MODEL LING THE EFFECT OF CALENDAR ANOMALIES ON STOCK PRICE VOLATILITY USING TGARCH: COMPARISON BETWEEN NSE ALL SHARE INDEX AND NSE 20 SHARE INDEX MARKETS.

BY

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DECLARATION

This dissertation is my original work and has not been presented previously, submitted and or published for award of a degree in any other university. I also declare that the contents have not been written by others except the acknowledged authors as referenced.

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Sign:.. Date………………………………..

I do hereby confirm that I have examined the master's Dissertation of

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And have certified that all revisions that the dissertation panel and examiners recommended have been adequately addressed.

Sign……………………… Date…………………………

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ABSTRACT

Inefficiency in the market may be explained by the volatility of the stock prices. This study was conducted with the main objective being to establish the effect of calendar anomalies on stock price volatility in NSE 20 Share Index market and NSE All Share Index market using TGARCH model. The scope of study was NSE20 share Index Companies from 1994-2015 and NSE All Share Index Companies from 2008-2015 daily observations and designed first by descriptive analysis then OLS lastly through Time series analysis. Results from NSE All Share Index market from descriptive analysis to TGARCH model indicated market efficiency concept and the time series as well as conditional variance plots showed response to political instability unlike NSE 20 Share Index market results which showed the presence of DOW effect and Calendar Month effect in time series analysis, OLS and descriptive analysis. On the other hand, conditional variance and time series plots for NSE 20 Share Index only identified postelection violence and not elections.

Keywords: NSE, NASI,EMH, GARCH models and Calendar Anomalies

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DEDICATION

I dedicate this proposal to my guardian angel for the proper guidance throughout the whole exercise.

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INTRODUCTION

1.1 Background of the Study

In financial markets, anomalies refer to situations when security or groups of securities perform contrary to the notion of efficient markets where security prices are said to mirror information at some point in time. Calendar anomalies are any deformity or inconsistent design that cannot be defined by means of any acquired finance theory. According to (Karadzic, 2011:110), calendar anomalies are anomalous stock returns related with the turn of the year, the month and the week, they tend to occur at turning points in time. Some seasons in returns are regularly recurring patterns of stock series on the basis of weekly, monthly or yearly. Therefore calendar anomalies can surface from seasonal returns.

There are a reasonable number of calendar anomalies provided by literature such as January effect called turn of the year effect which is an increase in buying securities before the end of the year at a lower price in order to sell them in January to occasion profit from the difference, the holiday effect which is related with markets doing well on any day prior a holiday, turn of the month effect where by stock prices rise during the last two days and the first three days of each month(Karadzic,2011) and day of the week effect associated with the disposition of investors to buy stocks on days with unusually low returns and sell the stocks on days with unusually high returns(Basher and Sadorsky,2006:621).

Sometimes, the turn of the year effect and January effect may be labeled as the same movement since much of the January effect can be accredited to the returns of small company stocks. Rozeff and Kinney (1976) were the first ones to unearth the unusually high returns in January studying the performance of the New York Stock Exchange. The most common explanation for high January returns is the tax loss selling hypothesis where investors involved in losses sell stock in December to qualify for tax loss and then buy in January.

Besides explaining January effect, some empirical studies have concentrated on exploring the April effect, Guttekin and Guttekin(1983) and Reinganum and Shapiro(1987) explained the presence of April effect on the UK stock market by the tax loss selling theory because the UK tax year starts on 6th April and ends on the following year 5th April. According to Allan and George (2013), examination of NASI and NSE20 for a period of 12 years up to 2011 using t-test and F-test the discovery were that coefficients of July, September and January were outstanding at 5% level and therefore recorded the presence of monthly effect in the NSE.

Concerning day of the week effect, a short term rise in stock prices during the last few days and the first few days of each month, some researchers connect the effect to the scheduling of monthly cash flows received by retirement welfare schemes and reinvested in the stock market. According to French (1980), Gibbons and Hess (1981) and Keim and Stambaugh (1984) average returns in the USA were significantly negative on Monday and significantly positive on Friday..

For the holiday effect, in Kenya there are 8 holidays in a year namely: New Year, Easter, Labour day, Madaraka day, Mashujaa day, Jamhuri day, Ramadhan day and Christmas day. Zafar et al.(2012) explain that holiday effect is all about the human behavior before the holiday which is associated with investors reacting very positively and participating highly in trading on the other hand, after holidays investors are psychologically depressed or not in form so their returns remain low. This theory helps us to understand how emotions and behaviors influence financial decisions causing investors to behave in unpredictable and irrational manner hence creating imperfections in the market that result in anomalies such as holiday effect. This study focus on the new year with holiday taken to be the month of December.

Lin and Liu (2002) explain that people live by the calendar and act accordingly, during the holidays production significantly scales down or may halt completely but consumption and shopping activities surge. Within the literature on calendar anomalies, one of the well-known anomalies is the holiday effect, most characteristically, a preholiday effect where abnormally high returns accrue to stock the day before a holiday. Lucey(2005) postulate that the preholiday effect refers to the fact that the share returns typically exhibit consistent patterns around holidays with high and consistent returns on days prior to major holidays As pointed out by Dodd and Gakhovich(2011), the phenomenon of abnormal returns around public holiday is well proven and documented in developing and emerging markets.

Price volatility is the degree of change in the price of a stock over time. There are investments opportunities with high degree of change or high price volatility and some with low degrees of change or low price volatility. It is well known that investments with high volatility can mean high returns on investments (ROI) meaning more money can be made faster than investing in low price volatility investments however, the higher the volatility, the riskier the investments tend to be. Volatility is also a parameter in option pricing blueprint showing the extent to which the return of the underlying asset will alternate between now and the options expiration, (Glosten L.R and P.R Milgrom1985).

In Capital markets, calendar anomalies are good examples of inefficiencies and the association between information and share prices in the market is described by the market efficiency.(Agrawal 2014) affirms that a major cause of uncertainty is fluctuation of stocks due to seasonality. Seasonality creates condition where stock returns exhibits systematic designs at certain times, month, week of the month or day of the week (Aly et al.2004).Therefore the existence of calendar anomalies is a contradiction of the weak structure of efficient market theory which states that stocks are invariant meaning there is no short term seasonal design in stock returns (Kuria & Riro 2013). Volatility being the amount of uncertainty or threat about the magnitude of changes in a security's value, it is important to note that there are disparities in volatility of stock prices by day of the week, month of the year and holiday besides a high (low) return is associated with correspondingly high (low) volatility for a given day. To balance these impressions, market participants devise trading strategy; by selling securities when returns are high and buying at spell when returns are low in order to make surplus profits (Pandey,2002).

The episode of spans of relative calmness and phases of high volatility is a universal element of market data. It is known that stock prices do not emanate a normal distribution suggesting they have long tails. Therefore, it is perfectly sensible to hypothesize that long tails are entirely due to GARCH effects whereby the application of normal distribution in the GARCH model would be the proper thing to do. Using the prospect of a longer tailed distribution almost always turns out to render a better fit. Rafique and Kashif-ur-Rehman(2011) studied the volatility clustering, heavy tails of time series and excess kurtosis of KSE using ARCH, GARCH and EGARCH processes and found that GARCH (1,1) fully captured volatility persistence while EGARCH successfully overcame the leverage effect in KSE-100 index. However, there are some constraints in GARCH (1,1) model such as: breach of non-negativity conditions by the estimated method since coefficients of model probably are negative, GARCH(1,1) model also does not allow for first hand feedback between the conditional variance and the conditional mean and it cannot also rationalize leverage effects. Leverage effects according to (Black 1976) states that losses have pronounced effect on future volatility than gains.

For these reasons, TGARCH model created by Glosten, Jagannathan, and Runkle (1993) and Zokian (1994) may be considered appropriate for measuring volatility. Threshold GARCH (TGARCH) model is commonly used to manage leverage effects and it utilizes zero as its threshold to disarticulate the impacts of past shocks. This model has been chosen by the researcher since it indicates clearly the reaction between volatility and market value changes.

1.1.1 Nairobi Stock Exchange (NSE20-Share Index)

In Kenya, Nairobi Securities Exchange (NSE) is the primary stock exchange (Iraya & Musyoki, 2013), where trading between borrowers and lenders takes place at a low cost. NSE 20-Share Index is the long –standing yardstick index used for equities traded on Kenya's Nairobi Stock Exchange (NSE) and constitutes the geometric mean of shares prices of the NSE's 20 top stocks. It was initiated in 1964 one year after allowing African locals to trade on the NSE for the first time. In February 2006, it was joined by NASI (NSE All Share Index) with an aim of manifesting the total market value of all stocks traded on the NSE in one day rather than just price changes of the 20 best performers expressed by the NSE 20. In the year 2008, the index took hit on various fronts beginning with economic incapacitation from post-election stalemate followed by investor fleeing stocks after brokerage subsided.

The listed companies that form the components of the NSE All Share Index are: Eaagads Ltd, Kakuzi Ltd, Kapchorua Tea Co. Ltd, The Limuru Tea Co. Ltd, Sasini Ltd, Williamson Tea Kenya Ltd, Car & General (K) Ltd,Marshalls (E.A.) Ltd,Sameer Africa Ltd ,Barclays Bank of Kenya Ltd CFC Stanbic of Kenya Holdings Ltd, Diamond Trust Bank Kenya Ltd , Equity Group

Holdings Ltd,Housing Finance Co.Kenya Ltd, I&M Holdings Ltd, Kenya Commercial Bank Ltd, National Bank of Kenya Ltd, NIC Bank Ltd, Standard Chartered Bank Kenya Ltd ,The Co-operative Bank of Kenya Ltd,Atlas Development & Support Services Ltd ,Express Kenya Ltd ,Hutchings Biemer Ltd, Kenya Airways Ltd, Longhorn Publishers Ltd, Nation Media Group Ltd, Standard Group Ltd TPS Eastern Africa Ltd, Uchumi Supermarket Ltd , WPP Scangroup Ltd ,Cement Ltd ,Bamburi Cement Ltd Crown Paints Kenya Ltd ,E.A.Cables Ltd, E.A.Portland Cement Co. Ltd, KenGen Co. Ltd, KenolKobil Ltd, , Kenya Power & Lighting Co Ltd, Total Kenya Ltd, Umeme Ltd, Britam Holdings Ltd, CIC Insurance Group Ltd, Jubilee Holdings Ltd, Kenya Re Insurance Corporation Ltd, Liberty Kenya Holdings Ltd, Pan Africa Insurance Holdings Ltd, Centum Investment Co Ltd, Home Afrika Ltd, Kurwitu Ventures Ltd, Olympia Capital Holdings ltd, Trans-Century Ltd, Nairobi Securities Exchange Ltd, A.Baumann & Co Ltd, B.O.C Kenya Ltd, British American Tobacco Kenya Ltd, Carbacid Investments Ltd, East African Breweries Ltd, Eveready East Africa Ltd, Flame Tree Group Holdings Ltd, Kenya Orchards Ltd, AIMMumias Sugar Co. Ltd, Unga Group Ltd, Safaricom Ltd andSTANLIB FAHARI I-REIT

1.2 Statement of the Problem

On an efficient market there are no investment opportunities which can lead to abnormal returns (differences between the actual and the expected returns of securities)(Bodie & Kane, 2002). Investors buying securities in an efficient market should expect to obtain an equilibrium rate of return. However, presence of calendar effect anomalies in any securities market is one of the biggest threat to market efficiency concept, as these anomalies may enable securities market participants beat the market by observing these patterns. In fact, no one can beat the market and earn the profit in excess of market; calendar effect can also influence the investors’ returns (Chen, 2001).

Several international studies that examined stock and fund markets have confirmed seasonality in the United Kingdom ((Jaffe & Westerfield, 1985), Japan, Canada and Australia, Sweden (Claessons (1987) and Graah-Hagelbäck & Kroon (2005), USA (Moosa, 2007) and other developed countries. These studies have confirmed both the January effect and the July effect.

Locally, Atiti, (2004) carried an empirical analysis of momentum in prices at the Nairobi Stock Exchanges. Nyamosi (2011) study tested the existence of January Effect and revealed that the January effect exists at NSE, which shows that seasonality’s exist at the NSE. Makokha (2012) studied the day of the week effect on stock returns at NSE using OLS regression by applying dummy variables using t-test and f-test and concluded the existence of the day of the week. Most of these studies used the OLS regression to model volatility which is prone to misleading results due to multicolinearity, heteroskedasticty and autocorrelation of errors.

Recently, Wakarindi (2015) studied the effect of calendar anomalies on stock returns by comparing OLS models and GARCH (1,1) model and found that the day of the week is significant in both models with Friday having the highest returns and Monday lowest returns but January effect is only explained in the OLS while GARCH(1,1) does not show any presence of it. However, from the mathematical representation of GARCH (1, 1), it can be clearly seen that there are some limitations in GARCH (1,1) model such as: violation of non-negativity conditions by the estimated method since coefficients of model probably are negative, GARCH(1,1) model also does not allow for direct feedback between the conditional variance and the conditional mean and it cannot also account for leverage effects. For these reasons, TGARCH model by Glosten, Jagannathan, and Runkle (1994) may be considered appropriate for measuring volatility. Therefore this study endeavors to contribute to the existing literature using the TGARCH model to model the effects of calendar anomalies on stock price volatility.

1.3 Objectives of the Study

1.3.1 General Objective

The study endeavors to estimate the effect of calendar anomalies on stock price volatility of the Nairobi Securities exchange (NSE 20 Share Index) and NSE All Share using TGARCH model.

1.3.2 Specific Objectives

1. To find out the day of the week effect on stock price volatility at the Nairobi Securities Exchange (NSE 20 Share Index) and NSE All Share Index.

2. To assess the calendar month effect on stock price volatility at the Nairobi Securities Exchange (NSE 20 Share Index) and NSE All Share Index.

1.4 Study Hypothesis

The study tested the following hypotheses to assess the day of the week and calendar month on Securities Exchange price.

H01a: The average prices of NSE 20 and NSE All Share in all of the days of the week are equal.

If the null hypothesis is accepted then the day of the week effect does not exist.

H02a: The average price of NSE 20 and NSE All Share is statistically not high in January.

If the null hypothesis is accepted then calendar month effect does not exist.

1.5 Significance of this Study

The study findings and recommendation will be beneficial to investors, national government, stockbrokers, academicians and researchers in giving guidance for investing, policy reviewing on stock markets, internal governance strengthening, investor confidence installation and research on related studies.

1.6 Scope of the Study

The scope of the study is mainly Nairobi Securities Exchange and specifically the daily observations of NSE 20 share index covering 22 years from 1994 to 2015 and NSE All Share Index from 2008 to 2015 covering 8 years.

1.7 Limitations

This study is limited in that it only focuses on effects of calendar anomalies on price volatility on NSE 20 Share Index and NSE All Share Index in the economy of Kenya and not all volatile markets.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter starts by reviewing existing theories that are relevant to the study and the models which have been developed by researchers to determine the stock price volatility. It continues by focusing on the empirical studies which have been carried out in the recent studies on anomalies due to seasonalities, summarizing the findings by studies reviewed to explain some of the anomalies discussed and addressing research gap. This chapter ends by operationalization of the conceptual framework

2.2 Theoretical Review

2.2.1 Market Efficiency theory

In perfect capital markets, transaction costs are assumed to be nil and markets are perfectly liquid (Copeland et. Al, 2005 353-354). To describe efficient markets, it is first beneficial to differentiate them with perfect capital markets. Perfect capital markets are without friction in that there are no transaction costs, taxes or tight regulations and all assets are divisible to the maximum and market oriented, there is also perfect competition on securities market which means that all stakeholders are price takers. Markets are informally efficient in that information is without cost and received by all individuals simultaneously. By fulfilling all these conditions, both products and securities markets are efficient in allocation and operation. In an allocationally efficient market prices are determined in a way that matches the risk adjusted marginal rates of return for all producers and savers and scarce savings are optimally allocated to attractive investments in a way that benefits everyone whereas operational efficiency I simply the cost of transferring funds.

Eugene Fama (1970) putting together the empirical evidence, subdivided the EMH into three sub hypothesis which identify three main categories of financial market efficiency. Each category is based on a different picture depending on the type of information understood to be dominant when prices fully reflect all relevant information. The weak form EMH asserts that current stock prices fully reflect all past information. The semi strong EMH asserts that prices fully reflect not only the past information but also all public. Finally the strong-form EMH states that stock prices reflect all information from past, public and private sources making not even an insider to achieve abnormal returns.

The efficient market hypothesis has been the underlying idea of finance nearly four decades. It assumes that stock prices adjust fast to the entry of new information and therefore current prices fully reflect all accessible information. The basic theoretical case for EMH lies on three notions such as investors are assumed to be rational and hence to value securities rationally, to the extent that some investors are not rational, their transactions are random and thus cancel each other without interfering with prices and lastly to the extent that investors are irrational similarly, their influence on prices is eliminated by rational arbitrageurs (Shleifer 2000,02). Hence the EMH has a clear message for average investors that they cannot hope to unvaryingly beat the market and resources used to scrutinize, pick and trade securities are useless. EMH rather prompts the investor to passively grasp the market portfolio and forget active management.

It is not easy to affirm that investors are fully rational. Many investors react to immaterial information in notifying their demand for securities. They trade on noise rather than information and hardly meet goals expected of uninformed participants. EMH does not rely on the rationality of individual investors as it was asserted that their random trades scrap each other out. It is exactly this logic that behavioral theories decline completely. Psychological proof shows that people do not stray from rationality randomly but most deviate in the same way and therefore investor sentiment reflects the common judgments errors made by significant number of investors and not correspond mistakes (Shleifer 2000 10-12).This theory is important to the study since without anomalies, investors cannot obtain abnormal returns but if they follow anomalies, they beat the market.

2.2.2 Behavioral Finance Theory

According to (Ritter 2003), boundary to arbitrage means predicting in what situation arbitrage drive will be effective and when they won't be effective. Behavioral finance has two parts which are cognitive psychology and the limits to arbitrage. Where cognitive is how people think such as depending on recent experience. According EMH correlation of sentiments across ignorant investors should not affect the position taken by arbitrageurs to bring the prices to underlying values. Comparing efficient market theory, behavioral finance states that real world arbitrage is risky and therefore scarce. Arbitrage effectiveness relies on accessibility of close substitutes for securities whose price is highly affected by noise. To minimize the risks, those who sell or sell short overvalued securities must be able to buy the same securities that are overpriced. For derivative securities, close replacements are usually available although arbitrage may still require notable trading.

Lo (2005) asserted that while all of us are subject to behavioral favoritism from time to time, economists maintain that market forces will always act to lead prices back to rational levels implying that the impact of irrational behavior on financial markets is insignificant and irrelevant. Fama (1998) criticized behavioral finance on grounds of the following logics: the discovered anomalies were just often a result of under reaction as overreaction and found this, secondly, anomalies tend to fade over time or when dissimilar methodology is used and lastly, he accuses that behavioral school has not provided a challenging theory since behavioral finance does not explain the big portrait. This theory is important to the study since it elaborates why people spend more during holidays unlike other days.

2.3 Stock market anomalies

The best known stock market anomalies are calendar anomalies. Since the introduction of EMH by Eugene Fama (1965) which asserts that the expected return on a financial asset should be evenly distributed across different units of time, researchers have reported several calendar anomalies in the stock returns such as January effect, Day of the week effect or Monday effect, Holiday effect and so on.

According to Bildik (2004) calendar anomalies show either market deficiency or scarcity in the underlying asset pricing model and evoke that recorded anomalies tend to disappear, fade or reverse over time as discovered by Schwert (2001). Bildik sees these changes as intensified market efficiency as rational traders exploit anomalous behavior. However, Brook (2004) in connection to this evokes that although calendar anomalies at first glance might entail market in efficiency, this might be wrong since the average returns might not produce net gains when used in trading system due to trade costs and the contrasts in returns on different time periods might be as a result of time varying stock market prospect premiums.

2.3.1 Calendar Month Effect

The January effect or turn-of-the-year effect is a condition where stock returns in January are higher than the average return in any other month (Riepe, 2001). This is the phenomenon of company stocks to produce more return than other asset classes and market in the first two to three weeks of January. Ligon (1997) found that January effect is due to sizeable liquidity in this month.

The higher January volume and lower interest rates correspond with greater returns in January. The most common explanation for high January returns is the tax -loss selling theory. Investors encountering losses sell stock in December to be eligible for the tax -loss and then buy in January. Thus, stocks encontering capital losses should have their prices lowered in December and raised in January; Dyl (1977), Givoly and Oradia (1983), Brown et al (1983), Jacobs and Levi (1988), Ogden (1990).

According to Floros (2008) most researchers realize evidence of a January effect. He provides the following rationale for the January effect: Year-end tax-loss selling, many traders go on break around this time and People exhaust more money at Christmas unlike other times of the year. Most people come to the end of the year, and start reasoning about their tax liability. They sell their losers sometime in December, and then they buy them back in January to lock in a tax loss (causing stock prices to rise). Many traders go on vacation around this time. Most traders sell all their positions before leaving on holiday in December.

Other clarifications of the January effect include the portfolio rebalancing (Ritter and Chopra, 1989) and the information arrival/insider trading theories (Williams,1986). The former asserts that the high returns in January are caused by systematic switches in the portfolio holdings of investors at the turn of the year. The information arrival/insider trading theory foretells that not enlightened traders are more likely to trade in January. The January effect is a vital factor in seasonality. The same sentiments are shared by Al-Saad and Moosa (2005).

Rozeff & Kinney (1976) established that in New York exchange average return is 3.5% than other months 0.5% in period 1904 to 1974.The general logic is that January effect is owing to tax loss hypothesis where investors sell in December and buy back in January. Keong (2010) finished that most of the Asian markets portray positive December expect Hong Kong, Japan, Korea and china. Few countries also indicate positive January, April and may effect and only Indonesia show negative august effect. January effect is because of tax loss saving at the end of the tax year, portfolio rebalancing and inventory accommodation of different traders and the capacity of exchange specialist (Agrawal & Tandon 1994). Alagidede and Panagiotidis (2009) claimed that the presence of April effect in Ghana stock exchange is owing to the consent of firm reports in late March. In Kenya, it is likely that the need for cash rise at the end of the year due to school fees and other devotions that are heaviest in January the following year. This may persuade investors to sell of their stocks in December and January thus frowning the prices in these months.

2.3.2 Day of the Week Effect.

Existence of the day of the week effect on price volatility has been widely recorded in finance literature. Studies by Padhi Puja (2010) affirmed that the average return on Friday is known to be high and for Monday less designating it day of the week effect or week-end effect, she examined the presence of the day of the week in the gross indices including Sensex and Nifty, BSE 100, BSE 500 and S&P CNX 500 by modeling linear regression, GARCH (1,1), GARCH-M(1,1) and asymmetric model EGARCH and GJR model. The linear regression indicated the days of the week effect in Sensex. In the GARCH (1,1) model Nifty reported the days of the week effect, all other indices recorded statistically insignificant results.

Aboudou Maman Tchiwou (2010) on his studies found the first proof of the day of the week effects in West African regional stock market in the illustration for the period September 1998 to December 2007.In local currency terms, a design of lower returns around the middle of the week, Tuesday and then Wednesday and higher pattern near the end of the week.

2.3.3 Holiday Effect

Chong et al. (2005) explored existence of pre-holiday effect across three financial markets for the period 1973 – 2003. The markets were: U.S, U.K and Hong Kong. S&p 500, FT 30 and Hang Seng indices were used for U.S, U.K and Hong Kong markets appropriately. The study asserts proof supporting presence of pre-holiday effect in all the three financial markets and the effect is more notable for U.K and Hong Kong markets. The study initiates that average returns on days particularly before a holiday was more than the average returns on normal trading days or non pre holidays. A further test was done to affirm if the preholiday anomaly persists over the years or has diminished over the years in all the three financial markets. Time series regression analysis results point to decline in the U.S financial markets is not extant in the U.K and Hong Kong financial markets.

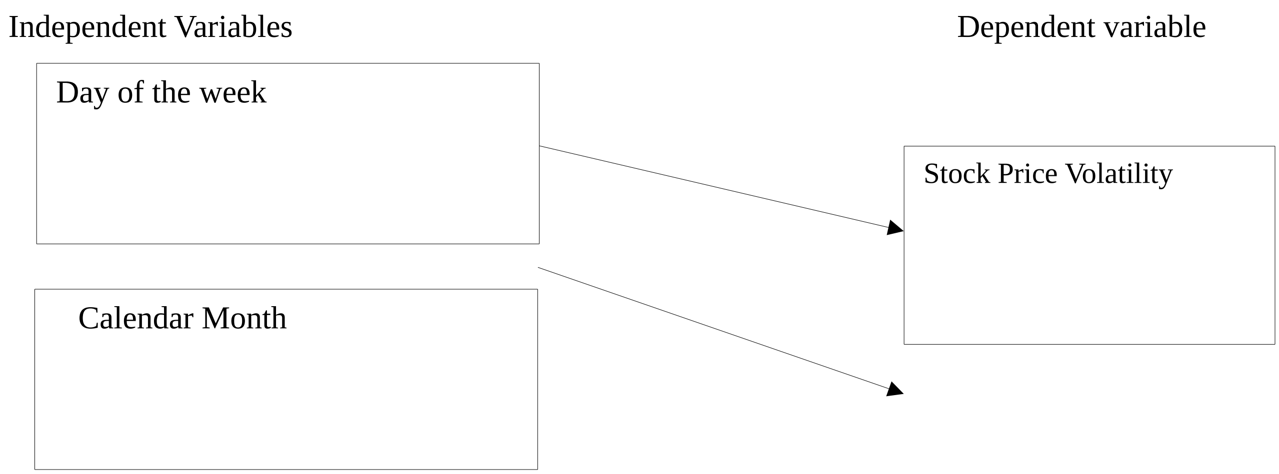
Osman (2004) perceived that it is presumed that stocks display higher returns on average on the day's prior holidays. In study investigating the holiday effect at the NSE, the researcher confirmed that no holiday effect prevailed on stocks at the NSE. The study overspread a period of nine years from January 1998 to December 2006 taking into account the eight-day window, for the four days before and four days after the holiday. The study was on NSE listed companies and used regression and correlation analysis in surveying the data.

Al-Loughan (2005) analyzedthe holiday effect at the Kuwait stock exchange (KSE) for the period 1984 – 2000. The stock returns during trading days right before a holiday (pre-holiday) and the rest of trading days of the year (normal trading days) were compared. The study findings show no noticeable dissimilarity between invasion and post invasion periods recommending no existence of the holiday effect at the KSE. A further scrutiny investigating particular designs of returns during the time encompassing holidays established that post-holiday returns were higher than pre holidays returns and other normal trading days returns. The ground basis for this observation was that investors usually captivate in selling prior to the holidays and promptly after the holidays, the investors re-construct investment portfolios gain.

2.4 Summary of Research Gaps and Conclusion

The literature review reveals that most studies on stock markets seasonality have tended to focus on January, holiday, day of the week and turn of the month effects and results have been varying such as Choudhary (2001), Thomas (2002), Lucey and Whelan(2002). The literature review reveals that most studies on market anomalies have concentrated extensively on developed economies. However, the findings have been inconsistent based on the location of the market and the timing of the study. In fact the studies have been done on Nairobi Securities Exchange some of which have been biased towards the calendar anomalies (Mokua 2003) and and at the same time they are based on OLS model (Makokha 2012) and basic GARCH model (Wakarindi 2015). There is therefore need for an alternative study to give insights into the interrelationship of the calendar anomalies and price volatility at the NSE using TGARCH models which should be able to add knowledge about modeling of conditional variance in time series.

Figure 1: Conceptual Framework



2.5 Operationalization of the conceptual framework.

This study looked at the day of the week with the assumption that Fridays had highest returns and Mondays had lowest returns (Mbuthia, 2000). This is significantly affected by the settlement period. Further, on Calendar Month, the study concentrated on January, April and July as supported by Ligon(1997), Guttekin and Guttekin(1983) and Allan and George(2013). Finally, price volatility was measured as:

$$R_t = ((P_t - P_{t-1})/(P_{t-1})).$$

Where: R_t is price volatility,

P_t is today's closing price,

P_{t-1} is yesterday's closing price.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

In this chapter, the research design, the population of study, the data collection methods and the data analysis techniques are covered.

3.2 Research Design

Since this study aimed at finding out the relationship between calendar anomalies and stock price volatility, a research design which is appropriate will be descriptive research design.

3.3 Population of Study

The population of interest for this study was 20 companies that are listed at the NSE that make up the NSE 20 share index from January 1994 to December 2015 comprising of 5,458 daily observations excluding non-trading days and 1971 daily observations from NSE All Share Index from year 2008 to December 2015.

3.4 Data Collection

The study obtained secondary data from the NSE database by mainly concentrating on the daily closing prices of the NSE 20 share index for 22 years covering the period 1994-2015 from the best 20 performing stocks listed at the NSE and the closing prices of the NSE All Share Index market from inception to December 2015. The data was edited and entered in an excel sheet and analyzed using STATA and TGARCH.

3.5 Data Analysis

Descriptive design was be used where: Mean. Median, Maximum value, Kurtosis and Skewness for price volatility of the whole period, each month as well as of each day were analyzed.

3.5.1 OLS Analysis

Next, the ordinary least squares method (OLS) was applied initially to anticipate the parameters of ARIMA type simple specifications in estimating day of the week and calendar month effects whose results are to be compared with the findings from GARCH models. However, problems such as: intercept biasness, wrong determinants, spatial correlation and model uncertainty variance from observation to observation rendered OLS inadequate since these problems cannot be handled by OLS model. The study used the following OLS equations.

a). Day of the Week effect

$$R_t = D_M R_M + D_T R_T + D_W R_W + D_H R_H + D_F R_F + \varepsilon_t$$

Where $R_{(t\ )}$is the price volatility of the day and D_1 to D_5 represent the dummy variable from Monday to Friday.

b). Calendar Month Effect

$$R_t = \sum_{i=1}^{12} \beta_i D_{it} + \varepsilon_t$$

Where $R_{(t\ )}$is the price volatility of the calendar month and D_1 to D_{12} represent the dummy variable from January to December.

3.5.2 Time Series

For time series analysis, Engle (1982) proposed a model called ARCH model with the variation of conditional variance where the restricted variance depends on the previous squared error terms of different lags.

This is represented as:

ARCH (q)

Ɛ_t˜ (0, δ_t^2)

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

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

Where:

δ_t^2 is the time varying conditional variance.

q is the number of lagged terms

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

Implying, the conditional variance grows and shrinks with respect to the size and movements of past shocks with the error structure being the ARCH model. The ARCH model with a higher series shows the model comprises of several variables making estimation, difficult, lengthy and different to intercept. Later Bollerslev (1986) proposed GARCH model to control the higher order ARCH model problem. GARCH (p, q) conditional variance can be represented as follows:

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

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. ($\alpha_0, \alpha_1, \alpha_2 \ldots\ldots \alpha_q$)

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

To fit this model, the study first ran Philip Peron test on data for stationarity and incase of non-stationarity, data was transformed through differencing. GARCH (1,1) was then selected which according to Chong et al (1999), French et al (1987) and Franses & Dijk (1996) is already sufficient for financial time series data since it has properties which OLS cannot capture such as; 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. Dummy variables were then introduced to help analyze the calendar anomalies with specific reference to the day of the week effect and the January effect using the GARCH models (Wakarindi, 2015)

As shown above, it was clearly seen that there are limitations in GARCH(1,1) model such as violation of non-negativity conditions by the estimated method since coefficients of model probably are negative, GARCH(1,1) model also does not allow for direct feedback between the conditional variance and the conditional mean and it cannot also account for leverage effects. For these reasons, TGARCH model by Glosten, Jagannathan and Runkle (1993) and Zokian (1994) was considered appropriate for measuring volatility. A mathematical form of TGARCH model can be represented as:

$$\sigma^2 ¿ a_0 + \sum_{i-1}^{s} (\alpha_i + Y_i N_{t-i}) \alpha^2_{t-i} + \sum_{i-1}^{m} \beta j \, \sigma^2_{t-j}$$

Where N_{t-1} is an indicator for negative α_{t-1}

and α_i, Y_i and β_i are non-negative parameters satisfying conditions similar to those of GARCH models. It can be seen that a positive α_{t-i} contributes $\alpha i \alpha^2_{t-i}$ to σ^2_t, whereas a negative α_{t-i} has a larger impact $(\alpha_i + Y_i)$ with $Y_t > 0$. The model uses zero as the threshold to separate the impacts of past shocks.

3.6 Model Specification

(a) Day of the Week Effect

To measure DOW effect, we introduced dummy variables to the TGARCH model as follows:

$$\sigma^2 ¿ a_0 + \sum_{i-1}^{s} (\alpha_i + Y_i N_{t-i}) \alpha^2_{t-i} + \sum_{i-1}^{m} \beta j D \sigma^2_{t-j}$$

where: σ^2 is the conditional variance/price volatility of the day of the week and D_1 to D_5 represent dummy variables for the days of the week (Monday to Friday).

(b) Calendar Month Effect

To measure Calendar Month Effect, we introduced dummy variables to TGARCH model at the same time we excluded constant from the model to avoid dummy variable trap especially when examining January effect.

$$\sigma^2 \text{ ¿ } a_0 + \sum_{i-1}^{s} (\alpha_i + \gamma_i N_{t-i}) \alpha^2_{t-i} + \sum_{i-1}^{m} \beta j D \sigma^2_{t-j}$$

where:

σ^2 is the conditional variance/price volatility of the calendar month and D_1 to D_{12} represent dummy variables for the months of the year (January to December).

To test for model adequacy, we checked the underlying assumptions such as:

When $\alpha+\beta<1$ then TGARCH is unstable.

When $\alpha+\beta=1$ then TGARCH is stable.

When $\alpha+\beta>1$ the TGARCH is exploding.

CHAPTER FOUR

ANALYSIS AND FINDINGS

4.1 Introduction

Chapter four contains presentations of data analysis and findings. Data transformation has been carried out by adding 280 to NSE20 Share Index price and 10 to NSE All Share Index price to eliminate negative figures, and then logs were introduced in order to reduce variation.

4.2 Descriptive Statistics

Tables 4.1a and 4.1b give the mean, maximum, minimum, standard deviation, skewness and kurtosis for each day of the week and the entire period for NASI and NSE20 Share Index, whereas tables 4.2a and 4.2b give the mean, maximum, minimum, standard deviation, skewness and kurtosis for each month of the year and the entire period for NASI and NSE20 Share Index.

Table A4.1

Descriptive Statistics for NSE All Share Index-Day of the Week

Statistics	Monday	Tuesday	Wednesday	Thursday	Friday	Total
Observations	388	399	400	399	384	1970
	%	%	%	%	%	%
Mean	2.301585	2.2996	2.301045	2.302318	2.303367	2.301569
Max	2.608598	2.704711	2.772589	2.546315	2.700018	2.772589
Min	1.90806	1.726332	1.865629	1.983756	1.722767	1.722767
SD	.0750255	.0925089	08054192	.0797029	.0893269	.0845722
Skewness	.3031062	-.9408874	-.7131741	-.5513238	-.753792	-0.6236862
Kurtosis	6.613774	10.10697	8.854879	4.867371	33.65387	8.976953

Table B4.1

Descriptive Statistics for NSE20 Share Index-Day of the Week

Statistics	Monday	Tuesday	Wednesday	Thursday	Friday	Total
Observations	1062	1104	1106	1106	1079	5457
	%	%	%	%	%	%
Mean	5.627908	5.627833	5.623175	5.626407	5.638772	5.628777
Max	6.183386	6.253425	6.310027	6.541521	6.23178	6.541521
Min	4.802791	3.795939	.8544179	4.678328	4.680092	.8544179
SD	.1053789	.1310132	.1818768	.1151509	.1091267	.13189
Skewness	-.8676887	-3.509524	-16.51108	-1.206728	-.926084	-9.846779
Kurtosis	13.67039	46.3935	429.8664	18.84341	16.85243	330.0925

From the two tables above, the mean for the entire period in 4.1a is 2.301569% and standard deviation of .0845722, skewness of -0.6236862 and kurtosis of 8.976953. For each day, Friday reported the highest mean of 2.303367%, showing presence of day of the week effect while Tuesday the lowest mean of 2.2996%. The highest price index was reported on Wednesday of 2.772589 and the lowest observed on Friday of 1.722767. The highest standard deviation was reported on Tuesday of .0925089 and lowest on Monday of .0750255. Skewness for all days were negative indicating non normality of data with slightly excess kurtosis on Friday. Table 4.1b on the other hand reported the overall mean to be 5.628777% with a standard deviation of 0.13189, skewness of -9.846779 and excess kurtosis of 330.0925 hence failing to accept normality of the data studied in the period. For each day, highest mean was reported on Friday of 5.638772% and the lowest mean on Wednesday 5.623175%, this showed existence of the day of the week effect, the highest price index was observed on Thursday of 6.541521 and lowest on Wednesday of 0.8544179. The highest standard deviation was observed on Wednesday of 0.1818768 and lowest observed on Monday of 0.1053789. Skewness was observed to be negative for all days with the highest on Monday of -0.8676887 and lowest of -16.51108 on Wednesday; extremely excess kurtosis was also observed on Wednesday of 429.8664 indication of leptokurtic condition.

Analyzing the Price Index for the Calendar month, in table 4.2a the highest mean of 2.307314% was observed in March and the lowest of 2.286208% in August, the lowest NSE All Share price index was reported in January of 1.722767 and the highest of 2.772589 in November, standard deviation was observed highest of 0.1034388 in August and lowest in May of 0.0634378. All months were negatively skewed except February and November. Table 4.2b also reported the highest mean of 5.647967% in December and the lowest of 5.606404% in March, the highest NSE20 Share price index was observed in January of 6.541521 and the lowest in the same month of 0.8544179, the highest standard deviation was observed in January of 0.2801962 and lowest of 0.0825195 in May which showed presence of January effect in stock price volatility. Skewness was negative in all months and January reported excess kurtosis of 190.1713 indication of leptokurtic condition.

Table A4.2

Descriptive Statistics for NSE All Share Index-Calendar Month

Month of the Year	Observations	Mean	Max	Min	SD	Skewness	Kurtosis
Total	1970	2.301569	2.772589	1.722767	.0845722	-.623686	8.976953
January	148	2.30638	2.542389	1.722767	.0945906	-1.45937	12.06123
February	145	2.306342	2.664447	2.09556	.0748532	.5147768	5.940164
March	171	2.307314	2.639057	1.987874	.0926262	-.043305	5.080750
April	160	2.320085	2.615204	2.048982	.0665018	-.169387	6.382242
May	168	2.301459	2.509599	2.055405	.0634378	-.579998	5.154048
June	164	2.305016	2.550226	1.726332	.0848841	-1.68063	15.6717
July	178	2.288806	2.536866	2.006871	.0712795	-.237557	4.628099
August	168	2.286208	2.640485	1.856298	.1034388	-.713038	7.460084
September	172	2.302304	2.53517	1.951608	.081188	-.370258	5.061363
October	168	2.289145	2.700018	1.865629	.096992	-1.04025	8.069843
November	166	2.306548	2.772589	1.951608	.093436	.5819594	10.44673
December	162	2.302132	2.524928	1.983756	.0772198	-1.13253	6.838155

Table B4.2

Descriptive Statistics for NSE20 Share Index- Calendar Month

Month	Observation	Mean	Max	Min	SD	Skewness	Kurtosis
Total	5457	5.628777	6.541521	.8544179	.13189	-9.846779	330.0925
January	457	5.629025	6.541521	.8544179	.2801962	-11.49769	190.1713
February	425	5.631406	6.241464	4.890951	.1287997	.2827354	11.79208
March	477	5.606404	6.166426	4.678328	.1641574	-1.794833	12.96703
April	433	5.625741	6.109426	4.517322	.106626	-3.384192	34.08185
May	470	5.634162	5.928045	5.331945	.0825195	-.1586554	4.719897
June	452	5.640185	5.977467	5.128892	.0882144	-.597303	8.216189
July	486	5.626473	5.895724	4.849292	.0848007	-2.142672	19.65725
August	472	5.620999	5.93028	5.045681	.0913906	-1.238098	9.236794
September	453	5.624419	6.151881	4.99917	.1059871	-1.163161	10.6123
October	458	5.631704	6.19677	5.113192	.1093689	-.9455704	9.36887
November	457	5.629856	6.310027	5.073673	.1047232	.3139185	12.68712

December	417	5.647967	6.151114	5.090186	.0998613	.2856355	9.840614

Further, the study looks at the time series trend and autocorrelation functions of the price index function as shown in figures below. Figure 4.1a indicated high volatility between 0 and 250 trading day for NSE All Share Index, the same was also observed at 1500 trading day and in figure 4.2a, the Autocorrelation function showed that the decay is not exponential thus the trend is stationary. High volatility observed in the time series plot paves way for application of GARCH models which appreciate the conditional variance variation. Analyzing NSE20 Share Index, figure 4.1b showed high volatility between 3000 and 4000 trading days, autocorrelations as per figure 4.2b showed that the trend in not dying out slowly indication of stationarity trend.

Figure A4.1

Time series Plot-NSE All Share Index

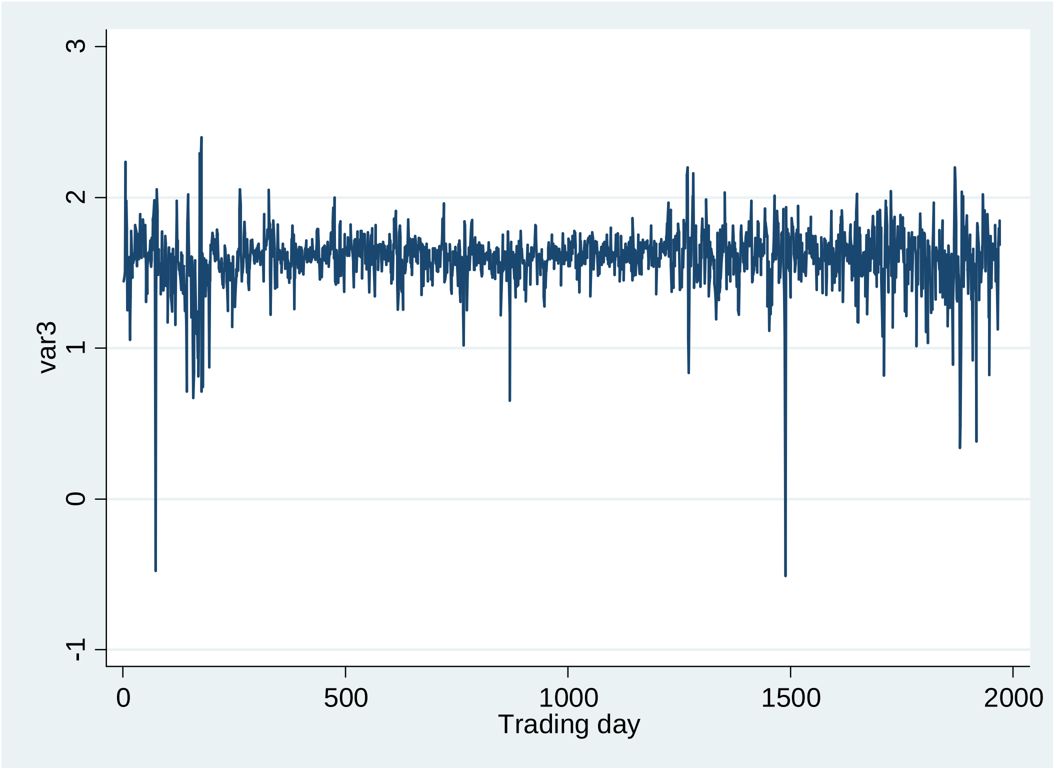
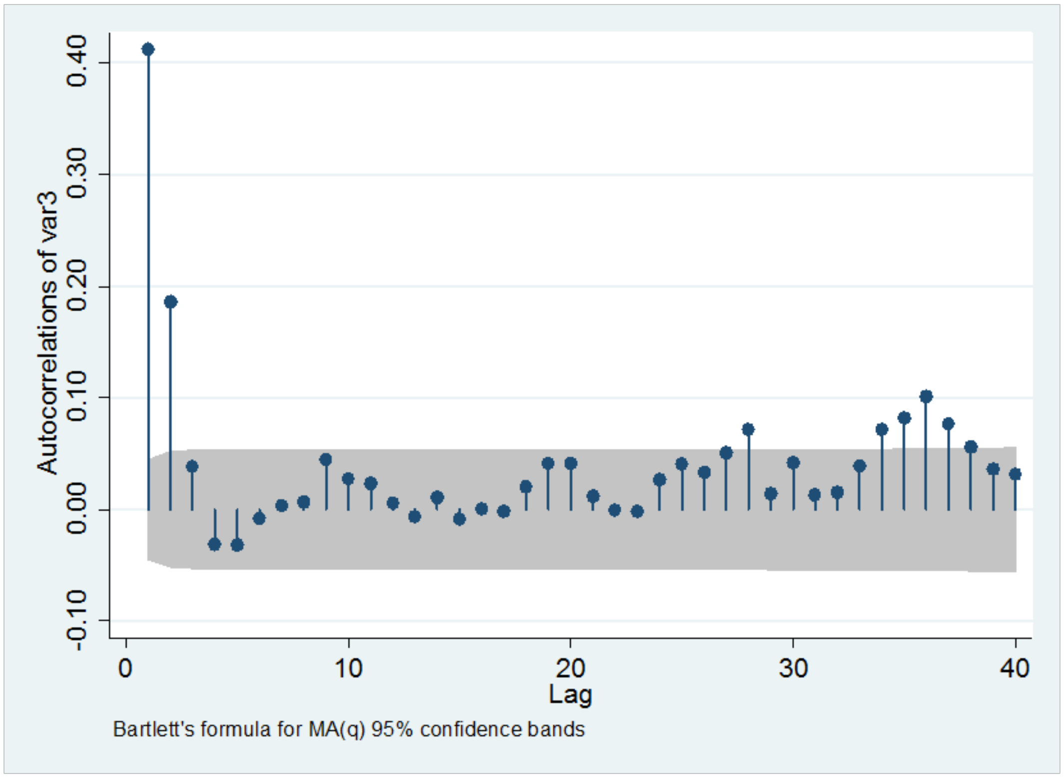


Figure A4.2

Correlogram-NSE All Share Index



Autocorrelations of var3
-0.10
0.00
0.10
0.20
0.30
0.40
0
10
20
30
40
Lag
Bartlett's formula for MA(q) 95% confidence bands

Figure B4.1

Time series Plot- NSE20 Share Index

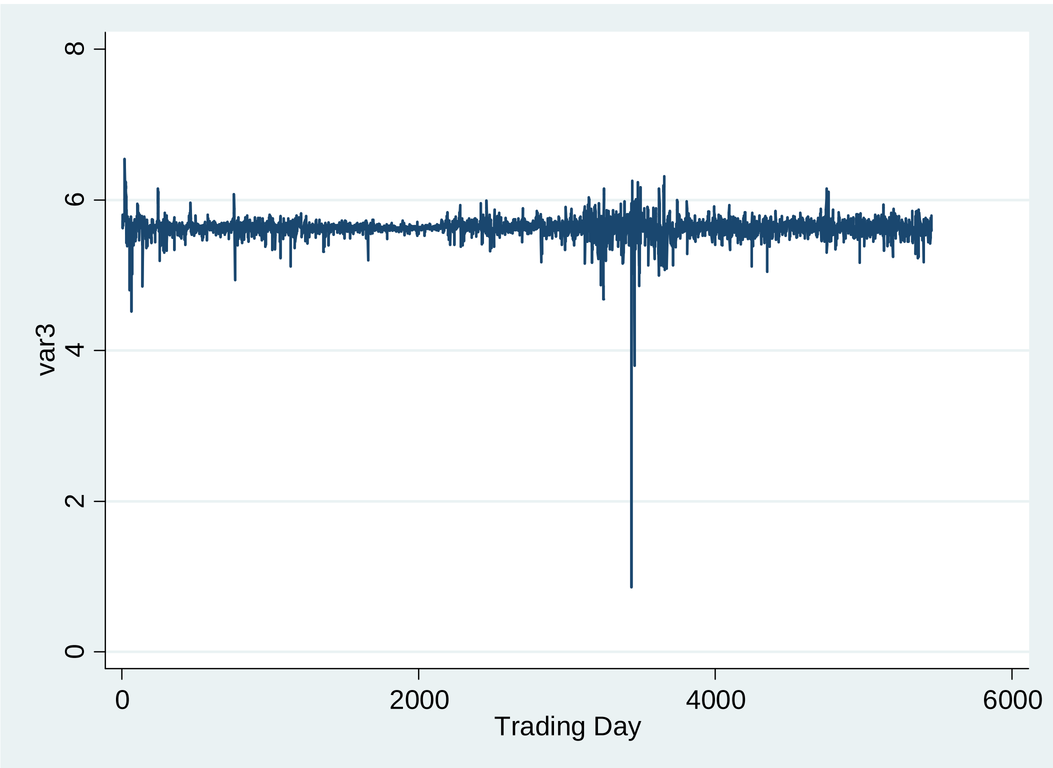
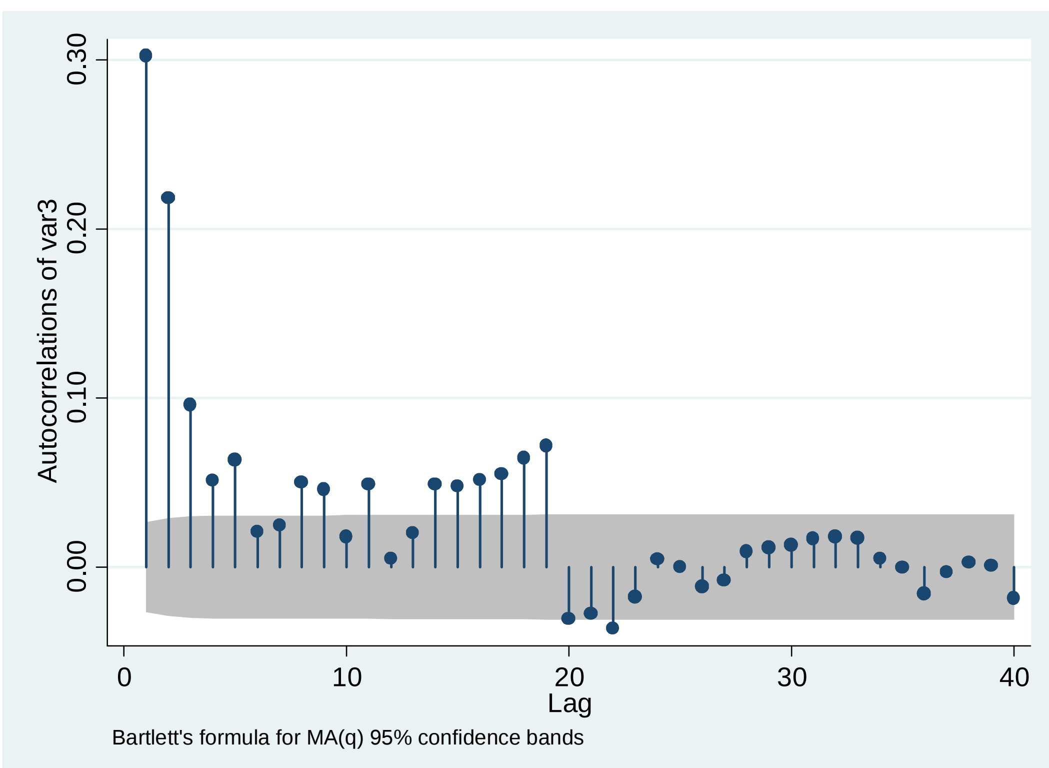


Figure B4.2

Correlogram- NSE20 Share Index



4.3 Econometric Analysis

The study then analyzed data by applying both linear regression and time series econometric models, running linear regression first then stationarity tests by Philip peron and Augmented Dicky Fuller and lastly GARCH models.

4.3 OLS model Analysis

First, linear regression was done followed by post estimation diagnostic tests.

Table A4.3

OLS Model for NSE All Share Index- Day of the Week

Day of the Week	Coefficient	P Value	95%confidence Interval
Monday	.0183505	0.666	-.0650326 .1017336
Tuesday	.0118045	0.778	-.0704212 .0940302
Wednesday	.0204	0.626	-.0617228 .1025228
Thursday	.0286216	0.495	-.0536041 .1108472
Friday	.0470313	0.271	-.036785 .1308475

Table B4.3

OLS Model for NSE20 Share Index-Day of the Week

Day of the Week	Coefficient	P Value	95%confidence Interval
Monday	-.4066007	0.672	-2.291859 1.478658
Tuesday	.1992935	0.833	-1.649756 2.048343
Wednesday	-.5914738	0.530	-2.438851 1.255903
Thursday	-.5464467	0.562	-2.393824 1.30093
Friday	2.759259	0.004	.8889106 4.629607

Analyzing DOW OLS Model, table 4.3a showed insignificant positive price index in all days of the week, this fails to indicate the presence of day of the week effect in NSE All Share Index whereas table 4.3b showed insignificant negative price index on Monday, Wednesday and Thursday, insignificant positive price index on Tuesday and significant positive price index observed on Friday indicating the presence of DOW in NSE20 Share Index. Implying that investors of NSE 20 Share Index are able to make predictions by market timing unlike investors of NSE All Share Index market.

According to table 4.4a, July August and October showed insignificant negative price index and insignificant positive price index was observed in all the other months, this is not enough to prove the existence of Calendar Month effect in NSE All Share Index. In table 4.4b, significant positive price index was observed in January and December reports the highest significant positive price index, significant negative price index in March is also observed. This shows the presence of both January effect and holiday effect in NSE20 Share Index since December is always a holiday month in Kenya.

Table A4.4

OLS Model for NSE All Share Index- Calendar Month

Month of the Year	Coefficient	P Value	95% confidence Interval
January	.0809459	0.238	-.0535452 .2154371
February	.066	0.341	-.0698753 .2018753
March	.0903509	0.157	-.0347691 .2154708
April	.198875	0.003	.0695255 .3282245
May	.0085119	0.895	-.1177202 .1347441
June	.0588415	0.367	-.0689208 .1866038
July	-.1120225	0.073	-.2346575 .0106126
August	-.1110714	0.085	-.2373036 .0151607

September	.0297093	0.641	-.0950464 .154465
October	-.088631	0.169	-.2148631 .0376012
November	.0843976	0.193	-.0425927 .2113879
December	.024321	0.711	-.1042275 .1528695

Table B4.4

OLS Model for NSE20 Share index- Calendar Month

Month of the Year	Coefficient	P Value	95% confidence Interval
January	4.27779	0.003	1.410073 7.145506
February	1.429412	0.346	-1.544307 4.40313
March	-4.44088	0.002	-7.247834 -1.633927
April	-1.094804	0.466	-4.040923 1.851316
May	.7734468	0.592	-2.054332 3.601225
June	2.594027	0.078	-.2895078 5.477561
July	-1.372469	0.333	-4.15331 1.408372
August	-2.720403	0.059	-5.542184 .1013787
September	-1.384945	0.346	-4.265295 1.495405
October	.7609607	0.603	-2.103624 3.625545
November	.181488	0.901	-2.686229 3.049205
December	5.150504	0.001	2.148396 8.152612

4.4 Analysis of Post Estimation Diagnosis

OLS models assumptions were tested as below and if proved otherwise then GARCH (1,1) model was applied.

Table A4.5

Day of the Week post estimation diagnostic analysis for the Regression Model- NSE All Share Index

Test	Results (P Value)	Conclusion
Durbin's alternative Test	0.0000	$P<0.05$, reject H_0 which shows that

		the errors are serially correlated
White Test	0.3897	P>0.05, fail to reject H_0 which shows that the errors are homoskedastic
Arch effect	0.0000	P<0.05, reject H_0 which shows that the conditional variance is not constant

Table B4.5

Day of the Week post estimation diagnostic analysis for the Regression Model- NSE20 Share Index

Test	Results (P Value)	Conclusion
Durbin h Watson Test	0.7272	P>0.05, fail to reject H_0 which shows that the errors are not serially correlated
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

Table A4.6

Calendar Month post estimation diagnostic analysis for the Regression Model- NSE All Share Index

Test	Results (P Value)	Conclusion
Durbin’s alternative Test	0.0000	P<0.05, reject H_0 which shows that the errors are serially correlated
White Test	0.0322	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

Table B4.6

Calendar Month post estimation diagnostic analysis for the Regression Model- NSE20 Share Index

Test	Results	Conclusion

Durbin h Watson Test	0.0000	P<0.05, reject H_0 which shows that the errors are serially correlated
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

According to tables 4.5a 4.5b, 4.6a and 4.6b, it was confirmed that OLS classical assumptions have been violated since errors are heteroskedastic, serially correlated and conditional variance is not constant and therefore if OLS is applied, type 1 error may be committed. Therefore Auto Regressive model was applied to take care of the above OLS violations. GARCH (1,1) model was used after testing for stationarity of stock price index.

4.5 Stationarity testing

To avoid spurious regression of Time Series data set, Philip Peron and Augmented Dickey Fuller (ADF) (1979) tests were carried out.

Table A4.7

Stationarity Test for the Price Index- NSE All Share Index

Variable	Test Statistic	1% Critical Value	5%Critical Value	10% Critical Value	P Value
Price with trend					
Philip Peron	-27.178	-3.430	-2.860	-2.570	0.0000
ADF Test	-27.530	-3.430	-2.860	-2.570	0.0000

Table B4.7

Stationarity Test for the Price Index- NSE20 Share Index

Variable	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value	P Value
Price with trend					
Philip Peron	-56.231	-3.430	-2.860	-2.570	0.0000
ADF test	-54.060	-3.430	-2.860	-2.570	0.0000

Analyzing tables 4.7a and 4.7b above, t-statistics are greater than t-tables in both tests considering absolute values proving that price index are stationary in trend at 5% levels, confirming the results of the time series plot and the correlogram.

4.6 Selection of Lags Length

In this study, the researcher used GARCH (1,1) for both DOW and Calendar month and not any other criteria in lags selection. Some researchers such as Wakarindi (2015), Goudarzi and Ramanarayanan (2010) proved GARCH(1,1) to be the most appropriate model to explain mean reverting and clustering of volatility.

4.7 GARCH Models

The study used GARCH (1,1) to determine the DOW and Calendar Month on stock price volatility for NSE All Share Index and NSE20 Share Index since in this model, conditional variance is influenced by the lagged values of errors squared as well as past value of conditional variance itself making its structure more robust and flexible as compared to OLS model.

The results as per table 4.8a showed significant and positive price index for all days, the coefficients of conditional variance were also positive and the sum of ω and λ was approximately one indicating stability. Thursday reported the highest of 1.625215 and lowest observed on Monday of 1.595601 this contradicted the DOW. Since the null hypothesis is rejected at 5% level in this case, Wald test was therefore against the null hypothesis that all coefficients in variables in the mean equations are zero. Table 4.8b on the other hand showed highest mean on Friday of 5.633739 and lowest on Monday of 5.62176 which strongly indicated the presence of the day of the week effect, the coefficients of conditional variance were all positive and the sum of ω and λ was approximately one. The Wald test P value of 0.0000 supporting the rejection of null hypothesis that all the coefficients on the independent variables in the price equations are zero since the null hypothesis in this case is rejected at 5% level.

Table A4.8

Price and Volatility equation for Day of the week Effect-NSE All Share Index

Price Equation	Day of the Week	GARCH(1,1) Coefficient	TGARCH Coefficient
	Monday	2.297885 (0.0000)	-.4503833(0.0000)
	Tuesday	2.304781 (0.0000)	-.4424123(0.0000)
	Wednesday	2.309939 (0.0000)	-.4359311(0.0000)
	Thursday	2.311204 (0.0000)	-.4341627(0.0000)
	Friday	2.310706 (0.0000)	-.4365551(0.0000)
Volatility Equation			
			abarch .2786593
	ω	.3150269 (0.0000)	atarch -.0111571
	Λ	.6855377 (0.0000)	sdgarch .7306575
	α(constant)	.000294 (0.0000)	.0051202
Wald Test P Value		0.0000	0.0000

Table B4.8

Price and Volatility equation for Day of the week Effect-NSE20 Share Index

Price Equation	Day of the Week	GARCH(1,1) Coefficient	TGARCH Coefficient
	Monday	5.62176 (0.0000)	2.311267 (0.0000)
	Tuesday	5.628858 (0.0000)	2.313933 (0.0000)
	Wednesday	5.632757 (0.0000)	2.316782 (0.0000)
	Thursday	5.629796 (0.0000)	2.31592 (0.0000)
	Friday	5.633739 (0.0000)	2.320337 (0.0000)
Volatility Equation			
			abarch .2745425
	ω	.4505489 (0.0000)	atarch .0889615
	Λ	.6479614 (0.0000)	sdgarch .7574208
	α (constant)	.0003762	.0031285
Wald Test		0.0000	0.0000

Further, TGARCH was used to determine day of the week effect and Calendar Month effect. Results in table 4.8a showed all days to be negative and insignificant with the highest on Thursday of-.4341627 and lowest on Monday of -.4503833 failing to indicate the DOW whereas, the volatility equation coefficients (abarch and sdgarch) added up to one indicating stability of the model whereas the leverage parameter (atarch) was negative at 1% showing how slow volatility reacts to negative insignificant market values. Table 4.8b on the other hand supported DOW since all coefficients of Price index equation are positive and significant with the highest on Friday of 2.320337 and lowest on Monday of 2.311267, volatility equation coefficients also added up to one hence a stable model and atarch was positive at 8% supporting the slow reaction of volatility to small changes in market value.

Table A4.9

Price and Volatility equation for Calendar Month- NSE All Share Index

Month of the Year/Price Equation	GARCH(1,1) Coefficient	TGARCH Coefficient
January	1.64120 (0.0000)	-.2015395(0.0000)
February	1.623341 (0.0000)	-.2094498(0.0000)
March	1.612814 (0.0000)	-.2086962(0.0000)
April	1.64430 (0.0000)	-.1973814(0.0000)
May	1.60754 (0.0000)	-.216651(0.0000)
June	1.60299 (0.0000)	-.21343(0.0000)
July	1.59670 (0.0000)	-.2259994(0.0000)
August	1.61471 (0.0000)	-.2168707(0.0000)
September	1.61976 (0.0000)	-.2094046(0.0000)
October	1.63223 (0.0000)	-.2062395(0.0000)
November	1.61250 (0.0000)	-.2153358(0.0000)
December	1.63558 (0.0000)	-.2035071(0.0000)
Volatility equation		
		abarch .2975982
	ω .6022282 (0.0000)	atarch .0104903
	Λ .9084676 (0.0000)	sdgarch .6985173
	α (constant) -.3110978	.0064213
Wald Test	0.000	

Table B4.9

Price and Volatility equation for Calendar Month- NSE20 Share Index

Month of the Year/ Price Equation	GARCH(1,1) Coefficient	TGARCH Coefficient
January	5.631289 (0.0000)	0.573811 (0.0000)
February	5.632648 (0.0000)	0.574365 (0.0000)
March	5.614312 (0.0000)	0.5574224 (0.0000)
April	5.626589 (0.0000)	0.5689292 (0.0000)
May	5.626985 (0.0000)	0.5665302 (0.0000)
June	5.637556 (0.0000)	0.5806301 (0.0000)
July	5.633304 (0.0000)	0.575621 (0.0000)
August	5.621137 (0.0000)	0.5643789 (0.0000)
September	5.621701 (0.0000)	0.5684694 (0.0000)
October	5.657957 (0.0000)	0.6045868 (0.0000)
November	5.632343 (0.0000)	0.5747792 (0.0000)
December	5.631115 (0.0000)	0.5726705 (0.0000)
Volatility Equation		abarch .2867985
	ω .4294548 (0.0000)	atarch .881039
	Λ .6907126 (0.0000)	sdgarch .7563572
	α(constant) .0001907	.0025585
Wald Test P Value	0.000	

Analyzing GARCH (1,1), Table 4.9a above showed positive significant results in all the months with the highest price equation in April of 1.644309 and the lowest in July of 1.596709, this contradicted the famous January effect, the estimated coefficients of the volatility equation are both significantly positive and insignificantly negative and the sum of ω and λ was greater than one showing the model was unstable. Wald test was against the null hypothesis that all the coefficients on the independent variables in the price equations were zero since the null hypothesis is rejected at 5% level. On the other hand, table 4.9b showed all positive and significant results both for all months and volatility equation coefficients, the highest mean of 5.657957 was observed in October and lowest of 5.614312 in March, this also contradicted the January effect. The sum of ω and λ was greater than one, showing instability of the model. Wald test rejected the null hypothesis that all coefficients on the independent variables in the price equations are zero.

Further, TGARCH results in table 4.9a showed all price equation coefficients to be negative and insignificant with the highest in April of -.1973814 and lowest of -.2259994 in July, this did not support the Calendar Month effect, the sum of volatility equation coefficients was less than one indicating a stable model and the reaction of volatility to market value changes is very low at 1%. Table 4.9b on the other hand reported price equation coefficients to be positive with the highest in October of 0.6045868 and the lowest of 0.5574224 in March, this neither supported Calendar Month effect nor holiday effect. The sum of volatility equation coefficients was one proving the model is stable and reaction of volatility to market value changes was highest at 88%.

Figure A4.3

Conditional Plot- NSE All Share Index

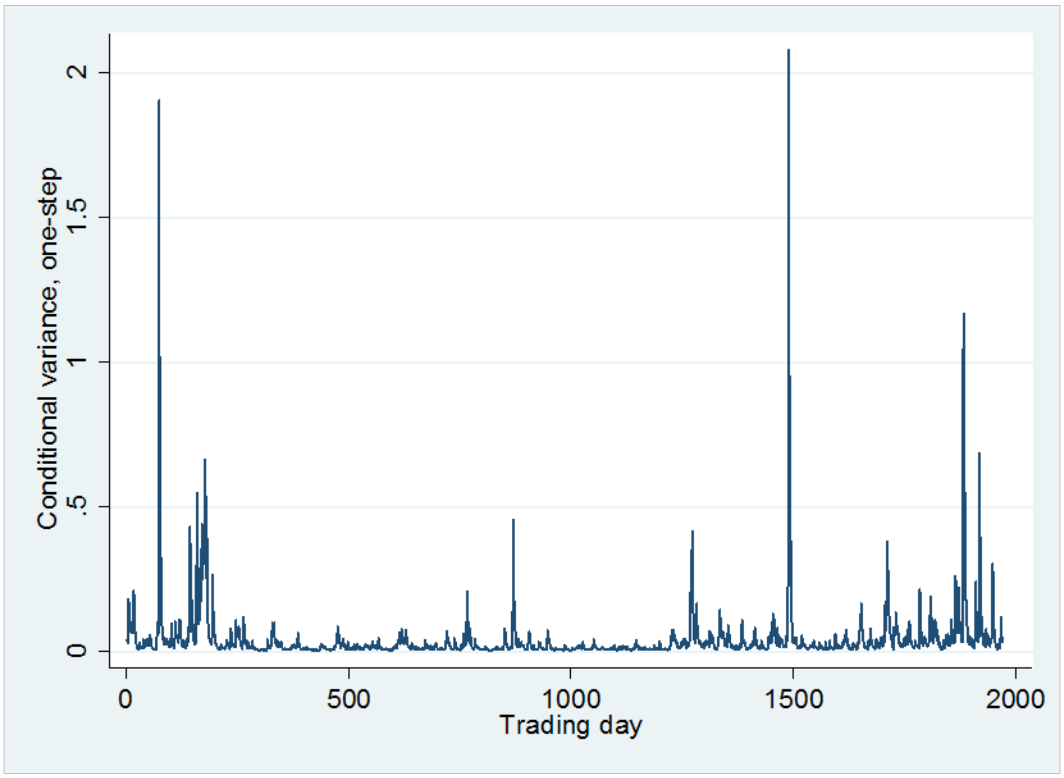
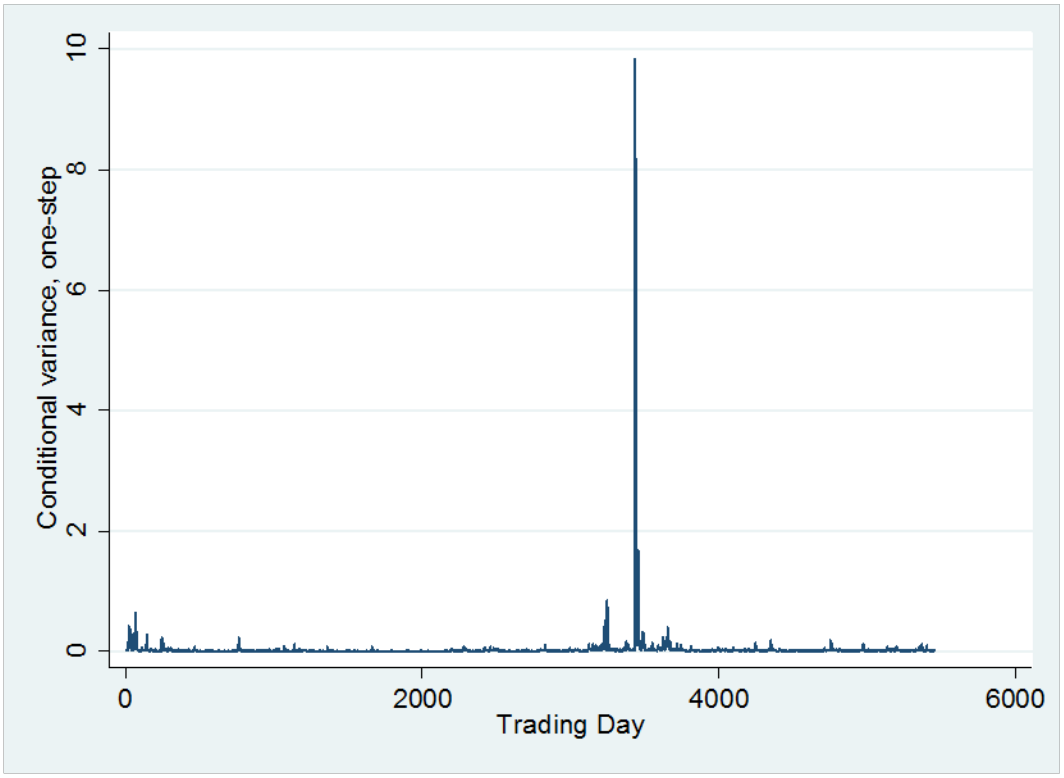


Figure B4.3

Conditional Plot- NSE20 Share Index



Analyzing figure 4.3a the conditional variance plot showed high volatility between 3000 and 4000 trading days as shown above. This occurred at around end of year 2007 running to the year 2008 when there was a postelection violence. Figure 4.3b shows high volatility between 0 and 250 trading days which covers the year 2008 and beginning 2009 characterized by postelection violence and another occurrence from 1300 trading days, reverted to mean and again occurred at around 1500 trading days, reverted and another at around 2000 trading days this period covers the whole of years 2013 and 2014 characterized by 2013 elections.

CHAPTER FIVE

SUMMARY, CONLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter presents the summary of the study, conclusion from findings and recommendations for further studies.

5.2 Summary

The general objective of this study was to compare the effect of calendar anomalies on stock price volatility for NSE All Share Index and NSE20 Share Index using GARCH models from inception to December 2015. The daily closing prices were transformed. Descriptive statistics was carried out first on the data sets. The transformed price index was then regressed against the dummy variables for the days of the week and the months of the year.

The findings of OLS model on NSE All Share Index supported the presence of DOW effect since the coefficients for all days were positive with the highest on Friday but the existence of calendar month effect was not seen, for NSE20 Share Index, the presence of DOW effect was strongly indicated since Friday had the highest significant and positive results. Calendar month (January and December) effects were shown where January had the second highest result which was positive and significant and December had the highest results also positive and significant which supported the holiday effect in Kenya..

Further, GARCH (1,1) was applied where NSE All Share Index results did not show the presence of DOW effect whereas the volatility equation proved stability of the model since the sum of the coefficients was approximately one, the opposite was the case for NSE20 Share Index where Friday had the highest mean and Monday the lowest indicating the presence of DOW effect but volatility equation proved stability of the model. For Calendar Month effect, it was not seen in NSE All Share Index results which also proved the model to be unstable. The same was observed in NSE20 Share Index where the model was unstable and there was no presence of calendar month effect.

Lastly, TGARCH was used where NSE All Share Index did not show the presence of DOW effect but proved stability of the model and NSE20 Share Index indicated the presence of DOW effect and stable model. For calendar month effect, the results of NSE All Share Index did not indicate its presence but showed stability of the model, NSE20 Share Index on the other hand produced similar results where there was no presence of calendar month effect but the model was stable.

5.3 Conclusion

From descriptive statistics to TGARCH model results; it is clear that NSE All Share Index and NSE20 Share Index markets behave differently. NSE All Share Index market in most cases neither show the DOW effect nor the Calendar Month which is the opposite case for NSE20 Share Index. This implies that investors of NSE All Share Index market follow Efficient Market Hypothesis where stocks always trade at their fair value on stock exchange, making investors unable to either purchase undervalued stocks or sell stocks for inflated prices hence to outperform the overall market is impossible through expert stock selection or market timing but for investors to obtain higher returns, the only way is to purchase riskier investments. NSE20 Share Index on the other hand shows the presence of DOW effect and calendar month (both January effect and holiday effect) implying that investors of this market are able to make predictions through market timing and stock selection hence beating the market. NSE All Share Index market also responds to political instability like elections which is not the case for NSE20 Share Index. This is supported by the TGARCH leverage results which showed very low percentages in NSE All Share Index but high percentages in NSE 20 Share Index indicating high volatility which is an indication of large changes in market returns.

5.4 Limitations of the study

There are many calendar anomalies existing but the study only covered two which are, DOW and calendar month since the researcher had challenges in measuring the holiday effect.

5.5 Recommendations

For proper decision making, investors must take into account the leverage effect of an asset portfolio since just considering returns and ignoring volatility could be risky. It is also advisable to follow anomalies in order to obtain abnormal returns. This has been clearly reported in chapter four analysis results where NSE All Share Index market follow efficient market hypothesis in that, securities trade at their fair values and it is impossible for investors to beat the market whether through market timing or asset selection. The opposite is observed in NSE 20 Share Index Market where the presence of anomalies is a threat to efficient market theory since by observing the patterns, investors are able to predict when to purchase securities at low prices and when to sell the at high prices hence obtaining abnormal profits.

5.6 Recommendations for Further Studies

This study compared GARCH(1,1) and TGARCH models and focused on NSE All Share Index and NSE20 Share Index markets, further studies may be carried out on other volatile markets using GARCH model extensions like E-GARCH, I-GARCH, M-GARCH and A-GARCH. Additional anomalies should also be considered in further studies.

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APPENDIX 1

SAMPLE OF HOW DATA WAS TRANSFORMED

Date	Closing Price	Var1=today's closing price-yesterday's closing price	Var2=Var1+10	Var3=log(Var2)

25, Feb 2008	96.18	-	-	-
26, Feb 2008	95.42	-0.76	9.24	0.965672
27,Feb 2008	94.75	-0.67	9.33	0.969882
28, Feb 2008	94.24	-0.51	9.49	0.977266
29,Feb 2008	98.6	4.36	14.36	1.157154
3, Mar 2008	99.86	1.26	11.26	1.051538
4, Mar 2008	102.08	2.22	12.22	1.087071
5, Mar 2008	103.09	1.01	11.01	1.041787
6, Mar 2008	103.69	0.6	10.6	1.025306
7, Mar 2008	102.19	-1.5	8.5	0.929419
10, Mar 2008	101.75	-0.44	9.56	0.980458
11, Mar 2008	100.73	-1.02	8.98	0.953276
12, Mar 2008	99.22	-1.51	8.49	0.928908
13, Mar 2008	99.19	-0.03	9.97	0.998695
14, Mar 2008	97.07	-2.12	7.88	0.896526
17, Mar 2008	95.15	-1.92	8.08	0.907411
18, Mar 2008	93.98	-1.17	8.83	0.945961