobi Securities Exchange.

Hypothesis of the Study

In order to test for both the day of the week effect and the January effect the null hypothesis (H_0) will be tested against the alternative hypothesis (H_1) as follows:

Day of the Week Effect

H_0: The variance is constant for each day of the week.

H_1: The variance is time varying for each day of the week.

If the null hypothesis is rejected then the day of the week effect does exist.

January Effect

H_0: The variance is constant for each month of the year

H_1: The variance is time varying for month of the year

If the null hypothesis is rejected then the January effect does exist.

Significance of the Study

At the end of the day we have to look at some of the reasons as to why the study will be of importance, which stakeholders who benefit from the research and how do they use the information to their benefit.

(i) The scholars who wish to carry out any further studies in this area, they can use this research as a body of knowledge.

(ii) To the market player, that is the investors, they can be able to reap returns from repetitive patterns by designing strategies on when to buy low and sell high. If the investors are able to identify these patterns, they can also be able to balance between risk and return therefore making higher returns.

(iii) To the stock brokers any information in the stock market volatility will enable them plan their trading activities in terms of when to buy and when to sell. This will enable them make supernormal profits which can be used as a marketing strategy to the investors in the highly competitive market.

(iv) The government is known to be a regulator of the trading activities in order to monitor the economic activities of a country; it can use this information to regulate the activities of the market players thus achieving one of the macroeconomic goals of economic stability.

(v) The treasury and investment firms can use this information in their investment management so that they can maximize their interest income which contributes positively to the statement of comprehensive income.

Scope of the Study

The scope of this study is limited to the Nairobi Securities Exchange with specific reference to the NSE 20 share index in the Kenyan economy.

Limitations of the Study

This study will assess the effect of calendar anomalies in the NSE 20 Share index. This gives it a generalization limitation since its findings and conclusions cannot be applied to the stock market as whole or individual stocks. Furthermore, this study is only applicable in Kenya as compared to other countries since its focus on the NSE located in Kenya.

Literature Review

Introduction

This chapter looks at the research and conclusions that have been on the various types of calendar anomalies observed both locally and internationally, taking into consideration the developed, the developing and the less developed markets. It will look into the need of the study and what explanation the researchers have given to the existence of the anomalies.

Theoretical Review

This section looks into the theories that will guide the study. These will be the efficient market hypothesis and the mean reversion theory.

Efficient Market Hypothesis

The anomalies observed in the stock market may at times be brought about by the miss-pricings of the securities in the short run which eventually fades out in the long run, the miss-pricing at times cannot be detected this is according to EMH which states that in a perfect market stock prices reflect all the available information, may it be public or private information i.e. the market is assumed to be efficient in a given information set. As we struggle to answer the question as to whether the anomalies are just a miss-pricing of securities or it's a long run trend which investors can adapt and even make profits from their existence, we must first look at the EMH and see if they are related in any way.

The Efficient Market Theory is a subjective speculation theory operating under ideas and assumptions, which can be traced back to two individuals; Fama (1963) and Samuelson (1963). Both support that an efficient market is one where the stocks trade at fair values and reflect all possible information making it impossible for market players to determine the undervalued stocks that can aid in reaping of returns through market timing and stock selection strategies. The EMH developed from the RWH which was developed by Regnault (1863), which states that the market prices follow a random walk and therefore cannot be predicted. Fama (1970) refined the theory and classified it in three forms, weak, semi-strong and the strong form. The weak form stipulates that current stock prices reflect all historical information (publicly available information) and it is not possible for anyone to utilize past data for predicting future prices and earning abnormal returns through technical analysis. Fama(1965) found that the serial correlation coefficients for a sample of 30 Dow Jones stocks were significantly too small. The stock returns are serially uncorrelated and have a constant mean (Liam et al, 2010). In this form the stock prices are assumed to be following a random walk. Brock, Lakonishok & Lebron (1992) found that technical analysis is useless in the predictability of future prices thus supported the weak form efficiency. Despite all the previous academic works, recent studies have shown the connotation of technical analysis.

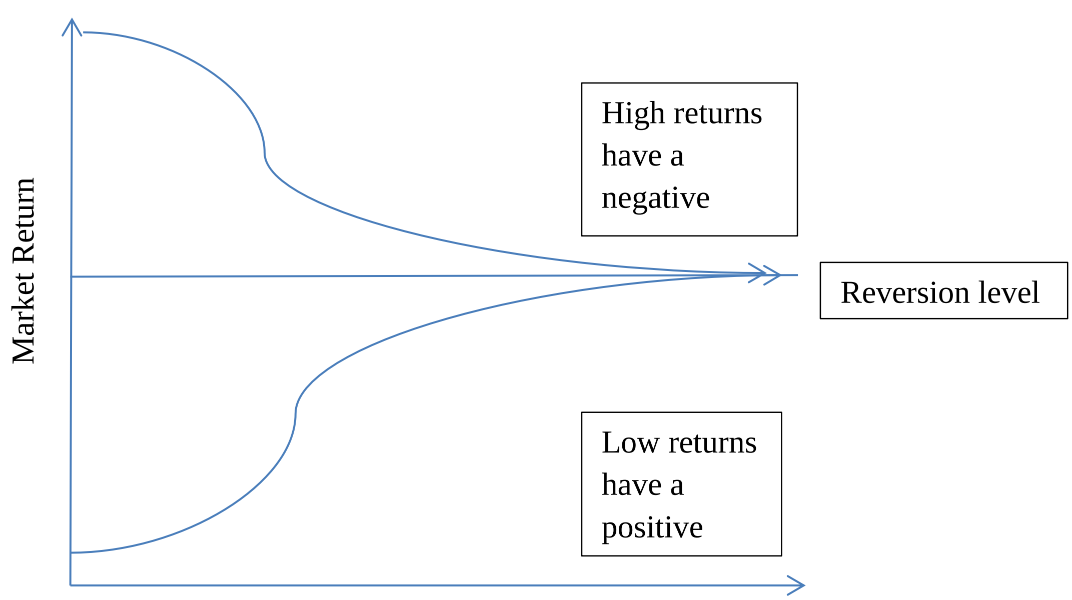
The Semi-strong form of EMH stipulates that the current stock price reflects all the publicly available information and instantly and briskly responds to reflect this information. Whether an investor uses the fundamental or technical analysis they may not be able to reap any returns. The publicly available information not only includes the historical stock price but also the company's financial statements, earnings and dividend announcement, merger plans, the competitors' strategies and macro- economic expectations among others. Multiple studies have been carried out in the support of this form and found that mutual funds returns that have been professionally managed do not exceed the returns of the market index returns. On the other hand studies have shown the insignificance of this form, Tobias (2012) did a test on the form at the NSE by studying the relationship between dividend announcement and firm value. He found out that NSE is not a semi-strong form and some investors can earn abnormal returns by having unequal access to public information. Similar results have been found by Elijah et al. (2014) and Patrick (2014) using the NSE.

The Strong form includes both the weak and semi-strong forms such that current stock prices reflect all available information whether it is public or private, the private information is also known as the insider information and no one can earn abnormal return by using private or insider's information (Khan & Ikram 2010, Fama, 1986). Jaffe (1974) finds considerable evidence that insider trades are profitable which is supported by Rozeff & Zaman (1988) implying the strong form does not exist.

EMH states that all relevant information is fully and immediately reflected in a security's market price, thereby assuming that an investor will obtain an equilibrium rate of return. In other words, an investor should not expect to earn an abnormal return (Dhar & Chhaochharia, 2008).
Samuelson (1965) argued that the financial market is micro-efficient and not macro-efficient and thus EMH only applies the individual stocks but not a portfolio of stocks. The back and forth between market inefficiency and market efficiency has prompted a lot of research and this will be one among the thousands.

Mean Reversion Theory

Everything that goes up must come down. Prices in the financial markets are very volatile bringing about the negativity and positivity experienced in returns and volatility, therefore mean reversion can either occur in returns or in volatility. In returns if there is a positive change, mean reversion causes a negative change and after a negative change it causes a positive change, this is demonstrated in the figure 2.1 below. This contradicts the efficient market hypothesis in that the investor is allowed to be rational (Graffin and Tversky, 1992).



The concept of mean reversion was first developed by DeBondt and Thaler, Lawrence Summer (1986) who showed that mean reversion is highly persistent in stock prices and they are statistically indistinguishable from a random walk. Mean reversion can be described as a process that slowly returns to its mean.

Mean reversion in volatility may sometimes provide an explanation for leptokurtosis and volatility clustering characteristics of financial time series data as documented by Mandelbrot (1963). According to Ping, Engle and Granger (1993) mean reversion in volatility takes an autoregressive structure and time varying conditional variance with slowly decaying autocorrelations and therefore cannot be modeled with simple ARIMA models. The main difference between the mean reversion in returns and volatility is that the return reversion is microeconomic in nature while the volatility one is macroeconomic.

Financial Market Anomalies

In the non-financial world an anomaly is an unusual occurrence. In the financial world an anomaly is a reliable pattern in the financial instruments prices that can be used to predict future prices thus investors are able to reap returns. It can be viewed as the most common challenge to EMH. Hubbard (2008) defined an anomaly as a trading opportunity that can result in high returns through various strategies. The fact that traders are able to develop trading strategies to benefit from stock returns and the investors have different ways of valuing stocks creates a problem with EMH. According to EMH prices should follow a random walk and not a predictable pattern, if this is observed then an anomaly does exist. Anomalies often indicate either market inefficiency or inadequacy in the asset pricing model used.

Not only have anomalies been studied in the equity market but also in the currency market, the futures market and the treasury bills markets. This study will focus on anomalies in the stock market with the assumption that they will indicate market inefficiency. Investors have been able to use fundamental and the technical analysis to reap returns which is against the semi-strong form of EMH, this creates an anomaly. Many investment managers believe that they can outperform the market by using various investment strategies, if they can achieve this then it shows that the market is inefficient. Since the documentation of these anomalies, most of them have been observed to have disappeared, diminished, faded, reversed or weakened, Schwert (2001).This sections will look into fundamental anomalies, technical anomalies and calendar anomalies and see if they still exist and some studies have proved otherwise.

Fundamental Anomalies

Fundamental analysis deliberates on fundamental factors affecting the company like Earnings Per Share (EPS) of the company, the dividend payout ratio, the competition faced by the company, the market share, quality management among others. Thus the share prices are affected by these fundamental factors. Fundamental analysis requires investigation at the macro-economic level, the industry level and the firm level. If an investor can be able to use these factors and predict the future prices of securities then it creates an anomaly referred to as fundamental anomalies. Some of the anomalies that have been discussed include:

Value Effect

The value of any asset can be calculated as the sum of all its future cash flows that have been discounted to the present. Fama & French (1992) analyzed data from a cross section of countries and found that the premium for investing in value stocks instead of growth stocks was about "three and half to four percent". Thus trading strategies that are based on value stocks offer high returns not because they are more risky but because they take advantage of false assumptions by investors (Graham & Dodd, 1934). Fama & French (1992, 1993) explain that value stocks tend to have higher volatility than growth stocks. Value trading involves buying stocks that have low prices relative to their accounting values and historical prices.

Other studies have proved otherwise; according to Lakonishok, Schleifer & Vishy (1994) the difference in average returns between the value stock and growth stocks was 10% with an explanation that investors overestimate the returns on growth stocks. This study was supported by Fama & French (1996) who used a 3-factor model to explain the value effect.

Price-to-earnings (P/E) effect

This effect occurs where portfolios of low P/E ratio outperform portfolios of high P/E ratio. An explanation to this is the possibility that stocks of low P/E ratio have a higher risk thus greater return.

This is documented by various scholars in support of the same Guin, (2005). Basu (1977) & Goodman & Peary (1983). French, (1992) explain that an investor can outperform the market with low P/E ratio stocks only because he is taking on more risk.

Book to Market Ratios

This effect occurs where stocks with high book to market ratios tend to outperform those with a low market to book ratio. The explanation provided is that companies with low book to market values tend to grow rapidly and this growth will at some point decline thus lowering the P/E ratio which in turn reduces the expected future returns thus the returns. On the other hand companies with high book to market ratio decline less in bear markets because of the low risk associated with them as the market value is close to the book value.

This effect is studied and supported by scholars like; Eugen & French (1992) & Fama (1991).

Small Size Effect

According to this anomaly small capitalization stocks tends to outperform large capitalization stocks. This is mostly experienced over the turn of the calendar year. Popularly known as the January effect. This is supported by Rolf Banz (1981), Keim (1983), Roll (1983) & Rozeff & Kinney (1976). The disappearance of this effect has been known to disappear as documented by Schwert (1982).

Neglected Stocks

This anomaly state that stocks that are less liquid tend to have minimum investors' attention but once they are discovered they tend to outperform prior stocks that investors were keen on. This is most common with small firms, when they are small no market player tends to associate with them but as they grow they catch the eye of the investors making them outperform larger firms that earlier existed and also the market index. This is documented by De Bondt & Thaler (1985).

Technical Anomalies

Prices of securities in the stock market fluctuate daily on account of continuous buying and selling. Stock prices moves in trends and cycles and they are never stable. Any market player hopes is interested in buying securities at low prices and selling them at high prices in order to make some arbitrage profit from them. Any technical analyst believes that the share prices are determined by the forces of demand and supply and these demand and supply forces are in turn influenced by fundamental, psychological and emotional factors. Technical analysis refers to forecasting techniques that utilize historical share price data.

Technical anomalies therefore anomalies that are based on the interpretation of technical analysis. The validity of the weak form in EMH depends on the existence of technical anomalies. Some of the technical anomalies that have been studied include:

Moving Averages

These are average prices of a security or an index over a specified interval which is continually updated forming smoother line known as a trend. The greater the slope of the moving average the stronger is the trend. These are used to smooth historical data in order to confirm the trend; this is done through simple moving average, weighted moving average or exponential average. Traders chose a trend that is convenient with their investment time frame. Moving average can also be used to detect and profit from fluctuating prices. Stocks that suddenly divert from their trading trend and revert within a short period of time can be used by traders to reap returns. That is buy stocks when the short period averages raises over the long period averages and sell the stocks when the short period average falls below the long period average. This is only if there are no other news that would have caused the same. This is documented by Brock (1992), Josef (1992) and Lakonishok et al (1992).

Trading Range Break

This refers to the spread between the high and low prices traded during a period of time. When a stock breaks below its trading range it means that there is thrust build up. This is based on the resistance and support levels. The resistances levels occur when a buying signal is created thus investors are under pressure to sell making the resistance level to break out than the previous level. The support level is the minimum price level which is the selling level. Technical analysis recommends a sale at support level and a buy at a resistance level which is a very difficult strategy to implement. This was studied by Brock (1992), Josef (1992) and Lakonishok et al (1992).

Momentum Effect

Momentum in technical analysis is the rate of change of security prices or the market index. This anomaly assumes that securities that have experienced high returns in the short run tend to continue to generate high returns in ensuing periods. There are various ways of measuring the momentum of a stock so as to determine whether it's overbought or oversold, if its overbought then traders get a buy signal and if its oversold traders get a sale signal. First is the rate of change in the current market price, which is used as a gauge of price extremes that will eventually revert back to the mean. Second is the relative strength index which compares the stock gains over the losses in a specific period of time, this period is usually 14days. If the gains are greater than the stock was overbought and if the losses were greater than the stock was oversold. Third is the stochastic oscillator where the highest high and the lowest low are selected in a 14 day period and the last closing price used to calculate the oscillator, last but not least is the William R which compares the most recent close to the high of a window period rather than to the low.

It is through these strategies that investors are able to pinpoint the patterns that the security is taking thus taking advantage of them to make abnormal profits.

Calendar Anomalies

They are also called seasonal anomalies. These are anomalies that are linked to a specific timing. They assert that the stock market is inefficient since stocks perform better in specific calendar periods. Studies have been carried out in various economies be it the developed, developing and the less developed. In this section we will look at the various calendar anomalies that have been studied and whether recent studies have proved their disappearance. According to Brooks (2004) calendar anomalies are the tendency of stock returns to display a predictable pattern at certain times of the day, week, month or year.

January effect

In this effect the average stocks in January are higher as compared to other months. It was first statistically examined by Rozett & Kinney (1976) who used data from 1904-1974 of the NYSE and discovered that January had abnormally high returns of 3.48% as compared to a return of 0.42% in the remaining months of the year, confirming the idea by Watchel (1942) who was the first economist to describe the January effect in the financial markets, he found that the DJIA from 1927 to 1942 showed frequent bullish tendencies from December to January in eleven of the fifteen years he studied.

The January effect occurs between the last trading day of the previous year in December and the 5th trading day of the new year in January, the explanation that has been given to this effect is the tax loss selling effect where investors prefer selling off their stocks in order to reduce the tax due, Chen & Singal (2004).

Ho (1990), studied the daily returns of eight Asian pacific stock markets in the period 1975-1987 and found the January effect is significant in six of them. Mehian & Pery (2002) studied three indices in the US market namely DJIA, NYSE & S&P 500, during the period 1964-1998, they found that the January effect is significant in all of them. Gultekin & Gultekin (1983), investigated the January effect in seventeen major industrialized countries and found the January returns to be high in most of them.

In Kenya studies at the NSE on the January effect have been studied, Peter (2013) used the NASI & NSE 20share index to investigate the January effect and stock returns, he found the effect to be significant in both indices, this is supported by Aligidee (2012) who studies the Nigerian and Egyptian stock markets. Nyamosi (2011) also had the same results, concluding that the January effect still does exist at the NSE.

Day of the week effect.

This effect refers to a pattern in on the part of stock returns in which the returns are systematically negative & positive returns are linked to a particular day of the week (DOW). Cross (1973) and French (1980) were among the first to study this effect. French examined the S&P 500 index returns in the period 1953-1977 and he observed that returns on Monday were negative as compared to the other days of the week where the returns were positive.

DOW effects are evident in the developed markets Jaffe Wasterrfield (1985) studied different markets which include Australia, Canada, Japan & UK and they concluded that high low days are not always on Friday or Monday, however Gregonous & Tsitians (2002) concluded that the DOW effect disappears once the bid-ask spread is considered in the study. He used the UK market. Gibbon & Hess (1981) also did an investigation of the S&P 500 index from 2nd July 1962 to 28th Dec 1978 and found that Monday has the lowest returns in the week thus strong support for the DOW effect. Kiymaz & Berumet (2003) found evidence of the DOW effect in both returns and volatility in four major indexes. The volatility varied with the DOW, with the highest volatility being on Monday for Germany & Japan, on Friday for Canada & USA and Thursday for UK.

Studies in the emerging markets have also been carried out; McGowan, Yener & Johnson (1989) studied the Manila Mining Index in 1976-1987 and found existence of the DOW effect. Use of the GARCH modeling which takes into consideration the time series properties has also been used to prove the existence of the same, Al-Loughai & Chappell (2001) used GARCH (1,1) in the Kuwait stock exchange and prove existence of the DOW effect with high returns on Friday and low returns on Monday. Poshakwale (1996) supported this by doing a study in Bombay Stock exchange, India, and come up with the same results. Tis was reinforced further by Choundy (2000) who did a study in seven emerging Asian stock markets to concluded a DOW effect in both returns and volatility.
In Kenya similar studies have also been carried out, Onyuma (2009) examined the NSE 20 share index using the GARCH modeling and found positive returns on Friday and negative ones on Monday. Kulavi (2013) also documented similar results with a study on the DOW effect on stock market volatility using the regression analysis. Makokha (2012) also come up with the same results with his study on the DOW effect on stock returns.

Recent studies have also proved disappearance of the same as documented by Santemases (1986), Marashdeh (1994), Pena (1996), Domirer & Karan (2002) among others who documented non-significance of the DOW effect. Alagidede (2008) also rejects the DOW effect in African countries among them Kenya, Egypt, Morocco & Tunisia.

This study will investigate if it still does exist through use of the recent data.

Turn of the month effect

This refers to the tendency in stock returns rising during the last day of the month and the first three trading days of the month. Nosheen et al. (2007) & Chandra (2009). Lakonishok & Smidt (1988) investigated the DJIA and found that the mean return of the turn of the month effect trading days is about eight times than the other trading days. Toucher & Kim (2004) investigated the turn of the month effect in Czech Republic, Slovakia & Slovenia and found that in Czech the January and May returns were the highest while they were lowest in June, he found no significant turn of the month. In Kenya Melex (2014) studied the turn of the month effect at the NSE and found it to be insignificant.

Holiday effect

It refers to the tendency of markets doing well the days just before a holiday. This effect occurs when the stock returns just before a holiday are high as compared to hose during the holiday. This can be contributed to the market players being optimistic about the stock prices just before a holiday in comparison to the prices after the holidays. This can also be attributed to the players selling off their stocks before holidays in order to raise money for vacations. According to Petengill (1989) abnormal returns are mostly experienced just before public holidays. In most cases the pre-holiday and post-holiday returns are unusually high as compared to returns of regular days. Rusugu (2005) studied the holiday effect at the NSE and found that the means returns of trading days just before a holiday were 1.6 times higher as compared to those of regular days but this was insignificant.

Causes of Financial Market Anomalies

Various researchers have attempted to give an explanation to the existence of the stock anomalies but none has been proven to be satisfactory enough. Some of the possible explanations provide are; first is the Measurement error which indicates that inefficient economical methodologies that have been used to been used to measure stock returns cause the anomalies. According Keim & Staugh (1984) the negative returns on Monday are caused by the positive errors in the price of Friday returns. Though this is not a congenial explanation to the Monday effect.

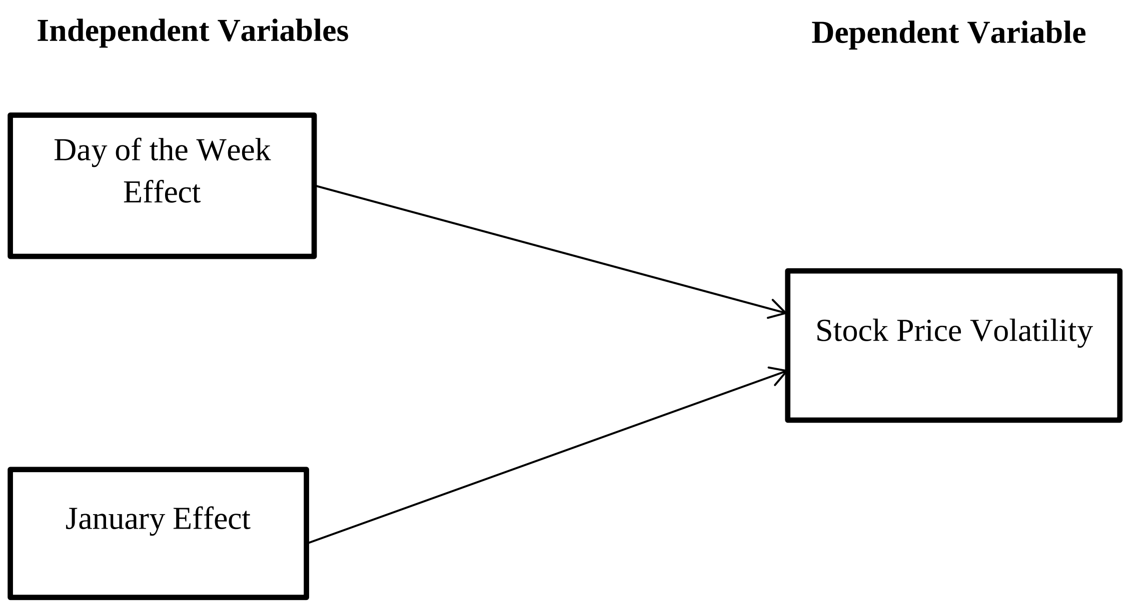
Another possible explanation is the Tax loss selling at year end where investors sell off their stocks at years end to cash in gains and sell losing stocks to offset their gains for tax purposes. Researchers have speculated that, in order to reduce their tax liabilities, investors sell their “loser” securities in December for the purpose of creating capital losses, which can then be used to offset any capital gains. A related explanation is that these losers tend to be small-cap stocks with high volatility. This increased supply of equities in December depresses their prices, and then these shares are bought in early January at relatively attractive prices. This demand then drives their prices up again. Overall, the evidence indicates that tax-loss selling may account for a portion of January abnormal returns, but it does not explain all of it. Roll (1983) documented that the high volatility of small firms caused them to experience short term capital losses for the purpose of taxation before the year end. This selling pressure cause the investors to sell off their stocks in December and buy them back in January in order to re-establish their original investment positions causing the January effect.

Another is Information asymmetry- Rystrom & Benson (1989), found that good news and bad news are not even during the weekend. It is believed that companies announce the bad news at the weekend to allow the affected to absorb the news during the two days, while the good news is announced on Monday. During the week interested investors get recommendations from stock brokers and trade news while during the weekend they are exposed to different sources of information which in turn influences their trading pattern in the week. French (1980) suggested that the negative returns on Monday are caused by the bad news that is released over the weekend when the market is inactive. Despite the market having time to rejuvenate before Monday, market players sell their stocks due to panic causing the negative returns on Monday.

The absence of negotiations during the weekend also is attributed as one of the causes of the weekend effect. Brokers are not available over the weekend in order to give advice to investors, according to Miller (1988) their absence gives time to investors to search for information and determine their own investment strategy. According to Groth, Leweillen, Schlarbaum & lease (1979) a higher percentage of stock broker (77%) recommend purchases as compare to 23% who recommend sales. This explains the negative returns on Monday.

Last but not least is behavioral science which is the study of psychology on the behavior of financial practioners and subsequent effect in the market. Some of the behaviors that have been studied include overconfidence (Fischoff & Slovic, 1985), over-reaction (DeBondt & Thaler, 1985), loss aversion (Kahneman & Tversky, 1979), psychological accounting (Kahneman & Tversky, 1981) and regret (Bell, 1982) among others. It is through these human decision-making strategies under uncertainties that investors are able to make returns thus making the markets inefficient.

Conceptual Framework



Data and Methodology

Introduction

This chapter looks into the research design, the population used, the data collection method (s) and the data analysis techniques.

Research Design

A research design is mostly based on the research question. According to Yin (2009) it consists of a logical sequence that links the study objective to the data and the conclusion. This study will use a descriptive research design. In a descriptive research design we aim at answering what, who, where, when, and how questions in order to describe a relationship, a situation, or characteristics. Since this thesis aims at finding out the relationship between calendar anomalies and stock volatility a descriptive research design was appropriate.

Population of Study

The populations of interest for this study will be 20 companies that are listed at the NSE that make up the NSE 20 share index. Though the companies in the index have been changing since its inception in the year 1964, appendix 1 shows the companies that currently are in the NSE 20 share index. The study will use the NSE 20 share index from January 1994 to December 2014. There is a total of 5,204 daily observations excluding non-trading days and public holidays.

Data Collection

This study relied entirely on secondary data which was obtained from the NSE database. The daily closing prices of the NSE 20 share index for 20 years covering the period 1994-2014 was sourced giving a total of 5204 observations. This index is a composite index measured from the best 20 performing stocks listed at the NSE. The data will be edited and entered in an excel sheet and analyzed using STATA using the GARCH modeling.

Data Analysis

The index stock returns for the will be defined by the following expression:

$R_t = \log\,(P_t - P_{t-1})$ ……………………………………………………………………….(1)

Where P_t is the current day closing price and the P_{t-1} is the previous day's closing price.

OLS Analysis

The ordinary least squares method (OLS) has been used by some scholars in the past to study the calendar anomalies. This study will initially apply this model to estimate the day of the week effect and the January effect. The following equations will be used.

Day of the Week effect

$$R_t = D_M R_M + D_T R_T + D_W R_W + D_{TH} R_{TH} + D_F R_F + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

Where R_t is the index return of the day and D_1 *to* D_5 represent the dummy variable from Monday to Friday.

January Effect

$$R_t = \sum_{i=1}^{12} \beta_i D_{it} + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3)$$

Where R_t is the index return of the day and D_1 *to* D_{12} represent the dummy variable from January to December.

Equations 2 and 3 will work with some assumptions like constant mean of error term, constant unconditional variance of the error term, normal distribution in the error term and no correlation in the error term in different periods among others. However financial time series data has been known to show some properties which include; volatility clustering where periods of high volatility are followed by periods of high volatility and periods of low volatility are followed by periods of low volatility, leptokurtosis where the distribution of returns is fat tailed and leverage effect where the volatility of a negative shock is higher than that of a positive shock taking into consideration that they are of the same magnitude. These properties cannot be captured by OLS and thus a good volatility model is required.

Time Series Analysis

Before 1982 time series data was modeled using the ARIMA models which were critiqued since they assumed constant volatility and conditional expectation thus ignoring the properties of financial data. Engle (1982) come up with ARCH models which allows for the modeling of the varying conditional variance in financial data. This conditional variance can be represented as:

ARCH (q)

$\varepsilon_t \sim (0, \delta_t^2)$

Where the ε_t is the disturbance term equation and δ_t^2 is:

$$\delta_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, e_{t-1}^2$$

Where:

δ_t^2 is the time varying conditional variance.

q is the number of lagged terms

α represent a vector of parameters. $(\alpha_0, \alpha_1, \alpha_2 \ldots \ldots \alpha_q)$

This implies that the conditional variance grows and shrinks with respect to the magnitude of past shocks with the error structure being the ARCH model. The ARCH model requires long lags in the conditional variance equations making it a limitation in its use, thus an extension to the ARCH was introduced by Bollerslev (1986), the GARCH model which include the lagged values of conditional variance and he demonstrated that a GARCH model with a small number of terms is way more appropriate than an ARCH with a large number of terms. A mathematical form of GARCH (p, q) conditional variance can be represented as follows:

$$\delta_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, e_{t-1}^2 + \sum_{j=1}^{p} \beta_j \, \delta_{t-j}^2$$

Where ;

δ_t^2 is the time varying conditional variance.

q Is the number of lagged terms

p is the lagged values of the conditional variance

α & β represent a vector of parameters to be estimated. $(\alpha_0, \alpha_1, \alpha_2 \ldots \ldots \alpha_q)$

This implies that all past shocks influence the current value of conditional variance.

Model Specification

In this study the data will first be tested for stationarity using the Phillip Peron test and any non- stationarity in the data will be corrected before modeling. AIC and BIC are the most commonly used criteria in selecting sufficient models. In this study these will not be used and the GARCH (1,1) will be selected which according to Chong et al (1999), French et al (1987) and Franses & Dijk (1996) is already sufficient for financial time series data. To analyze the calendar anomalies with specific reference to the day of the week effect and the January effect using the GARCH models, dummy variables will be introduced into the model.

January Effect

In order to examine the January effect we add dummy variables to the GARCH (1,1) model. The model will be defined as

$$R_t = \beta_0 + \sum_{i=1}^{12} \beta_i D_{it} + \mathcal{E}_t$$

Where R_t is the index return of the day and D_1 *to* D_{12} represent the dummy variable from January to December.

To specifically examine the January effect, the constant will be excluded from the model to avoid the dummy variable trap. The model will be defined as:

$$R_t = \sum_{i=1}^{12} \beta_i D_{it} + \mathcal{E}_t$$

Where $\mathcal{E}_t \approx (0, \delta_t^2)$, δ_t^2 is the conditional variance of $\mathcal{E}_t$ which in the GARCH (1,1) can be defined as:

$$\delta_t^2 = \alpha + \varpi\, e_{t-1}^2 + \lambda\, \delta_{t-1}^2$$

Day of the Week Effect

As the case above, to measure the DOW effect we introduce dummy variable to the GARCH (1,1) model as follows:

$$R_t = \beta_0 + \sum_{i=1}^{5} \beta_i D_{it} + \mathcal{E}_t$$

Where R_t is the index return of the day and D_1 *to* D_5 represent the dummy variable from Monday to Friday.

But $\mathcal{E}_t \approx (0, \delta_t^2)$, therefore:

$$R_t = D_M R_M + D_T R_T + D_W R_W + D_{TH} R_{TH} + D_F R_F + \varpi\, e_{t-1}^2 + \lambda\, \delta_{t-1}^2$$

With the conditional variance defined as:

$$\delta_t^2 = \alpha + \varpi\, e_{t-1}^2 + \lambda\, \delta_{t-1}^2$$

Results and Discussions

Introduction

In this chapter, the study presents results of data analysis and the findings. The data will be transformed to smoothen it by adding 300 to the index return so as to eliminate the negative returns then introduce logarithms to reduce the variation. The study begins by giving descriptive statistics of the data and then proceeds to linear regression analysis which will be compared to the time series analysis using the GARCH (1,1) models.

Descriptive Statistics

Table 4.1 gives the mean, median, maximum value, minimum value, skewness and kurtosis for the returns of the entire period as well as return for each day of the week, while Table 4.2 gives the mean, median, maximum value, minimum value, skewness and kurtosis for the returns of the entire period as well as return for each month of the year.

Table 4.1: Descriptive Statistics – Day of the Week Effect.

Statistics	All Days	Monday	Tuesday	Wednesday	Thursday	Friday
Observations	5203	1012	1054	1052	1056	1029
Mean	5.699614	5.697847	5.698462	5.695706	5.697142	5.709065
Median	5.703716	5.699356	5.703204	5.703274	5.70259	5.708206
Maximum	6.569958	6.223825	6.29118	6.345742	6.569958	6.270346
Minimum	3.103827	4.95477	4.166975	3.106827	4.848822	4.85031
Std. Dev	0.112521	0.981329	0.120286	0.130978	0.107266	0.101557
Skewness	-3.57054	-0.75858	-2.89186	-7.711289	-1.01014	-0.75784
Kurtosis	72.5115	13.28411	36.67841	150.2769	18.61344	16.40323

From table 4.1 above, the mean for the entire period is 5.699614% with a standard deviation of 0.1125207, skewness of -3.570535 and kurtosis of 72.5115 thus rejecting normality of the data in the study period. The returns are showing excess kurtosis indicating that they are leptokurtic.

Analyzing the returns for each day, Friday has the highest mean return of 5.709065% while Wednesday reports the lowest mean return of 5.695706%. The lowest NSE 20share index return of 3.106827 is observed on Wednesday with the highest NSE 20share index return of 6.569958 being on Thursday. All the days shows that the returns are negatively skewed and excess kurtosis is also observed in the index returns. The highest standard deviation of 0.981329 is observed on Monday with lows of 0.1015568 being observed on Friday, this is in line with studies by Kiymaz and Berumet (2003) in Germany and Japan indicating the presence of the Day of the Week Effect in the NSE 20 share index.

Analyzing the returns for month of the year, December has the highest mean return of 5.716944% while March has the lowest mean return of 5.678956%. The lowest NSE 20share index return of 3.106827 is observed in January with the highest NSE 20share index return of 6.569958 is also on the same month. All the months shows that the returns are negatively skewed except for February, November and December which are positively skewed and excess kurtosis is also observed in the index returns. The highest standard deviation of 0.199433 is observed in January with lows of 0.076722 being observed in June. This may temporarily show the presence of the January effect in Stock price Volatility.

Table 4.2: Descriptive Statistics – January Effect.

Month Of the Year	N	Mean	Median	Max	Min	SD	Skewness	Kurtosis
All Months	5203	5.699614	5.703716	6.569958	3.106827	0.112521	-3.570535	72.5115
January	437	5.702355	5.709632	6.569958	3.106827	0.199433	-6.134792	76.58709
February	404	5.699392	5.700315	6.279665	5.030961	0.121774	0.4779741	11.62647
March	455	5.678956	5.691191	6.207543	4.848822	0.153652	-1.618378	12.00053
April	413	5.696769	5.701012	6.152903	4.714831	0.098688	-3.155751	31.01981
May	450	5.705792	5.705364	5.979949	5.424245	0.076722	-0.1447458	4.826966
June	431	5.708517	5.709268	6.026928	5.240847	0.082806	-0.5584721	8.054536
July	463	5.699849	5.703106	5.949287	4.994844	0.07593	-2.196621	21.34877
August	451	5.692968	5.695347	5.98207	5.166784	0.078375	-1.18821	10.04185
Sept	431	5.69414	5.70138	6.193589	5.125689	0.099633	-1.087297	10.28789
October	437	5.70381	5.709787	6.236683	5.226821	0.100667	-0.8260322	9.465629
Nov	437	5.698325	5.70168	6.345742	5.191623	0.098591	0.4762947	12.94647
December	394	5.716944	5.711023	6.192853	5.206312	0.0938	0.4085389	10.06114

The research also looks at the trend and the Auto-Correlation functions of the index return function, this is represented in the figure 4.1 below. According to the figure below the index return has a trend which is stationary as per the time plot and the ACFs indicate that the decay isn't exponential indicating that the returns are stationary. The time plot also indicates that the index returns are highly volatile thus the ARIMA

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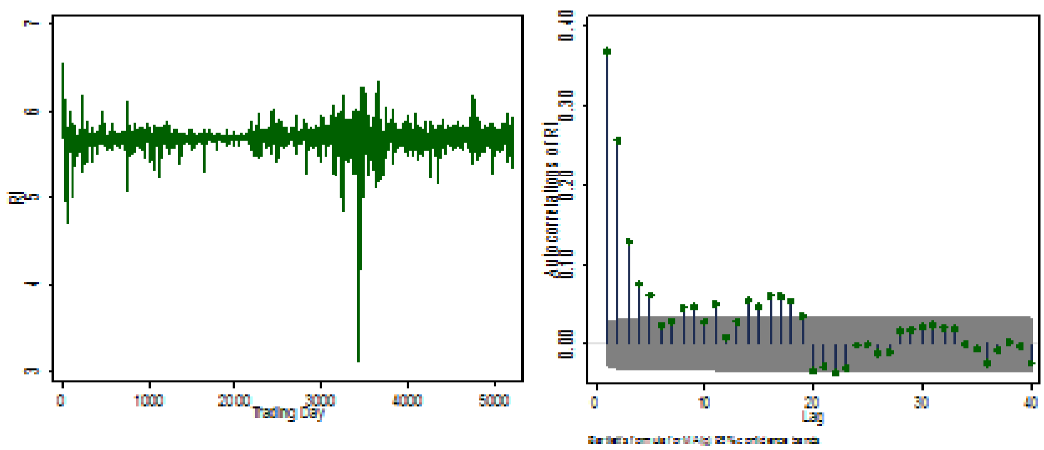
models that assume a constant conditional variance may not be appropriate for this study therefore the study will use the GARCH models which appreciate variation in the conditional variance.

Figure 4.1 Time Series Plot and Correlogram



Econometric Analysis

The study will use both linear regression and time series econometric models for data analysis. The first step is to run the linear regression then use Augmented Dickey Fuller and phillip peron stationarity test then run the GARCH (1,1) model.

OLS Analysis

A linear regression will be ran in Stata and post estimation diagnostic test carried out to determine the adequacy of the model.

Table 4.3 Day of the Week Effect for the Regression Model

Day of The Week	Coefficient	P Value	95% confidence Interval
Monday	-0.3619859	0.715	-2.303822 1.579851
Tuesday	0.3921392	0.686	-1.510615 2.294893
Wednesday	-0.3630204	0.709	-2.267582 1.541541
Thursday	-0.3044037	0.754	-2.205355 1.596547
Friday	3.123492	0.001	1.197762 5.049221

The results above show insignificantly negative returns on Monday and significantly positive returns on Friday, indicating the presence of the day of the week effect. Insignificant negative returns are also observed on Wednesday and Thursday with insignificant positive returns observed on Tuesday.

According to the table 4.4 below, the month of December and that of January show positive significant returns. This can be explained by two anomalies either the January Effect or the Holiday effect. The January effect is seen where the month of January has the second highest significant returns while the Holiday effect is seen where December has the highest significant returns. In Kenya December is assumed to be the holiday month.

Table 4.4 January Effect OLS Model

Month of The Year	Coefficient	P Value	[95% Conf.Interval]	
January	4.100214	0.006	1.150167	7.05026
February	0.970075	0.535	-2.09809	4.038241
March	-4.121091	0.005	-7.0122	-1.22999
April	-0.7683359	0.62	-3.80289	2.266216
May	1.484897	0.317	-1.42223	4.39202
June	2.443525	0.107	-0.52698	5.414035
July	-0.3578992	0.807	-3.22392	2.50812
August	-2.341158	0.114	-5.24506	0.56274
September	-1.448484	0.339	-4.41899	1.522025
October	1.49477	0.321	-1.45528	4.444817
November	-0.1473728	0.922	-3.09742	2.802674
December	5.335319	0.001	2.22846	8.442177

Post Estimation Diagnostic Analysis

These analyses are carried out to justify if the assumptions made by the OLS models above do apply, if there is violation of the OLS assumption then the GARCH (1,1) model is applied.

Table 4.5 Day of the Week post estimation diagnostic analysis for the Regression Model

Test	Results (p-value)	Conclusion
Durbin h Watson Test	0.0000	$P<0.05$, reject H_0 which shows that the errors are autocorrelated.
White Test	0.7201	$P>0.05$, fail to reject H_0 which shows that the errors are homoscedastic.
Arch effect	0.0000	$P<0.05$, reject H_0 which shows that the unconditional variance is not constant.

Table 4.6 January Effect diagnostic analysis for the Regression Model

Test	Results (p-value)	Conclusion
Durdin- h Watson Test	0.0000	$P<0.05$, reject H_0 which shows that the errors are autocorrelated.
White Test	0.0000	$P<0.05$,reject H_0 which shows that the errors are heteroskedastic.
Arch effect	0.0000	$P<0.05$, reject H_0 which shows that the conditional variance is not constant.

Many classical assumptions in OLS are violated when modeling financial data and this can be confirmed from the above results in Table 4.5 and Table 4.6 where the errors are either autocorrelated, heteroskedastic or both. The conditional variance is not constant indicating presence of ARCH effects, thus if we use the OLS we will underestimate the variance leading to a large t-statistic value thus concluding that the parameter is significant. This leads to a higher chance of committing the type 1 error. Having this in mind the researcher will ignore the OLS results and use an Auto Regressive model that will take into consideration the above violations, in this case the GARCH (1,1) model will be used. The study starts with testing for stationarity of the Index Returns.

Testing for Stationarity

Testing for stationarity of Time Series data is important to avoid spurious regression. To test for stationarity of the variables, the Augmented Dickey Fuller (ADF) (1979) and the Phillip Peron tests were carried out.

Table 4.7: Stationarity Test for the Index Return

Variable	**Test Statistic**	**1% Critical Value**	**5% Critical Value**	**10% Critical Value**	**p-value**
***Rt* (with trend)**					
ADF test	-49.017	-3.96	-3.41	-3.12	0.0000
Phillip Peron	-51.085	-3.96	-3.41	-3.12	0.0000

In both tests the test statistics are greater that the critical proving that the index returns are stationary in trend at 5% levels, confirming the results of the time series plot and the correlogram.

Lags Length Selection

In this study the researcher will not use any criteria to select the lags in the mean and conditional variance equations, instead the model GARCH (1,1) for both the Day of the Week Effect and January Effect will be used which to some researchers like Chong et al (1999), French et al (1987) and Franses & Dijk (1996) is already sufficient for financial time series data.

GARCH (1,1) Model

The GARCH Model was developed by Engle (1982) and Bollerslev (1986) to provide a basis for analyzing the time varying mean and variance effects in time series data. The model provides a more flexible structure in that it allows all lags to exert influence on the conditional variance including the past value of conditional variance itself and in addition to lagged values of the squared errors.

The researcher will use the GARCH (1,1) to determine the effect of the January Effect and Day of the Week Effect on stock price volatility. The results are presented in the tables below:

Table 4.8 The Return and volatility equation for Day of the Week Effect.

	Day of the Week	GARCH(1,1)
Return Equation		
	Monday	5.696014 (0.0000)
	Tuesday	5.698871 (0.0000)
	Wednesday	5.699845 (0.0000)
	Thursday	5.698831 (0.0000)
	Friday	5.702636 (0.0000)
Volatility Equation		
	φ	0.2336369 (0.0000)
	λ	0.8062349 (0.0000)
	α (constant)	0.0000901 (0.0000)
Wald Test p-value	0.0000	

The value in parenthesis shows the p-value of the coefficient at 5% level

The table 4.8 shows that all the returns are significant and positive including the coefficients of the conditional variance. In the Return equation Friday has the highest returns of 5.702636 with Monday recording the lowest returns of 5.696014which provides support for evidence of the day of the week effect. This supports the results of the OLS model above. These results are in line with a study by AL-loughani & Campbell (2001) who studied the Kuwait Stock Exchange. The estimated coefficients of the volatility equation are positive and significant and the sum of φ and λ is approximately one. Their significance indicates that the volatility is persistent both in the short run and in the long run. The wald test p value of

0.0000 makes us reject the null hypothesis that all the coefficients on the independent variables in the mean equations are zero. Here the null hypothesis is rejected at the 5% level.

The table 4.9 below shows that all the returns are significant and positive including the coefficients of the conditional variance. In the Return equation October has the highest returns of 5.717026 with March recording the lowest returns of 5.6854, this brings contradicting results of the January effect. The estimated coefficients of the volatility equation are positive and significant and the sum of φ and λ is approximately one. Their significance also shows that the volatility is persistent both in the short run add the long run. Wald test is against the null hypothesis that all the coefficients on the independent variables in the mean equations are zero. Here the null hypothesis is rejected at the 5% level.

Table 4.9 The Return and volatility equation for January Effect.

	Month of the Year	Coefficient
Return Equation		
	January	5.702211 (0.0000)
	February	5.700489 (0.0000)
	March	5.685402 (0.0000)
	April	5.69668 (0.0000)
	May	5.697672 (0.0000)
	June	5.705023 (0.0000)
	July	5.702969 (0.0000)
	August	5.691432 (0.0000)
	September	5.692842 (0.0000)
	October	5.717026 (0.0000)
	November	5.698814 (0.0000)
	December	5.704013 (0.0000)
Volatility Equation		
	φ	0.24511 (0.0000)
	λ	0.80358 (0.0000)
	α (constant)	6.97e-05
Wald Test	0.0000	

The value in parenthesis shows the p-value of the coefficient at 5% level

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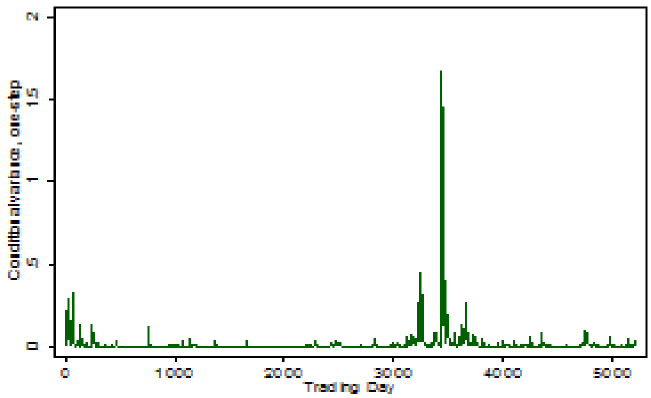
Figure 4.2 Conditional Variance Plot



The conditional variance plot clearly state that there is a lot of volatility between the 3000-4000 trading day of the study period. The period was approximately between the years 2007-2008 which might be explained by the post-election violence which occurred at the same time but the volatility reverted to its mean as observed from the above plot.

4.7 Post Estimation Diagnostic Analysis for the GARCH(1,1) Model

					-1 0	-1 0 1	
LAG	AC	PAC	Q	Prob>Q	[Autocorr	[Partial Autocor]	
1	0.0147	0.0147	1.1229	0.2893	I	I	
2	-0.0046	-0.0048	1.2317	0.5402	I	I	
3	-0.009	-0.0088	1.6521	0.6476	I	I	
4	-0.0133	-0.0131	2.5789	0.6306	I	I	
5	-0.0048	-0.0045	2.7008	0.746	I	I	
6	-0.0164	-0.0165	4.099	0.6633	I	I	
7	-0.0097	-0.0095	4.5858	0.7104	I	I	
8	-0.0022	-0.0024	4.612	0.7981	I	I	
9	-0.0142	-0.0147	5.6707	0.7724	I	I	
10	-0.0099	-0.0102	6.1827	0.7997	I	I	
11	-0.0061	-0.0064	6.3783	0.847	I	I	
12	-0.0094	-0.01	6.8359	0.8683	I	I	
13	-0.0096	-0.0103	7.3154	0.8852	I	I	
14	-0.0142	-0.0148	8.3679	0.8693	I	I	
15	-0.0016	-0.0023	8.3814	0.9076	I	I	
16	-0.0084	-0.0096	8.7491	0.9234	I	I	
17	0.0144	0.0136	9.832	0.9105	I	I	
18	0.0007	-0.001	9.8346	0.9372	I	I	
19	0.0196	0.0186	11.837	0.8925	I	I	
20	-0.0052	-0.0067	11.977	0.9169	I	I	

The GARCH(1,1) mode for the day of the week effect seems to be sufficient since the p-value of the Q-statistic is greater than 0.05thus failing to reject H_0 indicating absence of the ARCH effects.

					-1 0	-1 0 1	
LAG	AC	PAC	Q	Prob>Q	[Autocorr	[Partial Autocor]	
1	0.0138	0.0138	0.99444	0.3187	I	I	
2	-0.0052	-0.0054	1.1372	0.5663	I	I	
3	-0.0097	-0.0096	1.6319	0.6522	I	I	
4	-0.0145	-0.0142	2.7199	0.6057	I	I	
5	-0.0036	-0.0033	2.7876	0.7327	I	I	
6	-0.0172	-0.0174	4.3319	0.6319	I	I	
7	-0.0096	-0.0094	4.8098	0.6832	I	I	
8	-0.0036	-0.0038	4.8762	0.7707	I	I	
9	-0.015	-0.0155	6.0489	0.735	I	I	
10	-0.0122	-0.0126	6.8256	0.7418	I	I	
11	0.0028	0.0025	6.8658	0.8098	I	I	
12	-0.0107	-0.0118	7.4686	0.8252	I	I	
13	-0.0088	-0.0096	7.8757	0.8516	I	I	
14	-0.0149	-0.0155	9.0345	0.8288	I	I	
15	-0.0055	-0.0061	9.1949	0.8671	I	I	
16	-0.0101	-0.0114	9.7314	0.8803	I	I	
17	0.0139	0.0132	10.736	0.87	I	I	
18	0.0023	0.0006	10.764	0.9041	I	I	
19	0.0188	0.0176	12.606	0.8581	I	I	
20	-0.0046	-0.006	12.716	0.8892	I	I	

The GARCH(1,1) mode for the January effect seems to be sufficient since the p-value of the Q-statistic is greater than 0.05thus failing to reject H_0 indicating absence of the ARCH effects.

Summary of the Results

Introduction

In this chapter the summary, conclusions and from the research findings of the study and recommendations on areas of further research study are presented.

Summary

The general objective of this study was to investigate the effect of calendar anomalies on stock price volatility using the GARCH Models in Kenya for the period January 1994 to December 2014. The daily index closing prices were used to generate the index returns and their logarithms found. The specific objectives focused on the day of the week effect and the January effect on stock price volatility. An insight into the characteristics of the data was presented by the descriptive statistics. The index returns were seen to have a trend as per the time series plot. Stationarity of the data in trend was then tested using Augmented

Dickey Fuller (1957) test and the Phillip Peron test, the returns were stationary. The logarithms of the daily returns were regressed against the dummy variables for the days of the week and the months of the year where the two models modeling were adopted.

The first model, OLS, assumed the constancy in the residual terms and the findings were that Friday had positive significant returns as compared to Monday which had negative insignificant returns indicating that the DOW effect is present if the return equation. These findings are consistent with previous studies at the Nairobi Securities Exchange by Onyuma (2009). On the other hand January and December are seen to have positive significant returns indicating the presence of the January effect and the Holiday Effect as December is seen to be the vacation month in Kenya. The post estimation analysis for both effects were carried out and some of the classical assumptions of OLS were violated specifically autocorrelation of the residual errors, homoscedasticity and constant unconditional variance. Thus the efficiency of the model was affected.

The second model allowed the time varying conditional variance to follow GARCH (1,1) specification. The model has two equations, the mean equation and the volatility equation. In the volatility equation the estimated coefficient of the constant term for the conditional variance is α, while λ and φ are the estimated coefficients of the lagged value of the squared residuals term and the lagged value of the conditional variance respectively. The mean equation in the DOW effect shows Friday has the highest significant returns with Monday having the lowest significant returns. These findings are similar to those of the OLS model. In the volatility equation the sum of the coefficients excluding that of the constant term is approximately one and both are positive and significant indicating a strong and persistent effect on volatility. On the other hand the mean equation of the January effect indicates the October has the highest significant returns with March having the lowest significant returns. The volatility equation shows that the sum of the coefficients excluding that of the constant term is approximately one and both are positive and significant indicating that we absence of negative or implied variance as suggested by Bollerslev (1986) for the specification test. Post estimation diagnostic analysis were also carried out for both effects and ARCH effects were no more for lags 1-20 indicating the efficiency of the model. These findings indicates that the standardized residuals terms have constant variances and do not exhibit autocorrelation.

Conclusion

The variance δ is a function of an intercept α, a shock from the previous period φ and the variance of the prior period λ. From the data analysis all the coefficients are positive and significant for both DOW effect and the January effect indicating that they satisfy the non-negativity of the conditional variance for each given time *t*. In both instances the sum of the coefficients in the volatility equation excluding the constant term coefficient is approximately one indicating that there is a unit root in the conditional variance, past shocks do not disperse but persist for very long periods of time. For determination of the returns for each day of the week and each month of the year both the short run and the long run shocks must be taken into consideration.

Since the volatility is persistent and has no negative implied variance we reject the null hypothesis for both effects and allow for the time varying conditional variance to detect the existence of the DOW effect and the January effect. The results indicate that although it takes a long time for the volatility process in the long run it does return to its mean, this is commonly known as mean reversion meaning that there is a normal level that volatility will eventually return to and the current information do not have an effect on the long run forecast, Engle and Manganelli (1999).

Recommendations

The analysis conducted in chapter 4 and presented in the summary and conclusions above indicate that the conditional volatility is essential in determination of the day of the week effect that's evident in the return equation of the GARCH model. On the other hand the January effect has disappeared as proven by the mean equation in the GARCH model and despite this the conditional variance must be considered when getting the returns. The study finds patterns of persistent volatility and mean reversion found in the variance might be useful to different stakeholders in speculation, hedging, portfolio analysis, risk management and valuation of index options.

In decision making the stakeholder must take into account not only the returns that are expected but also the volatility of the same asset. Although Friday has higher returns compared to Monday and October has higher returns compared to all other months of the year in the GARCH(1,1) model it will be a risky affair for an investor to use this information to obtain profits especially from the NSE 20 Share index which shows lots of volatility clustering and sudden movements which can't be followed reactively.

This study used the GARCH(1,1) model, further studies maybe carried out for different lags and even for other extensions to the GARCH model like M-GARCH, E-GARCH, T-GARCH, A-GARCH and I-GARCH and compare the results. This study only focused on the stock markets thus a similar study can be carried out on the bond market. A wider scope can also be taken into consideration.

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