

**ANALYSIS OF ASSYMETRIC AND PERSISTENCE IN STOCK RETURN
VOLATILITY IN THE NSE MARKET PHASES**

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A research submitted to the School of Management and Commerce in partial fulfilment of the
requirements for the degree of Master at Commerce at Strathmore University



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April 2014

DECLARATION

This research is my original work and has never been submitted and approved for the award of degree by this or any other University.

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ACKNOWLEDGEMENT

Sincere appreciation to God for His grace and my supervisor Dr. Freshia Waweru, kindly receive my sincere gratitude for your intellectual insight in writing this thesis. Special thanks to my Dad Festus Ogega & Mum Sara Akinyi, and not forgetting my sisters & brothers and course mates who gave me encouragement to pursue and excel in the course.



Abstract

Asymmetric and persistence in the volatility of stock returns are very fascinating features of the behaviour of securities market. The persistence in volatility has a major effect on the future volatility of the security market under the influence of shocks and asymmetric features increases the volatility. This study examined salient features of financial time series of the stock market phases and the behaviour of stock return volatility in the Kenyan stock exchange during the market phases for the 20 share index and the 10 sampled companies over a period of 2003 to 2013. The results obtained shows that bullish market phase takes a longer time to die out than the bearish market phase and fluctuations in the series are variable in time with bear phase much more frequent than bull phase. The asymmetric effect, volatility persistence and clustering volatility behaviour of the volatility are fitted by the Fractionally Integrated Exponential GARCH (FIEGARCH) model. The volatility in the Kenyan stock market during both phases exhibits long-run memory and volatility asymmetry. Volatility estimate and diagnostic tests show volatility clustering, that is, shocks to the volatility process persist and the reaction to news arrival is asymmetrical, indicating that the effect of good and bad news is unsymmetrical with positive news impacting more during bullish and negative news more during bearish. In addition, the bullish phase exhibits a higher degree of long memory persistency meaning when there is a shock on volatility it takes a longer time to decay during bull than bear phase. The findings also lead to the rejection of efficiency market hypothesis (EMH) in NSE. The empirical results would be helpful to investors, policy makers and stock exchange administrators as these give indication of the behaviour of the volatility during the market phases. Furthermore, if traders know the behaviour during the phases, they will adjust to the market's moods.

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ABBREVIATIONS AND ACRONYMS

ARCH	Autoregressive Conditional Heteroskedastic
ARFIMA	Fractionally Integrated Autoregressive Moving Average
CAPM	Capital Asset Pricing Model
CMA	Capital Market of Kenya
EGARCH	Exponential GARCH
EMH	Efficient Market Hypothesis
FIEGARCH	A Fractionally Integrated Exponential GARCH
FIGARCH	Fractional Integrated GARCH
GARCH	Generalized Autoregressive Conditional Heteroskedastic
GJR-GARCH	Glosten, Jagannathan and Runkle GARCH
i.i.d.	Identical and independently distributed
ICSS	Iterated Cumulative Sums of Squares
IGARCH	Integrated GARCH
KNBS	Kenya National Bureau of Statistics
NASI	Nairobi all share index
NSE	Nairobi securities exchange
STAR	Smooth Threshold Parameter Nonlinear Market model
TGARCH	Threshold GARCH
VaR	Value-at-Risk
NBER	National Bureau of Economic Research

Chapter 1: Introduction

1.1 Introduction

Access to investment capital, mainly through well-functioning financial markets, is crucial for economic development (Obstfeld, 1994). Financial market is where equity and long-term debt securities are exchanged and a platform where governments and business enterprises can raise finances for long term investment (Nisar & Hanif, 2012). Afego (2012) and Nyamongo & Misati (2010) assert that developing regions of the World, including Africa have seen an increasing prominence of stock markets which is widely seen as a positive development in view of the potentially significant role financial markets play in the economic growth process. The existence of a well regulated and well organized stock exchange is very much essential for the smooth functioning of the financial markets in any country (Baloch et al., 2013).

According to Olweny & Omondi (2011), stakeholders, investors, and the government are greatly concerned about the stock market and its importance in the development of a country. Kimani & Mutuku (2013) further argue that stock markets stimulate savings and investments by offering an opportunity for portfolio diversification to both corporate and individual investors, hence fueling economic development through diversification, mobilizing and pooling of savings from different parties and availing them to companies for optimal utilization. Stock markets experience periods of upward and downward market phases which infers bull and bear periods (Maheu & McCurdy, 2000). Candelon, Piplack, & Straetmans (2008) define upward periods as periods when the market return is more than 0, whereas downward periods as periods when the market return is less than 0. Silvapulle and Granger (2001) divided stock market into bullish and bearish phases by using quantiles of return distributions. Further, Dukes, Bowlin & MacDonald (1987) using the S&P500 index, explained bull markets as episodes in which the index is increased by at least 20% from a trough to a peak while the bear markets as episodes in which the index decreased by at least 20% from a peak to a trough.

Vijayalakshmi & Gaur (2013) argue that volatility in the stock return is an important part of stock market with the alternating bull and bear phases. Ramos, Iul, & Vermunt (2008) underline that, bulls markets relate to periods of positive returns or a generalized upward trend and bears markets relate to negative returns or a generalized downward trend. Stocks returns are noticed to

last longer in the upward market than in the downward market, hence it is riskier for investors to hold portfolios when the market is at bull phase (Yaya, Shittu, & Tumala, 2013).

According to Chordia, Roll, & Subrahmanyam (2001), the different observed behavior in the stock market liquidity in bull and bear markets may be associated with volatility. Moreover, they concluded that bull markets are subject to more investments and liquidity whereas bear markets are characterized by higher volatility and liquidity problems. Therefore, volatility should be considered across bull and bear stages and forecasted so as to detect its characteristics from financial time series. For long spanning data sets like in this study, the volatility modeling should take into account the market structures and important events (bull and bear) which may trigger the time varying asymmetry and long memory volatility (Cheong, Hassan, Mohd, & Isa, 2006).

Mittal & Goyal (2012) define volatility as the ups and downs in the stock prices and can be a threat in attracting investment in small developing economies like Kenya. Cont, (2010) and also Tripathy & Gil-Alana (2010) argue that stock market return volatility exhibits the following common properties; Time varying volatility which is the variation of stock markets volatility with time, Volatility pooling/clustering (It has been found that large shocks are followed by large shocks and small followed by small in either sign), long-term dependence or long memory (slower decay in the autocorrelation of time series) and lastly Leverage effect (volatility is greater after negative news than after positive news of the same magnitude in the stock market). The association between the stock market returns and their volatilities is usually dynamic and nonlinear (Mishra & Rahman, 2010).

Daily stock market return movements are quite natural and an upsurge in stock market volatility results into a huge stock market return change. Generally, a rise in stock market volatility is interpreted as an upsurge in the risk of stock investment and therefore stimulate the investors to redesign or take decisions regarding their investment portfolios in the short and long run (Baloch et al., 2013; Goudarzi & Ramanarayanan, 2011). Vijayalakshmi & Gaur (2013) accentuate that, policy makers depend on stock market volatility as an indicator for the susceptibility of the economy and financial markets which shows the importance of volatility forecasting. Furthermore according to Ahmed & Suliman (2011) besides other interdependent factors like stock liquidity, volume traded, price, among others, investment decisions are governed substantially by volatility.

Minimal volatility is preferred as it allows market participants to liquidate their assets without huge price movements due to unnecessary risk borne by investors. The daily information shocks, in addition to the differences in investor views and prospects, are the source of stock market volatility (Mishra & Rahman, 2010). Volatility has therefore a special feature as it is not directly observable thus financial analysts are particularly keen to obtain suitable approximation of this conditional variance/volatility so as to improve risk management and portfolio allocation (Abdalla & Winker, 2012). According to Iyiegbuniwe, Ezike & Amah (2012) the increasing prominence of financial markets in the allocation resources in emerging and developed economies raises concerns about the pattern and level of volatility of financial time series.

Modeling the capital markets volatility is closely linked to the Efficient Market Hypothesis (EMH), a concept found in conjunction with the rationality of investor behavior (Pele & Țepuș, 2011). Fama (1970) and more recently Timmermann & Granger (2004) highlighted that EMH and the concept of information and the mechanism of reflection a set of information released in the trading price of a security are inseparable. Malkiel (2003) clearly describes the random walk hypothesis as the process where the information released is immediately reflected in security prices and the following day's price change will reflect only the tomorrow's information thus independent of today's price change. Price changes must then be unpredictable and random as the information is unpredictable. If an efficient market (in weak form) is assumed, then the security price follows a random walk model, that is, the time series of returns is a white noise process. Fama (1970) instituted the following three forms of Market Efficiency; The weak-form efficient market hypothesis where past information are fully reflected on the stock prices hence are useless in predicting future prices, the semi strong-form which implies that the past and current information that are publicly available are fully reflected on stock prices and lastly the strong-form which implies that no public or private information available should help predict stock prices.

According to Goudarzi & Ramanarayanan (2011), variation of security prices is an indication of market efficiency in stock markets where security price fully reflects all existing information. However, Karolyi (2001) asserts that the presence of excessive stock return volatility, or "noise," compromises the worth of equity return as a "signal" about the fair intrinsic value of a company, a concept that is essential to the paradigm of the informational efficiency of markets. In such a

case difference between the security related market value and intrinsic value is significant and acts as a restraint to efficient investment by causing lengthy periods of uncertainty (Goudarzi & Ramanarayanan, 2011). Nyamongo & Misati (2010) argue that excess equity market volatility similarly confounds monetary policy decision making process particularly when there are incidents of stock price bubbles, which are more likely to generate inflation.

Generally, volatility of stock markets returns may be affected differently by positive and negative shocks/news; more explicitly, volatility reacts more to negative shocks than to positive shocks (Oskooe & Shamsavari, 2011; Yaya et al., 2013). This phenomenon of stock returns reaction to good news and bad news differently is called as asymmetric volatility or leverage (Kalu & Friday, 2012; Oskooe & Shamsavari, 2011). Establishing of the presence of asymmetric volatility is significant in risk management, portfolio selection, valuation of stocks and asset management (Oskooe & Shamsavari, 2011; Parvaresh & Bavaghar, 2012). Good news typically is described as upward market activities witnessed if last period's stock return is positive and bad news is defined as downward market movements.

According to Tolvi (2003) and Boubaker & Makram (2012), long run persistence in stock return volatility occurs when the effects of volatility shocks decay slowly detected often by the autocorrelation and thus the ability to forecast future returns corresponds to market efficiency. Wu (2006) described volatility persistence process as a stochastic process whose auto covariance function decays very slowly as the distance between observations tends to infinity. Therefore there appears to be a predictable element in the conditional variance over time such that rises in current volatility leads to successive rises in future volatility (Krainer, 2002).

Slow autocorrelation decay rate and persistence in volatility refutes the intuition behind random walk hypothesis (Iyiegbuniwe et al., 2012). Andersen & Bollerslev (1997), Cheong et al. (2006) and Mike (2000) argue that the existence of volatility persistence behavior in the stock markets and this fractal scaling behaviour is significant in measuring the market risk, volatility and market efficiency. Typically, persistence in volatility is adopted to inform investors' investment decisions during the market cycles (Tolvi, 2003). Thus, a study of volatility persistence signifies the predictability in the long horizon for the developing markets of the world and should be of benefit to several investors and financial practitioners.

Nairobi security market is significant for economic growth as it enables unutilized funds to be invested in productive economic activities (Owido, Onyuma, & Owuor, 2013). The Nairobi Securities Exchange (NSE) share price movements are measured by the key indices tracking performance at the NSE. World over a stock exchange index is assumed to be an indicator of the political, economical and social volatility of a nation (Yaya et al., 2013). The stock market index is considered as an imperative indicator by the investors often employed as a benchmark by which the fund managers or investors relate the returns of their own portfolio. Ogilo (2008) establish that stocks experience both the bull and bear market at the NSE with January, February and March when most stocks experience the bear market while August to November majority of stocks experience bull market.

The Kenya National Bureau of Statistics (KNBS, 2010) reported that the NSE 20 share index by end of December 2008 recorded a sharp drop to 3531 points and further fell by 7.8% standing at 3247 points in 2009. In 2010, the index increased steadily reaching a high of 4,433 points compared to 2009 but in 2011, the NSE 20 Share Index lost by 26%. Capital Market Authority 2012 reported a gain on NSE 20 index of 29% in 2012, closing at 4,171.87 points as improved macroeconomic conditions and strong foreign investor interest pushed stock prices upwards, the total net equity foreign portfolio inflow during FY 2011/2012 was Kes.11.2 billion, the highest in the history of the NSE. NSE 20 share index closed at 5052.63 points as of 20th October 2013 with all share gaining 43.021% in 2013. In spite of the growth potential and investment opportunities, Kenyan market has faced several political, social and economic crises.

1.2 Statement of the Problem

Besides that good and bad news might influence stock return volatility differently, good news in a bull market may not elevate the stock market as much as in a bear market and vice versa. Naturally, given a persistent downward market movement, bad news may haul down the market more than if there has been upward market trend. Therefore, in a bear market, the market is anticipating for bad news and bad news wobbles market confidence greater than if it has been a bull market. Maheu, Mccurdy & Song (2009) assert that if bull and bear trends do exist, then it is imperative to extract them from the data to examine their properties and consider their use as inputs into investors' investment decisions. Anecdotaly, Batra (2004) argue that during a bear

market, news is more eagerly expected than in a bull market. Bear markets salivate in anticipation of news, digest it insatiably, and react more violently than bull markets.

Adequate knowledge therefore about the volatility, performance and efficiency of stock returns remains vital and essential information among economists, stock market analysts, investment fund managers, investors and policy makers as asymmetric volatility increases market risk (Forgha, 2012; Oskooe & Shamsavari, 2011). Stock volatility better explains investor's sensitivity to invest in an economy. Rajput, Chopra & Rajput (2012) argue that investors are not likely to invest in volatile stock market of any economy where returns are susceptible to higher risk. This hesitancy to invest in such a volatile economy hinders economic growth of that country (Verma & Mahajan, 2012). Participants at the NSE are concerned as the market exhibits turbulence with stock prices dropping to new levels and rising drastically (Julius, Andrew, Joel, & Lucy, 2011). Therefore, investment decisions as to when to buy, sell or hold is a major challenge to investors in Kenya given the nature of NSE market.

The study by Ogum, Beer & Nouyrigat (2005) established that, NSE is characterized by positive and significant asymmetric volatility signifying that positive shocks upsurge volatility more than negative shocks of similar scale in Kenya. They also established that expected returns can be forecasted and also that persistent volatility is exhibited in Kenya. Nyamongo & Misati (2010) study on modelling the time-varying volatility of equities returns in Kenya found out that the effect of news on volatility is not significantly asymmetric but leptokurtic and hence not normally distributed and volatility of stock returns is highly persistent. They also established that, the leverage effects are not significant. Further Olweny & Omondi (2011) study on impact of Macro-economic elements on the stock return volatility in the NSE, Kenya found that volatility of stock returns is not highly persistent and the volatility symmetric not significant.

The motivation for this research is that asymmetry and persistence in the volatility of stock returns are very fascinating features of the behaviour of securities market. The persistence in volatility has a major effect on the future volatility of the security market under the influence of shocks (Kumar, 2013). Furthermore, persistence in volatility can assist in forecasting future volatility which sequentially is helpful in predicting economic variables. The research therefore investigated whether a bull market responds to news differently than a bear market in

understanding of the asymmetric effect and volatility persistence in the NSE and the nature of events that seemingly causes the shifts in volatility.

1.3 Research Objectives

1.3.1 Main Objective

This study established the behaviour of volatility of stock return in the Nairobi Securities Exchange market cycles.

1.3.1 Specific Objectives

- I. To establish existence of salient features of financial time series in the NSE stock market phases.
- II. To evaluate the differential impact of change in returns on future volatility of stock return in the NSE market cycles.
- I. To investigate the length of volatility decay process of stock returns in the NSE stock market cycles.

1.4 Research questions

- I. Do the salient features of financial time series exist in the NSE stock market phases?
- II. What is the differential impact of change in returns on future volatility of stock return in the NSE market cycles?
- III. Is there evidence of persistence of the stock return volatility in the NSE market cycles?

1.5 Scope

The study duration covered from 2003 to 2013 utilizing data from Nairobi Securities Exchange on the daily share index. The study utilized both the sampled 10 companies' data and 20 share index. The period 2003-2013 under study in this research was characterized by both external and domestic shocks to the Kenyan economy, the effects of which created incidents of unprecedented volatility in the NSE. In 2003 Kenyan Government developed and launched the Economic Recovery Strategy (ERS) for Wealth and Employment Creation, as the blue print for setting the country back on the growth path after years of economic stagnation thus, restoring investor confidence.

1.6 Justification of the study

1.6.1 Current Investors, prospective Investors and Practitioners

Garvey, (2010) reveals that during a stock market fall, volatility increases and equally, as security prices increase volatility become subdued. Added to that, the author also indicated that a more statistical analysis to measure volatility in bears and bulls markets can help investors to improve the timing of their investment decisions. Maheu and Mccurdy (2000) further argue that, as the bull market persists, investors could become more optimistic about the future and thus desire to invest more in the stock market. This positive feedback indicates that the likelihood of switching out of the bull market decreases with time. Olweny and Omondi (2011) further assert that the Nairobi Securities Exchange behavior should be studied further to aid investors in making reasonable investment decisions and help the regulator in policy formulation

Through this investigation in bull and bear phases in NSE, this study can help investors with a better understanding of NSE bullish and bearish periods. Furthermore, Investors are interested in the volatility in stock prices during the holding period because they depend on capital gains for their returns as well as volatility presents opportunities to buy low priced stocks and sell overpriced stocks.

1.6.2 Policy makers

Policy makers may benefit from appreciating how shocks will affect volatility over time as the persistence in volatility is a significant parameter for precisely forecasting how major events could affect future stock return volatility. Furthermore, NSE stock prices behavior translate savings decision into investment decisions and therefore supporting economic growth. Geert Bekaert, Harvey, and Lumsdaine (2002) indicate that economic growth is related to financial development in developed countries.

Chapter 2: Literature Review

2.0 Introduction

Volatility of prices and returns in financial markets can be an impediment for attracting investment in a developing economy. The presence of high degree of volatility signifies that investors will demand for much premium thus creating high cost of capital which is inimical to the growth of the economy. An upsurge in stock market volatility is a sign of a rise in risk of stock investment and therefore a shift of funds to less risky security. Stock market volatility has several negative implications such as impairing the smooth functioning of the financial system, adversely affecting economic performance (Mala & Reddy, 2007). This chapter will start by discussing the theory of the market phases and the common properties of financial time series and also relate news impact on volatility with EMH. The study will further discuss volatility long memory and asymmetry in stock return taking into consideration various empirical studies and lastly a review of volatility modeling.

2.1 Theoretical framework

2.1.1 The Theory of Market Phases

Charles Dow theory classified market trends into three phases namely, the Public Participation, Accumulation, and Excess Phases in a bull market and the Panic Phase, Public Participation and Distribution in a bear market (Ray, 2012).

2.1.1.1 Bull Market

2.1.1.1.1 The Accumulation Phase

The Accumulation Phase is where the upward trend begin, which is typically at the bottom of a down trend. It is the point at which the savvy investors enter the market at the best prices when the market is undervalued and at the end of a downtrend when most of the bad news is priced into the market, thus restraining downside risk and offering attractive valuations. In the Accumulation Phase, stocks are bought by knowledgeable investors who expect an economic recovery and foresee a long-term growth. This is also considered the point at which knowledgeable investors start to join the market. The phase will also be characterized by persistent market pessimism because investors think that things will only get worse.

2.1.1.1.2 The Public Participation Phase

The Public Participation Phase occurs after the positive news starts to be taken on board by the wider population. The Participation Phase is characterized by increasing corporate profits and better economic conditions therefore, more and more Investors buy shares sending prices higher. Negative sentiment starts to drive away as business conditions and marred by earnings growth and strong economic information improve during this phase. This phase generally last longer and the prices moves the most than the Accumulation phase.

2.1.1.1.3 The Excess Phase

Fascinatingly, this is where the savvy and informed traders start to diminish their exposure and begin to make some profits. It is the last stage in the upward trend and the smart traders starts to scale down their positions, selling them off to those now come in the market. At this moment, the market is hot again for all investors. The view is that all is running fantastic and that only good occurrences lie ahead. It is also the time when the final buyers start to enter the market after huge gains have been realized. This is the part of the trend that investors should start examining for signs of upward momentum weakness. The phase is usually seen in a bubble market.

2.1.1.2 Bear Market

2.1.1.2.1 The Distribution Phase

This is the period in which the savvy traders short their positions deliberating that the market is overbought and the knowledgeable buyers are now selling into an overbought market rather than buying in an oversold market. Technical Analysis may be useful here to ascertain this phase as it normally comes after an upward trend and consolidation period. Overall sentiment remains to be optimistic, with anticipations of higher market levels in this phase. The final investors in the market continue buying, particularly those who unexploited the big move but are anticipating for a similar one in the near future.

2.1.1.2.2 Public Participation Phase

Like the Public Participation in a bull market, this is generally the lengthiest bit of the trend with the greatest price move. During this phase, the business circumstances in the market are worsening and the sentiment is becoming more negative as time goes on. Trend cohorts will

often leave the market or take a short position. The market continues to discount the worsening circumstances as selling increases and buying dries up.

2.1.1.2.3 The Panic Phase

The final phase of the bear market tends to be packed with market panic and can lead to very large selloffs in a very short period of time. A jerk of negativity enters the market and a stream of selling takes place occasionally at panic levels. The market is shaped up with negative sentiment, comprising weak outlooks on companies, the economy and the general market. Some savvy investors will start contemplating market entry at this point trying to profit on bad news.

Recently, Pagan & Sossounov (2003) proposed algorithms to categorize market based on the descriptions of the phases in terms of movements between troughs and peaks given in Dukes et al. (1987) and all the studies observe that bull market stays longer than the bear markets. Gonzalez, Hoang, Powell & Shi (2006) delineate bull and bear markets in terms of a basic regime-switching model. The description of two turning point detection methods is employed to investigate whether two periods of stock index returns can be estranged into statistically and economically significant bull and bear phases. Yaya et al. (2013) studied the two phases of the Nigeria financial market using Smooth Threshold Parameter Nonlinear Market model (STAR). Stocks returns were established to last longer in the upward market (bull) than in the downward market (bear), thus it is riskier for investors to maintain portfolios when the market is at bull phase.

2.1.2 Stylized facts about financial time series

Studies by Fama (1965) and Mandelbrot (1963) documented that, financial time series such as, stock returns, exchange rates, and other financial time series data are known to display certain stylized facts which are critical for right model specification, estimation and forecasting. The most popular stylized patterns include:

2.1.2.1 Volatility Clustering/ pooling and Persistence

Developed by Mandelbrot (1963), it is where small and large values in the log-returns have a tendency to occur in clusters that is, small movements being followed by small movements and the large changes in stock returns tend to be followed by large changes of either sign. Volatility clustering is nothing but clustering of information or accumulation i.e., news is clustered over

time (Cont, 2010). The inference of volatility clustering is that volatility shocks today will impact the anticipation of volatility in some times in the future.

2.1.2.2 Fat Tails or Non-Normality

Financial time series such as stock returns empirical distribution exhibits fatter or highly non-normal tails also referred to as excess kurtosis hence not normal distributed with fourth moment above 3, meaning that asset returns are normally leptokurtic (Fama, 1965; Mandelbrot, 1963). The existence of thick tails or excess kurtosis in stock returns implies that approximations based on the assumption of identical and independently distributed (i.i.d.) errors are unsuitable for stock returns.

2.1.2.3 Leverage Effects and Asymmetry

Downward movement is always followed by higher volatility in financial markets. Stock prices changes tend to be negatively associated with changes in volatility that is; volatility is higher after negative news than after positive news of the same scale (Fama, 1965). Asymmetry is attributed to leverage effects that is, negative news upsurge predictable volatility in stock markets more than positive news. Black (1976) postulated that when stock price drops, the value of the related firm's stock decreases. As a result, leverage the debt to equity ratio of the firm increases, thus signaling that the firm is more risky. The statistical interpretation of Black's leverage effect infers that negative surprises upsurges predictable volatility in stock markets more than positive surprises. Volatility feedback hypothesis is another explanation of volatility asymmetry (Engle & Ng, 1993; Nelson, 1991).

2.1.2.4 Volatility persistence

Particularly for high-frequency data like daily stock returns, volatility is extremely persistent or possesses long memory if it is characterized by very slow hyperbolic decay in autocorrelations of absolute or squared returns. The persistence in stock return volatility has a major effect on the future volatility of the market under the influence of shocks. Moreover, persistence in volatility can aid in forecasting future volatility which sequentially is beneficial in predicting economic variables. It is also imperative for option traders who want to value options with expirations spreading into the future (Kumar, 2013).

2.1.2.5 Daily Seasonality and Non-trading Periods

Generally, information accrues during the period when financial markets are shut and is immediately revealed in the price when the markets reopen. Therefore, variances are greater following holidays and weekends leading to the observation of daily seasonality in stock returns.

2.1.2.6 Regular Events

The announcement of significant information is realized to be related with extreme volatility. The behaviour of volatility during the trading day is found to be predictable as volatility is normally higher at the open and close of trading in stock.

2.1.3 Efficient Market Hypothesis (EMH)

Fama (1970) and Samuelson (1965) underline that under EMH, security market prices should follow a random walk process and immediately show an extensive reflection of all relevant and available information. Succeeding stock price changes are consequently independently and identically distributed (*iid*). Fama (1970) categorized the three types of efficient markets as weak-form (includes past prices and returns only), semi-strong-form (all public information), and strong-form efficient (any information public as well as private) base on the information set.

The theoretical asset pricing models by Merton (1980) and Sharpe (1964) which are based on market efficiency link returns of a security to its own variance and/or to the covariance between the returns of stock and market portfolio. Nevertheless, whether such association is negative or positive has been contentious. Cox & Ross (1976) confirm a negative relationship between returns and volatility while Pindyck (1984) shows that there is a strong positive association between volatility and stock return and further Poterba & Summers (1986) as well as Bekaert (2000) found negative relationship in a variety of USA market indices. French, Schwert & Stambaugh (1987) using data from the S&P index, found a negative association between unexpected volatility and stock returns which gives indirect indication of a positive association between expected risk premium and volatility.

2.1.4 Stock Market Volatility

Engle & Ng (1993) attributed influx of new and surprising information as the main source for the volatility. Shift in investor tolerance of risk, changes in trading volumes and pattern driven by the variations in macroeconomic policies and intensified uncertainty are also perceived as

causing volatility. Furthermore, civil security situation, global events and political changes are also cited as causes of return volatility (Mittal & Goyal, 2012). Poon & Granger (2003) further argue that the return and volatility of stock markets are significantly affected by regime shifts or infrequent sudden changes, corresponding to global and domestic economic events. For example the IT dot-com bubbles, the recent global crisis in 2007-2010 and domestic political events. Such sudden shift in the underlying economy and/or fundamentals is an imperative component of construction of investment portfolios, and in the managing market risk and uncertainty and the pricing of derivative securities.

The rationale and underlying logic of leverage effect or asymmetric is that the distribution of stock return is highly asymmetric. Bad shock is followed by huge upsurge in stock return volatility than good news of the same magnitude. It explains that as stock price falls, the debt-equity ratio of firms tend to rise and that will increase the volatility. Persistence in stock return volatility infers that the return and risk tradeoff changes in a foreseeable manner over the market cycles (Krainer, 2002). Stock return volatility stipulates some signal regarding the health of the financial markets and the economy. The results of studies such as Kang et al., (2013); Kumar & Maheswaran, (2012); Malik et al., (2005); Wang & Moore, (2009) show that, with the integration of sudden changes into GARCH-type models, a considerable decrease in the persistence of volatility in international stock markets.

2.2 Empirical review on Volatility Dynamics

2.2.1 Developed Markets

Engle & Ng (1993) measured the effect of positive and negative shocks on volatility in Japan market and established an asymmetry in stock market volatility towards positive shocks as compared to negative shocks. More precisely, market volatility is presumed to be related to the arrival of news as a sudden decline in price is correlated with bad news conversely, a sudden rise in price is attributed to good news. However, Koutmos (2012) while examining time-varying stock price and volatility dynamics of constituent industry sector indices in the Shanghai Stock Exchange demonstrated that good and bad news exert an equal impact on the conditional volatility process and presence of persistence volatility.

In investigating the impact of regime changes on volatility persistence, Lamoureux & Lastrapes (1990) found out that there is a substantial decrease in the projected persistence of volatility of stock returns when regime shifts were integrated in the standard ARCH model. Malik et al., (2005), also investigated the impact of regime changes on volatility persistence in Canadian Market by conducting ICSS algorithm to detect unexpected changes in the volatility and integrate those shifts into variance equation of GARCH model to circumvent overestimating the volatility persistence. They established that the persistent volatility decreases after considering sudden stock return volatility shifts.

Kang & Yoon (2006) employed the FIEGARCH model to capture the asymmetry features and long memory properties in the volatility of Japan, South Korea, Hong Kong and Singapore stock index returns and indicated that the entire sample returns exhibit asymmetries in volatility, and volatility is a long memory process. Using TGARCH-M model in India and Japan Mishra & Rahman (2010) indicated that the stock market of Japan is comparatively more efficient than that of India. They also noted evidences of asymmetric effects of bad news and good news on stock market returns of Japan and India. Seemingly, India's stock market is affected more by positive news and Japan's stock market is affected more by negative news. Presence of volatility persistence was also established in both markets.

2.2.2 Emerging Markets

Rousan & Al-khouri (2005) empirical analysis in Amman Stock Exchange (ASE) Composite Index (ASE) supported the symmetric volatility hypothesis, meaning that ASE returns are volatile and that positive and negative shocks of the same size have the similar effect on the future volatility level. Similarly, they established that the volatility response to a shock tend to persist in the market. However, Oskooe & Shamsavari (2011) who conducted similar study in the Iranian stock market established that positive and negative shocks of the same scale have the similar impact and effect on the future volatility level. Further Suleman (2012) analyzed the volatility on Karachi stock exchange 100 index and in addition, consequence of political news on stock market returns and established that bad news have almost double effect on the volatility than the good news.

Bahadur (2008) study established that the distribution of the daily stock return series for the Nepalese stock market exhibits significant time dependencies, leptokurtic and non-normal. Using

GARCH (1,1) model, the study also showed a strong evidence of the periods of high and low volatility to cluster and a high persistence and thus predictability of volatility in the Nepalese stock market. Frimpong & Oteng (2006) did a similar study on the Ghana Stock Exchange Index (GSI) using a random walk (RW), GARCH(1,1), EGARCH(1,1), and TGARCH(1,1) and established that GSI displays the stylized characteristics such as asymmetry effects, volatility clustering and leptokurtosis and hence random walk hypothesis was rejected for the GSI.

In Indian stock market, Maheshchandra (2012) studied the presence of long memory using ARFIMA, FIGARCH models and the results imply that there is a predominance of persistence property in volatility. Further, the volatility persistence property of the BSE market is discovered to be much stronger than NSE and it could be held that NSE might be having better participation of participating investors than BSE which could result to better informational efficiency in volatility in contrast to BSE. Mittal & Goyal (2012) used S&P CNX Nifty as a proxy to the Indian Stock Market. The return series exhibited heteroskedasticity, excess peakedness, volatility clustering and has fat tails. In addition, they established that return reacts differently to different news (volatility asymmetry). The long persistence in volatility indicates that Indian market is inefficient and information is not reflected in stock prices quickly. Study by Goudarzi & Ramanarayanan (2011) on BSE500 (India) echoed similar results.

The study by Iyiegbuniwe et al. (2012) applying AR(3) EGARCH (1, 1) in-Mean framework in Nigerian Stock Exchange Index. The empirical result showed that the Nigeria stock market exhibit the phenomenon of volatility persistence, thus inefficient. They also established that the Nigerian market does not exhibit leverage effects. Nkoro & Uko (2013) further studied the same market and observed volatility clustering in Nigerian stock market. Volatility of Nigeria's stock market returns was influenced by past volatility more than the economic news from the previous period. The time-varying volatility of the Nigeria's stock market returns last moderately long. However Kalu & Friday (2012) study in Nigeria using GARCH (1,1), EGARCH and GJR-GARCH models, obtained an evidence of volatility clustering and volatility persistence and also asymmetric volatility effect in Nigeria. Contrary to leverage effect theoretical sign, result of GJR-GARCH and EGARCH model estimate is positive suggesting that positive news increases volatility more than negative news.

Ahmed & Suliman (2011) used symmetric and asymmetric GARCH models that capture the most common properties about index returns to estimate volatility in the daily returns of the Khartoum Stock Exchange (KSE), Sudan. They established that the conditional variance process is highly persistent and also the presence of leverage effect. Abdalla & Winker (2012) also obtained similar results in their investigation of Stock market volatility in two African stock exchanges, Cairo and Alexandria Stock Exchange, CASE, Egypt and Khartoum Stock Exchange, KSE, Sudan. Their further empirical findings show that the volatility is an explosive process for the KSE stock index returns series, whereas it is quite persistent for the CASE stock index returns series.

Boubaker & Makram (2012) studied North African stock markets using FIGARCH model and established that the volatility series is a long-memory process. In addition, they modeled jointly long-memory processes in both returns and volatility using the joint ARFIMA–FIGARCH model and found that the double long-memory model can provide a suitable explanation for long-memory dynamics in both returns and volatility. Thus investors in North African stock markets may tend to react slowly and gradually to new information and that their actions do not follow the Martingale process.

Kumar & Maheswaran (2012) and Kasman (2009) used iterated cumulative sums of squares (ICSS) to determine regime shifts are then applied in the asymmetric volatility models GARCH and GJR-GARCH models to study the impact of shocks on volatility persistence and asymmetry. The results showed that the persistence and asymmetry in volatility are reduced considerably when regime shifts are taken into account in the volatility models. Therefore, ignoring sudden changes in volatility will lead to understating or overstating the persistence of volatility which in turn may lead to potential errors by risk managers to come up with the Value-at-Risk (VaR) measure. Yaya et al. (2013) studied the two phases of the Nigeria financial market using Smooth Threshold Parameter Nonlinear Market model. Stocks returns were realized to stay longer in the upward market (bull) than in the downward market (bear), thus it is riskier for investors to maintain portfolios when the market is at bull phase.

Batra (2004) studied the dynamics of stock return volatility in India and in addition, investigated unexpected shifts in volatility and the likelihood of concurrence of these unexpected shifts with important political and economic happenings both of foreign and domestic. He also investigated

stock market cycles for variation in duration, volatility and amplitude of the bear and bull phases over the reference period. The study showed that in general over the references period the bull phases takes long, the amplitude and volatility of the bull phase is higher. He further established that the gains during bull are greater than the losses during the bear phases of stock market cycles.

2.3.3 Nairobi Securities Exchange

Ogum et al. (2005) study considered two emerging markets, Kenya and Nigeria and reported that volatility clustering and asymmetric volatility found in the United States and other developed stock markets also exist in Nigeria. They also reported a positive and a significant asymmetric volatility coefficient in Kenya, which suggests that positive shocks increase volatility more than negative shocks of the same scale. On the other hand, Olweny & Omondi (2011), investigated the effect of Macro-economic factors on the stock return volatility on the NSE, using EGARCH and TGARCH. They established that negative news has a larger impact on stock return volatility than positive news and also that the stock returns are leptokurtic and therefore not normally distributed and further that volatility of returns is not highly persistent.

In further understanding of the behavior of stock return volatility in the Nairobi Stock Exchange, Nyamongo & Misati (2010) established that the asymmetric impact of news on volatility is not significant but leptokurtic and therefore not normally distributed applying GARCH(1,1), Threshold GARCH(1,1) and Exponential GARCH(1,1) models and further that volatility of returns is highly persistent. The same findings were echoed by Wagala, Nassiuma, Islam & Mwangi (2012) who determined the most efficient model from the symmetric and the asymmetric GARCH models applicable in Nairobi Securities Exchange. The results show that the AR-Integrated GARCH (IGARCH) models with student's t-distribution are the best models for modeling volatility in the NSE data. In addition, the volatility increases more with the bad news than the good news of the same scale for the NSE Index.

Tah (2013) established the stochastic behavior of monthly stock market returns in Nairobi Stock Exchange, Kenya and Lusaka Stock Exchange, Zambia. He established that, there is a negative and significant association between conditional variance and anticipated return for Zambia stock market. Conversely, no significant relation is found between conditional variance and expected return for Kenya stock market. These results imply that Nairobi Stock Exchange investors

consider some other risk measure to be more significant and the NSE is vulnerable to external shock. The study by Forgha (2012) on Cameroon, Nigeria and Kenya established that the risk return relationship measured by conditional variance of return from the quarterly data, are negative, and significant. This explains that the higher the risks, the lower the returns and vice versa. In the Nigerian and Kenyan markets, the sum of ARCH and GARCH is much closed to unity meaning that volatility in these markets is persistent.

2.3 Volatility Modeling Review

Financial time series like stock returns are generally observed to be autoregressive in nature or depend on their own past value, past information and display non constant variance (heteroskedasticity). Bahadur (2008) argue that volatility in asset returns also exhibits positive serial correlations (volatility clustering) and are established to be changing over time (time-varying) and also leptokurtic. Hence, employing constant variance models is inappropriate in financial time series as variance of the error depends on the volatility of the errors in the recent past.

Engle (1982) suggested Auto-Regressive Conditional Heteroskedasticity (ARCH) to deal with properties of financial time series. ARCH models are explicitly intended to model and predict conditional variances. Conditional variance infers to a dependence on the observations of the immediate past and the autoregressive and explains a feedback mechanism that integrated past observations into the present.

The formulation of his model is given below:

$$\varepsilon_t = v_t \sqrt{\alpha + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2} \quad \text{Where, } v_t \sim iid(0, 1)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \dots + \alpha_q \varepsilon_{t-q}^2$$

Where σ_t^2 is the variance at time t, q is the number of lags and ε_t^2 is the squared residual at time t.

The effect of a return shock i period ago ($i \leq q$) on current volatility is governed by the parameter α . In an ARCH model, old news arrived at the market more than q period ago has no effect at all on current volatility.

The ARCH model has many apparent advantages but has some weakness such as; First the model assumes that positive and negative shocks have the similar effects on volatility since it depends on the square of the previous shock. Second, ARCH model hardly provides any new intuition for understanding the cause of variations of a financial time series. It only provides the mechanical way of describing the behavior of the conditional variance. Finally, it over predicts the volatility since it responds slowly to large isolated shocks in time series data.

Going by the ARCH weaknesses, Bollerslev (1986) suggested a Generalized ARCH model (GARCH) for high order conditional variance to overcome the ARCH limitations. GARCH models have entered quick expansion phase and been successful in capturing a number of stylized facts of financial time series, such as asymmetric reactions to positive and negative shocks of equal magnitude, persistence and clustering and time-varying volatility (Morimune, 2007). GARCH process allows lagged conditional variances to enter in the model.

He suggested that the conditional variance function be specified as follows:

$Y_t = X_t\beta + \varepsilon_t$ is the mean equation. Where Y_t is the stock return, X_t is the exogenous variables or belonging to the set of information (Y_{t-1}) , β is a fixed parameter vector and conditional variance is,
$$h_t = \alpha_0 + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^p \beta_i h_{t-i}$$

Where, $\alpha_0 > 0, \alpha_1, \alpha_2, \dots, \alpha_q \geq 0$ and $\beta_1, \beta_2, \beta_3, \dots, \beta_p \geq 0$

The GARCH (p, q) above defined as stationary when $(\alpha_1 + \alpha_2 + \dots + \alpha_q) + (\beta_1 + \beta_1 + \dots + \beta_p) < 1$.

The GARCH model is an improvement over ARCH model but it also has some limitations. First, similar to the ARCH model, it equally responds to good and bad news. Second, based on the high frequency data, it is found that the tail behavior of the GARCH models remains too short even with standardized student t-innovations.

Though, ARCH and GARCH models are very useful in forecasting and modeling volatility but they do not capture information asymmetry and leverage effect. Nelson (1991) proposed an exponential GARCH (EGARCH) model to incorporate leverage effects between positive and negative returns on assets. Glosten, Jagannathan, and Runke (1993) later introduced the Threshold ARCH (TARCH) model and/or GJR's (TGARCH) models, to adjust the primary restrictions of GARCH-M model based upon the fact that GARCH model impose a symmetric reaction of volatility to positive and negative shocks.

The specification for the conditional variance in TGARCH is given by,

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} + \beta \sigma_{t-1}^2 \quad \text{Where } d_t = 1 \text{ if } \varepsilon_t > 0, \text{ and } 0 \text{ otherwise.}$$

$$d_{t-1} = \begin{cases} 1 & \text{if } u_{t-1} < 0, \text{ bad news} \\ 0 & \text{if } u_{t-1} \geq 0, \text{ good news} \end{cases}$$

In the model above, good news and bad news have differential impacts on the conditional variance with good news having an influence of α , while bad news an influence of $(\alpha + \gamma)$. If $\gamma > 0$, then a leverage effect exists, that is negative news has a larger effect on volatility than positive news. If $\gamma \neq 0$, the news impact is asymmetric

Exponential GARCH (EGARCH) proposed by Nelson (1991) which has form of leverage effects in its equation. In the EGARCH model the specification for the conditional covariance is given by the following form:

$$\log(h_t) = \alpha_0 + \sum_{j=1}^q \beta_j \log(h_{t-j}) + \sum_{i=1}^p \alpha_i \left| \frac{u_{t-i}}{\sqrt{h_{t-i}}} \right| + \sum_{k=1}^r \gamma_k \frac{u_{t-k}}{\sqrt{h_{t-k}}}$$

Two benefits stated in Brooks (2008) for the pure GARCH specification; by using $\log(h_t)$ though the parameters are negative, will be positive and asymmetries are allowed for under the EGARCH formulation.

In the equation γ_k symbolize leverage effects which accounts for the asymmetry of the model. While the basic GARCH model requires the restrictions the EGARCH model allows unrestricted estimation of the variance.

If $\gamma_k < 0$ it implies existence of symmetric and if $\gamma_k \neq 0$ impact is asymmetric.

Engle and Bollerslev (1986) propose the Integrated GARCH (IGARCH) model to capture the effect of a shock on the future volatility over an unlimited horizon. Nevertheless, these GARCH and IGARCH models are not capable of capturing the volatility persistence property satisfactorily. To manage this shortcoming, Bollerslev & Mikkelsen (1996) further developed Fractional Integrated (FIGARCH) model to model volatility from the data itself and the focus on the significance and the magnitude of the fractional integration parameter d without using a proxy for the volatility series of returns. This model approximates an intermediate process between GARCH and IGARCH. Bellalah, Aloui, & Abaoub (2005), Cavalcante & Assaf (2004), Kiliç (2004) and Wright (2002) examined long memory in volatility using a FIGARCH. The FIGARCH estimations produce a long memory parameter that is highly significant and different from both zero and one, which indicate long memory in the volatility series in all cases. To consider the volatility persistence effect along with the asymmetry feature in volatility, the literature provide approach by Bollerslev & Mikkelsen (1996) and fractionally integrated exponential GARCH (FIEGARCH) model

2.4 Conclusion

In the light of the difficulty by the investors in making investment decisions in Kenya during the bull and bear phases and the mixed results regarding asymmetric effect, volatility persistence and regime shifts in the literature, the study examined the asymmetric volatility and volatility persistence hypotheses and also the salient features of financial series during the two stock market phases. In this study since financial time series (stock returns) may display stylized facts such as, high peakedness, fat tails, non-normal distribution, volatility clustering, leverage effect and skewness and in view of the fact that FIEGARCH model is capable of capturing these features, to approximate the possible asymmetric volatility and volatility persistence. Furthermore, Olweny and Omondi (2011) recommended that further studies on persistence of news on stock return volatility will be beneficial to investors in making reasonable investment decisions and help the regulator in policy formulation.

2.5 Conceptual Framework on volatility behaviour in the market cycles

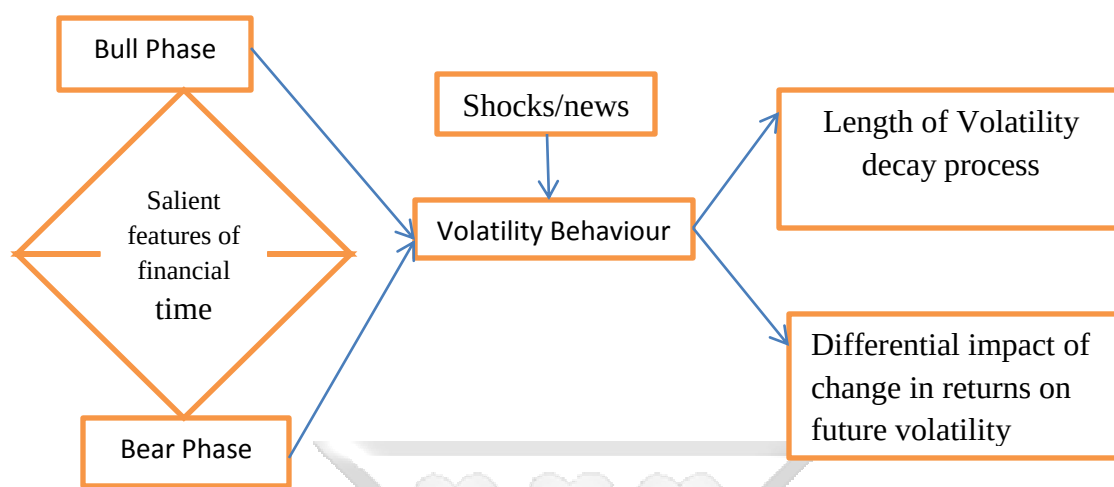


Figure 2.1: Volatility dynamics Conceptual Framework

2.5.1 Market cycles

The study focus is on the volatility behavior in the market cycles therefore, the study constructed a makeup of stock market cycles and considers the duration of downturns and upturns in the NSE and the scale of the cycles. The non-parametric approach employed allows for better flexibility in analysis and enables the study to examine issues related to predictability of the stock market. The periods of generalized upward trend, is to be classified as expansions and periods of generalized downward trend to be classified as contractions. The analysis key feature is to identify the turning points or regime shifts, troughs and peaks in the series. The regime shifts define the different phases of the cycle. Biscarri & de Gracia (2004) and Pagan & Sossounov (2003) applied the method for stock market analysis. Generally, despite the fact that good and bad news impacts differently on volatility, good news in a bull market may not elevate the market as much as in a bear market and/or vice versa.

2.5.2 Salient features of financial time series

To examine the distributional features of stock return series in the Kenyan stock market and understanding information about a probability distribution function of stock returns, assessment of location (mean), asymmetry (skewness), dispersion (standard deviation, and variance) and concentration in tails (kurtosis) are computed. The parameters mean and variance indicate the standardized first and second moments of a distribution, the skewness as the standardized third

moment measures the asymmetry of a distribution and the kurtosis as the central fourth moment determines the degree of peakedness and tail fatness of a distribution.

2.5.3 Volatility Behaviour

2.5.3.1 Asymmetric or leverage effect

Besides good and bad news might influence stock return volatility differently, good news in a bull market may not elevate the stock market as much as in a bear market and vice versa. Naturally, given a persistent downward market movement, bad news may haul down the market more than if there has been upward market trend. Therefore, in a bear market, the market is anticipating for bad news and bad news wobbles market confidence greater than if it has been a bull market

2.5.3.2 Length of volatility decay process

Happens when the effects of volatility shocks decay slowly and thus the ability to forecast future returns corresponds to market efficiency. Therefore there appears to be a predictable element in the conditional variance over time such that rises in current volatility leads to subsequent rises in future volatility (Krainer, 2002).

2.5.4 Two types of news: good and bad news.

Good news typically is defined as upward market movements and bad news is as downward market movements. It is commonly said that good news is witnessed if last period's stock return is positive and bad news if negative. This totally assumes zero-mean market return (Cont, 2010).

2.6 Volatility Modeling

2.6.1 Identifying market phases: A non-parametric approach

Instead of fitting a fully stipulated statistical data generating process, the approach takes a nonparametric perspective and looks at the original data series in search for the particular characters of the cycle. Explicitly, this procedure examines for periods of generalized upward trend, which will be recognized with the expansions, and periods of a generalized downward trend recognized with the contractions. The key element of the examination is the location of peaks, turning points, and troughs in the series. These turning points establish the different phases of the cycle, which can be consequently analyzed. The method was applied by Biscarri &

de Gracia, (2004) Gonzalez et al., (2006) Pagan & Sossounov, (2003) and Woodward & Anderson, (2009) to the analysis of business cycles and stock market analysis. The nonparametric approach allows for great flexibility in examining some vital features of the stock market cycles. Besides, this approach allows contrast of the actual stock market cycle to parametric benchmarks, and to examine issues associated with predictability of the market.

To ensure that spurious phases are not recognized the following three censoring measures are included:

- I. Turns of the beginning/end of the series are eliminated.
- II. Peaks or troughs next to the endpoints of the series are excluded if they are lower/higher than the endpoints.
- III. Phases of less than 4 months are excluded unless the fall/rise surpasses 20% (the traditional rule of thumb for identifying a stock market cumulative movement as bullish or bearish).

2.6.2 Volatility behaviour model

The study then applied the Fractionally Integrated Exponential GARCH (FIEGARCH) model on the market phases data an extension by Bollerslev & Mikkelsen (1996) of FIGARCH model, which captures both the asymmetric shocks and volatility persistence. Bollerslev & Mikkelsen (1996) formulated the FIEGARCH model and applied it to daily returns of the U.S. S&P 500 index. They established strong evidence that the conditional variance for the S&P 500 index is described well as a mean-reverting fractionally integrated process. Also, a recent study by Gandhi, Saadi, Ngouhouo, & Dutta (2006) found out that the FIEGARCH model provides the optimal fit for daily returns of the Tunisian stock market because it captures high volatility persistence and long memory in the volatility of returns.

The fractionally integrated EGARCH (FIEGARCH) of Bollerslev & Mikkelsen (1996) generalize the EGARCH (Nelson, 1991). FIEGARCH models have not only the capability of modeling clusters of volatility (as ARCH and GARCH models do) and capturing its asymmetry (as the EGARCH model does) but they also take into account the characteristic of long memory in the volatility (as the FIGARCH model does). The non-stationarity of FIGARCH models (in the weak sense) makes this class of models less attractive for practical applications. Another

drawback of the FIGARCH models is that d must be ≥ 0 and the polynomial coefficients in its definition must satisfy some restrictions so the conditional variance will be positive. FIEGARCH models do not have this problem since the variance is defined in terms of the logarithm function, moreover, they are weak stationary whenever the long memory parameter d is smaller than 0.5 (Lopes & Prass, 2013).

The general specification for the FIEGARCH (m,d,q) model that is estimated is given in equations (1-4). R_t is the stock return for a given market, which has a conditional distribution with mean μ_t and variance σ_t^2 . $\varepsilon_t \sim N(0, \sigma_t^2)$, and ν_t is an i.i.d. sequence with zero mean and unit variance.

$$R_t = \mu_t + \varepsilon_t \quad (1)$$

$$\mu_t = \lambda + \sum_{i=1}^a \phi_i R_{t-i} + \sum_{j=1}^b \theta_j \varepsilon_{t-j} \quad (2)$$

$$\varepsilon_t = \sigma_t \nu_t \quad (3)$$

$$\phi(L)(1-L)^d \ln \sigma_t^2 = \alpha + \sum_{i=1}^q (\beta_i |\nu_{t-i}| + \gamma_i \nu_{t-i}) \quad (4)$$

where $\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \dots - \phi_m L^m$.

The ϕ estimates measure GARCH effects or volatility clustering in the data with positive (negative) values meaning that higher (lower) volatility of stock returns in the past are followed by higher (lower) volatility today. In addition, the β estimates capture the ARCH effects or the impact of past news about volatility on current volatility. Also, asymmetric volatility or leverage of returns is modeled by the γ coefficients with negative values indicating that negative shocks have a bigger impact on volatility than positive shocks of the same scale. For purposes of this study, the coefficient estimate of primary interest is the fractional difference parameter d that models the long run persistence of volatility. Bollerslev & Mikkelsen (1996) indicated that, the FIEGARCH specification is stationary if $0 < d < 1$. The existence of volatility persistence is confirmed for significant values of d .

Chapter 3: Research Methodology

3.1 Introduction

To answer the research objectives, the chapter is organized as follows; research design, population and sample size, data collection and data analysis.

3.2 Research design

The study undertook descriptive statistics and advanced econometrics models which are appropriate to encapsulate the volatility behavior and its descriptive characteristics in the Nairobi Stock Exchange market phases that have been of a concern. E-views 8 package collaborated with WinRATS Pro 8 and Excel packages were used in the analysis.

3.3 Population Sampling and Sample Size

The target population consisted of 62 listed companies and the NSE. This is an appropriate population as it mirrors the true picture of active companies in the economy. Using purposive samplings, a sample size of 10 quoted companies out of the 62 listed equities was selected for the period 2003-2013. The study focused on actively and continuously traded stocks in the NSE for at least 80% of the study period from 3rd January 2003 to 31st December 2013. The 80% rule applied in this study, is consistent with Cronbach' alpha criterion also applied by Gliem & Gliem, (2003) and Ndegwa & Mboya (2013)

The inactively traded stocks are affected by the problem of thin or infrequent trading and will be omitted from the study which is consistent with case deletion solution to thin trading (Scheffer, 2002). If a company was on suspension from trading during the study period hence had missing data or if the company did share split or reversal, it was also omitted from the study. Furthermore Bollerslev & Mikkelsen (1996) and also Krishnan & Mukherjee (2010) deduce that non-trading day effect account for a significant effect on the return variance and contributes nearly one-fourth as much to the volatility as any trading day. Out of the population of 62 NSE listed companies, 10 fitted the sample selection criteria and hence became the sample which was drawn from all the sectors of Kenya's economy as arranged in the NSE listing.

3.4 Data collection methods and research instruments

The study used daily time series secondary data for NSE 20 share index and the 62 listed companies covering a period of 10 years from 3rd January, 2003 to December, 2013 from the

NSE registered data vendors of 29,700 observations. Bollerslev (1986) and Karmakar (2006) indicated that the change in the log of the stock price index yields continuously compounded series. Therefore in order to do time series analysis, transformation of original series is necessary. The series was transformed by taking natural logarithm of the series to obtain normal returns.

Volatility is to be estimated on return R_t defined as,

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

Where P_t the current stock closing price at time t and is P_{t-1} is showing the closing price of previous day at time $t-1$.

In order to evaluate the series, the study observed for extreme values, fat-tail (leptokurtosis), and temporal clustering in the graph and descriptive statistics. Values of kurtosis, skewness and Jerque-Bera statistics will reveal for non-normal distribution and volatility clustering in the series.

3.5 Data analysis

A non-parametric approach was used and moving average to identify stock market phases for the identified stocks and the index using excel and E-views 8. In order to achieve a reasonable analysis, statistical illustrations of stock prices and returns was carried out using E-Views 8 software. Financial series econometrics model AR-fractionally integrated exponential GARCH (FIEGARCH) (1,d,1) was used in the study to analyse the collected data as it extends the simple GARCH model to also account for asymmetric volatility effects and the long run persistence of volatility available on RATS (Regression Analysis of Time Series) version pro 9.8 used by Bollerslev & Mikkelsen (1996).

Both the length of stock return volatility decay process and the differential effect of change in the stock return on the future stock return volatility will be measured by the FIEGARCH (1,d,1) model to determine their significance at 95% confidence level. Returns during bullish and bearish periods will be analysed separately to obtain the volatility behaviour during phases.

Chapter 4: DATA ANALYSIS AND PRESENTATION

4.0 Introduction

The chapter presents the data used in the research, analysis and the findings. The analysis was done based on the specific objective and the variables that were selected for the study. The chapter 4 structure is as follows: 4.1 Data description, 4.2 Stock Market phases, 4.3 Behaviour of volatility in the stock market cycles.

4.1 Salient features of financial time series

In order to examine the series in the stock market phases, observe extreme values, temporal clustering, and fat-tail (leptokurtosis) in the graph and descriptive statistics are critical to establish typical feature of the time series data. Examination of the values of kurtosis, skewness and Jerque-Bera statistics reveals non-normal distribution and volatility clustering in the series that justify application of a non-linear model to capture the behaviour. The research begins with a visual inspection of the plot of daily prices and returns on the 10 sampled companies and NSE 20 index as shown in figures 4.2 and appendices 4.1 to 4.14. It can be observed that returns continuously oscillate around a mean value that is near to zero.

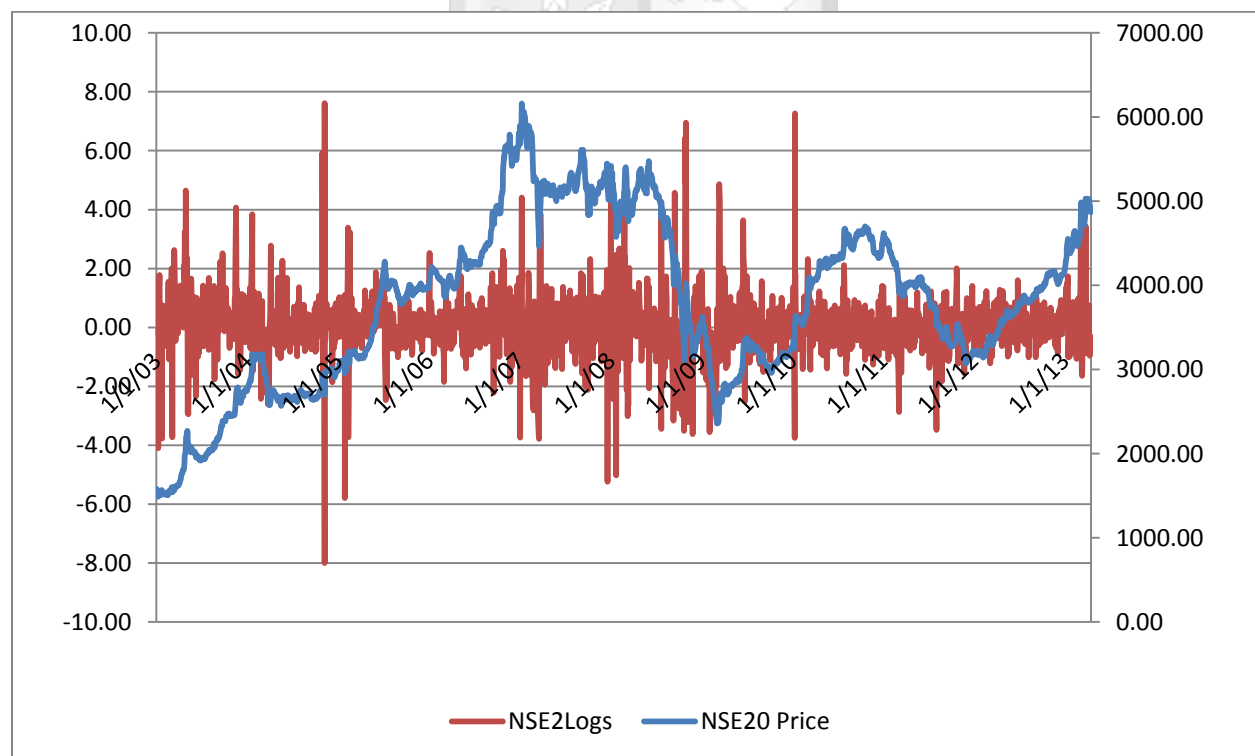


Figure 4.2: Nairobi Securities Exchange 20 Share Index visual analysis [Source: Author]

Kenya stock exchange has undergone series of bull and bear phases as well as breaks observed in the time plot. The sampled data range (2003-2013), and almost all the sampled stock prices and the NSE 20 share index tend to experience similar trend as can be observed in appendices 4.1 to 4.14. Observing returns fluctuations of the sampled stocks and the market index above highlights that, the bullish market phase takes a longer time to die out than the bearish market phase. For most companies, the stock market spends the vast majority of its time in bull market states that is consistent with findings of Pagan & Sossounov (2003) Woodward & Anderson (2009). It can also be observed that fluctuations in the series are variable in time and downward trends are much more frequent than upward trends. In-addition, the dating trends shows periods of persistent shocks of any sign, but there is no recurrence of instability. The chronic movements have fairly regular long term aspect. Lastly, the general trend of returns is also regular. There is an absence of a cyclic component. The series seems stationary, an intuition that is supported by analyzing the returns series' stationarity tests.

The fluctuations are both in the positive and negative regions with larger fluctuations tend to cluster together separated by episodes of relative calm that is coherent with Fama's (1965) conclusion that stock returns display volatility clustering or volatility pooling (a type of heteroscedasticity) where large returns tend to be followed by large returns and small returns by small returns (in either sign) leading to adjoining episodes of volatility and stability. The returns series seems stationary and exhibits dependence over time. The consequence of volatility clustering is that the current volatility shocks will influence the expectation of volatility in some periods in the future. Therefore, the current level of volatility tends to be positively associated with its level during the immediately preceding periods.

BEARISH	NSE20	BAT	CROWNBERGER	NATIONME	HFCK	CFC	JUBILEE
Mean	-0.134928	-0.0643	-0.162405	-0.192003	-0.205209	-0.10071	-0.208932
Median	-0.104668	0	0	0	0	0	0
Maximum	6.947677	9.156719	40.22236	9.445218	24.22646	27.30405	16.83353
Minimum	-5.233974	-10.5361	-65.44327	-25.38461	-22.31436	-12.3614	-31.58529
Std. Dev.	1.32733	2.101465	4.878775	2.558613	3.857297	2.944205	3.231061
Skewness	0.652229	-0.12724	-3.299627	-2.046178	0.189732	1.609149	-1.687445
Kurtosis	7.687539	8.035767	67.33828	22.41208	7.513492	20.43366	21.01373
Jarque-Bera	549.4487	590.0418	97079.64	9134.248	476.133	7294.145	7795.316
Probability	0	0	0	0	0	0	0
Sum	-75.15479	-35.8134	-90.45947	-106.9456	-114.3012	-56.0975	-116.3752
Sum Sq. Dev.	979.5629	2455.382	13234.16	3639.855	8272.579	4819.597	5804.504
Augmented Dickey-Fuller test statistic	-14.69381	-25.3332	-13.53918	-12.55437	-13.26096	-21.0741	-25.15436
Prob.*	0	0	0	0	0	0	0
Test critical values:							
1% level	-3.441882	-3.44188	-3.441989	-3.441903	-3.441946	-3.44188	-3.441882
Observations	1011	1011	1011	1011	1011	1011	1011
Kwiatkowski-Phillips-Schmidt-Shin test statistic	0.268826	0.073077	0.268626	0.18165	0.130207	0.266016	0.040445
1% level	0.739	0.739	0.739	0.739	0.739	0.739	0.739

Table 4.1: Representation of bear phase statistical analysis

The model building and application process should consider the salient properties of financial time series data or statistical illusions of stock returns to attain rational analysis. Furthermore, examining the distribution of features of stock returns or stock prices is vital in examination of the behavior of stock prices and returns, accurate model specification, estimation and forecasting (Oskooe & Shamsavari, 2011). To enable examination of the distributional features of stock return series in the Kenyan stock market during the phases, measures of location (mean), concentration in tails (kurtosis), dispersion (standard deviation) and asymmetry (skewness) are computed. The parameters of mean and variance indicate the standardized first and second moments of a distribution, the skewness as the standardized third moment assesses the asymmetry of a distribution and the kurtosis as the central fourth moment establishes the degree of tail fatness and peakedness of a distribution.

Bullish	BAMBURI	BAT	CROWNBERGER	CFC	DTBKENYA	HFCK	NSE20
Mean	0.084694	0.1592	0.137871	0.105228	0.168086	0.142401	0.107328
Median	0	0	0	0	0	0	0.070539
Maximum	6.28479	8.654046	23.24459	21.35741	10.60182	17.66235	7.269002
Minimum	-8.004271	-8.1678	-22.49437	-23.05237	-8.701138	-24.3002	-3.747276
Std. Dev.	1.562677	1.340015	3.544536	2.850213	2.238268	2.407628	0.882591
Skewness	-0.501704	0.054984	0.137293	-0.159999	0.162975	-1.38906	1.727783
Kurtosis	9.548104	13.15525	10.48495	20.18448	7.931925	32.58673	16.06647
Jarque-Bera	821.0058	1929.599	1049.535	5526.607	457.0469	16521.19	3417.516
Probability	0	0	0	0	0	0	0
Sum	38.02749	71.48087	61.90392	47.24758	75.47051	63.93808	48.19021
Sum Sq. Dev.	1093.997	804.4473	5628.554	3639.424	2244.409	2596.908	348.9773
Augmented Dickey-Fuller test statistic	-18.20336	-23.764	-16.91544	-18.36501	-24.10518	-19.6238	-10.73878
Prob.*	0	0	0	0	0	0	0
Test critical values:							
1% level	-3.444757	-3.44472	-3.444757	-3.444757	-3.444724	-3.44472	-3.44479
Observations	1812	1812	1812	1812	1812	1812	1812
Kwiatkowski-Phillips-Schmidt-Shin test statistic	0.114194	0.095744	0.079383	0.20935	0.188479	0.04649	0.086256
1% level	0.739	0.739	0.739	0.739	0.739	0.739	0.739

Table 4.2: Representation of bull phase statistical analysis

Table 4.5 and 4.6 provides the bearish and bullish descriptive statistics for 10 sampled and 20 share index stock returns. The extensive gap between the minimum and maximum returns confirms the high variability of price change in the Kenyan stock market during both phases. Similarly, the high standard deviation with regard to the mean is a sign of the high volatility in the Kenyan stock market and the riskiness of the market with bear phase giving the highest standard deviation thus a higher volatility. The means of stock return series during bearish are constant and negative while bullish are constant and positive, but the variances keeps fluctuating over time for all the series under study. Gonzalez et al., (2006) Grobys, (2012) & Pagan & Sossounov, (2003) obtained similar findings in their studies.

Positive skewness in both the bullish and bearish signifies that the Kenyan stock returns distribution are skewed to the right the mean and has a long right tail while the negative skewness indicates that the returns distribution are skewed to the left of the mean. With bullish phase in the Kenyan stock market mostly positively skewed, large positive returns tend to follow more frequently than large negative ones. Hence, large positive movements in stock prices are

not generally matched by equally large negative movements and vice versa for the bearish phase where 6 out of 10 exhibits negative skewness. Similarly, the degree of excess or kurtosis, in the Kenya stock returns series in both the phases is larger than the normal estimate of 3. Consequently, the distribution of Kenya stock returns is peaked and leptokurtic (heavily (thick) tailed and sharply peaked). The study findings is consistent with results of Gonzalez et al., (2006) Grobys, (2012) & Pagan & Sossounov, (2003) who established that skewness in bull markets is slightly positive, volatility in bear markets is about twice as much as the volatility in bull markets.

It is worth underlining that with respect to the kurtosis and skewness statistics of the Kenyan stock returns, the distribution of stock returns deviates from normal distribution. Besides, results of the estimated Jarque-Bera statistics and corresponding p-value in table 4.1 and 4.2, the stock return series is not well estimated by the normal distribution. By and large, in line with the conclusions of other empirical studies in emerging markets such as Abdalla & Winker (2012), Ahmed & Suliman (2011), Olweny & Omondi (2011) Wagala et al., (2012), Kenya stock return time series are characterized by some “stylized fact” such as skewness, fat tails, volatility clustering and high peakness (excess kurtosis). Mandelbrot (1963) observed volatility clustering and leptokurtosis are common observations in financial time series. The null hypothesis of the Augmented Dickey-Fuller test statistic (ADF) is that a time series has unit root while Kwiatkowski-Phillips-Schmidt-Shin test statistic (KPSS) has the null hypothesis of stationarity. Huge negative estimates for ADF test for all return series in all the phases strongly reject the null hypothesis of a unit root at the 1% significant level. Moreover, the statistics of the KPSS test signify that return series are stationary. Therefore both the series are stationary and appropriate for subsequent volatility persistency tests in this study.

4.2 Identifying market phases

The nonparametric approach allows for great flexibility in examining some significant features of the stock market cycles. Additionally, this approach allows comparison of the actual stock market cycle to parametric benchmarks, and to examine issues associated with predictability of the market.

The expected duration of bear markets is only 35% of the total study duration which is consistent with the findings of Grobys, (2012). On average, Nairobi stock exchange experienced 3 bull

cycles with 1812 data points over the period of study while bear phase experienced 2 cycles with 1011 data points. Commonly observed bullish periods during the study includes; 2003 to mid-2004, start of 2005 to the mid-2007, start 2009 to mid-2011 and finally start 2012 to end 2013 while bear periods includes mid-2004 to end of 2005, mid-2007 to end 2008 and lastly mid-2011 to end 2011.

4.3 Volatility behaviour in the stock market phases

Statistically significant values of δ in almost all the sampled results, confirms negative relationship of the risk-return tradeoff in most stocks in all the phases. Values of ψ are statistically significant at 5% for most stock both during bullish and bearish phase but mostly negative during bearish. Therefore, the Kenyan stock market relationship between changes in stock prices (unexpected returns) and variations in stock return volatility is negative. It can be concluded that there is propensity for stock returns volatility to upsurge when stock returns fall and to fall when stock returns rise consistent with the findings of Bollerslev & Mikkelsen, (1996), Forgha, (2012).

Bear	BAMBURI	CROWNBE	NSE20	DTB	JUBILEE	STANCHAI	UNGA	CFC
δ	-0.03563	-0.02198	-0.16801	0.443784	-0.32012	-0.5	0.280499	-0.08916
	0.56002	0.000159	1.86E-05	0.065861	0	0	1E-08	0.41131
ψ, Ψ	1.358115	-1.03237	1.01465	-0.22648	-0.91284	-0.75665	1.629494	3.244126
	0.114012	0	0	0	0	0	0	0.131275
ϕ, Φ	0.868151	0.977286	-0.97774	-0.30138	0.816558	-0.08592	-0.39344	0.82357
	0	0	0	0	0	0	0	0
Θ, θ	-0.03606	0.027229	-0.04541	-0.28839	-0.26312	-4.2458	-0.14741	-0.00023
	0.014651	6.48E-06	0.26842	0	0	0	4.05E-06	0.483147
Γ, Υ	0.015213	0.319703	0.549518	0.048047	0.698273	0.354147	0.449425	0.002481
	0.020644	0	0	0	0	0	0	0.179311
D	0.455937	0.672342	0.46259	0.142416	0.10826	0.07413	0.374841	0.218705
	0	0	0	0	0	0	0	0.010942

Table 4.3: Representation of bear phase asymmetric and long memory results

Bull	NSE 20	NATIONMEI	HFC	BAT	BAMBURI	JUBILEE	CFC
δ	-0.10094648	-0.2499993	-0.2059163	-0.192598	-0.12090158	-0.0369666	-0.13018945
	0.15141523	0	0	0	0.04135006	0.48643019	0.52111428
ψ, Ψ	0.402196031	0.86568554	1.88647162	0.0722588	0.055795428	1.09943096	1.053538722
	0.1202403	0.00000015	0.00000037	0	0.8432494	0.00002104	0
ϕ, Φ	-0.83381388	-0.3752653	0.47858788	0.5677009	0.425022258	-0.6250972	1.011288947
	0	0.00121033	0.00000084	3E-08	0.00000631	0.00149285	0
Θ, θ	0.314214091	0.07645602	0.02062834	-0.000159	0.082705045	0.1092669	0.14501
	0	0.04189589	0.07559211	0.0223794	0.00434875	0.0079322	0.0347
Γ, Υ	0.308547732	0.5997173	0.02153295	0.0005234	0.447377961	0.26181671	0.1534
	0.0023221	0	0.05535172	4.192E-05	0	0.00008016	0
D	0.769869301	0.52115589	0.73447945	0.5053089	0.631779397	0.39728543	0.451413846
	0	0	0	0	0	0	0

Table 4.4: Representation of bull phase asymmetric and long memory results

4.3.1 Analysis of Differential impact of change in returns on future volatility in the stock market phases

Table 4.3 and 4.4 demonstrates the findings of the application of FIEGARCH (1,d,1) model to the 10 sampled stock returns series and NSE 20 for bullish and bearish phases respectively. Given that the probabilities are smaller than the conventional level of significance 5% in both the bearish (8 out of 11) and the bullish (9 out of 11), the asymmetry term θ in FIEGARCH model are statistically significant. Intrinsically, there is significant asymmetric volatility in the Kenya stock return series. With regard to the results, it can be underlined that in the Kenyan stock market participant or investors overreact (underreact) to bad news and underreact (overreact) to good news with negative shocks impacting more during bearish phase (9 out 11 negative θ values) and vice versa during bullish phase (9 out 11 positive θ values) . Furthermore, the coefficients of the asymmetric term (θ) for bear phase are less than 0 for most of the stocks thus the future volatility will increase proportionately more following a negative shock than for a positive shock and vice versa for the bullish phase. Therefore, it can be concluded that the reaction to the stock returns shocks is asymmetrical in the Kenyan stock market and the variance equation of FIEGARCH (1,d,1) model is well specified.

Note that the coefficients of asymmetric response of volatility to news, Υ , are positive and highly significant at the 5% level in all the Kenyan stock and the index considered during both bullish and bearish phases. Υ measures the extent to which a volatility shock today feeds through into

the next period and a positive γ confirms presence of volatility asymmetry. This implies that unexpected positive returns during bull phase leads to high volatility than unexpected negative returns of the same magnitude, also that unexpected negative returns during bear phase resulted in more volatility than unexpected positive returns of the similar magnitude. The findings during bear phase are consistent with the negative relationship between current returns and future volatility observed by Black (1976).

The result implies that the volatility of Kenya stock returns during bullish phase is less sensitive to negative news probably because of market regularity, such as price limit. The degree of asymmetric volatility during bearish phase is high at an average of 0.3120 than the bullish phase at 0.2946. Besides good and bad news might influence stock return volatility differently, good news in a bull market may not elevate the stock market as much as in a bear market and vice versa. Naturally, given a persistent downward market movement, bad news may haul down the market more than if there has been upward market trend. Therefore, in a bear market, the market is anticipating for bad news and bad news wobbles market confidence greater than if it has been a bull market

Nelson (1991) implied that volatility is higher in bear markets and this was rationalized by the tendency for investors to engage in panic selling at such times. Contrary to the findings of Iyiegbuniwe et al., (2012) who suggested that for the developing markets, market booms induce higher volatility than market declines and is rationalized by the view that investors believe that booms behave more like speculative bubbles. A significant implication of these conclusions is that the good shocks and bad shocks have the different effects on stock prices in the Kenyan stock market with good shocks affecting prices during bullish phase than negative shocks and vice versa. In this sense, stock prices reflect asymmetrically new information. The potential elucidation for the presence of asymmetric effect can be derived from “inflation advantage”. In inflationary conditions (particularly in developing nations) the long term debts are regarded as an advantage to the firm. Therefore, growing debt to assets ratio (leverage) does lead to higher stock volatility (risk) in stock market. Additionally, the lack of “price limit” to control market volatility can be another explanation for the asymmetric effect.

Literature on the asymmetric volatility of stock returns alludes to the fact that there is no one explanation for asymmetry. Studies such as Sentana and Wadhwani (1992) and McQueen and

Vorkink (2004) present explanations of asymmetric volatility based on models of heterogeneous traders and behavioral finance. Such studies have considered the interaction between traders and the arrival of news in the context of modern trading practices, especially prevalent in developed and the more advanced emerging markets, which could contribute to asymmetric volatility. A recent study by Jayasuriya, Shambora, & Rossiter, (2009) establish asymmetric volatility for many mature and emerging markets and propose that asymmetry may be linked to trading costs and trading strategies such as short selling. Furthermore, Brooks (2007) examined asymmetric volatility for a group of 26 emerging markets and reported high asymmetry for markets in Latin America and low asymmetry for markets in Africa contrary to the research findings.

4.4.2 Analysis of the volatility decay process in the stock market phases.

The persistency parameter d is statistically significant in the all the Kenyan stocks under consideration implying prevalent of volatility persistence the stock return. That is, there is useful information embedded in the past stock return volatility series that can be utilized for future predictions. The finding that sampled stocks exhibits volatility persistence in the stock return implies that investors may gain unrealized trading profits by observing past behavior of return indices. Comparing the degree of parameter d between the bullish and bearish stock market phases, the volatility is highly persistence during bullish with an average of 0.4451 phase than bearish with an average of 0.3388. The reasons might be related to the reaction of investors and the fact that investors tend to gather lots of information that provides better platform to adopt broader investment strategy.

Consequently, the volatility of all sampled stocks and the index returns seem to be a persistent series which is in conflict with the assumption of the efficient market hypothesis that the stock returns should not exhibit persistence or it would be possible to generate trading profits by observing historical patterns. This result implies that investors in Kenyan stock market do not react to new information until a market trend is distinctly established when news arrives at the market. So the amount of information is accumulated and unexpectedly established in the market, instigating the volatility to persist in stock markets. Maheu and McCurdy (2000) furthermore argued that, as the bull market persists, investors could become more optimistic about the future and thus wish to invest more in the stock market. This positive feedback indicates that the likelihood of switching out of the bull market decreases with time.

In addition, it could be eluded that NSE bearish phase might be having greater participation of competing investors than bullish phase which could lead to better informational efficiency in volatility as investors are optimistic that the downward trade will be over soon. The presence of long memory in volatility, conversely, shows that uncertainty or risk is an imperative determinant of the behaviour of daily stock data in the Kenyan stock markets. Furthermore, Batra (2004) argued that during a bear market news is more eagerly expected than in a bull market. Bear markets salivate in anticipation of news, digest it insatiably, and react more violently than bull markets hence low volatility persistence.



Chapter 5: CONCLUSION AND RECOMMENDATION

5.0 Introduction

The chapter summarizes on the findings of the thesis and finally provides recommendations to the investors and stock market participants on various actions depending on the phase of the market. Lastly the study recommends related areas for further research and also highlights on the shortcomings faced during the study.

5.1 Conclusion

Kenya stock exchange has undergone series of bull and bear phases as well as breaks observed in the time plot with bullish market phase taking a longer time to die out than the bearish market phase. For most companies, the stock market spends the vast majority of its time in bull market states than a bear phase that is consistent with findings of Pagan & Sossounov (2003) Woodward & Anderson (2009). Further, the fluctuations in the series are variable in time and downward trends are much more frequent than upward trends thus a higher volatility.

The asymmetry and persistence are regularly observed in the conditional variances of stock returns. The previous contributions have dealt with persistence and asymmetries in volatility distinctly. This study extends the previous contributions by including two new topics, persistence and asymmetries in the volatility during the market phases in Nairobi stock Exchange. To capture the asymmetry and persistence properties in the volatility of stock index returns, FIEGARCH (1,d,1) model was employed which combines the asymmetric characteristics of the EGARCH model with the volatility persistence feature of the FIGARCH model. The FIEGARCH model is found to give a good representation of asymmetric persistence volatility features for sample stock returns. Approximations of asymmetric coefficient (θ) are mostly positive for bull and mostly negative for bear phase and highly significant for most samples, signifying that all sample returns exhibit asymmetries in volatility, rejecting the symmetric volatility models.

In-addition, coefficients of γ that measures the magnitude of the past errors on the future volatility, implies that unexpected positive returns during bull phase resulted in more volatility than unexpected negative returns of the similar magnitude, also that unexpected negative returns during bear phase resulted in more volatility than unexpected positive returns of the similar magnitude. Moreover, approximations of the volatility persistence parameter are found to be

considerably different from zero, indicating that the volatility tends to persist, thus rejecting an EGARCH process. Consequently, the volatility of stock index returns exhibits the long memory properties with asymmetry.

Recall that the earlier results clearly indicated that volatility during bull phase exhibit high persistency in almost all the samples while bear phase relatively low. The study finding depicts Nairobi stock exchange efficiency is in doubt. The possible explanations of the inefficiency might be the fact that the numbers of competing and profit-maximizing participants who analyze the arrival of new information are few. In such a setting, security prices will adjust slowly to the release of all public information so that current prices do not fully reflect all available information and there is useful information are left for future predictions. Also, with a few number of market participants, one group of investors typically has monopolistic access to information that is used to determine equity prices. Relevant information, therefore, will not be cost free and available to everyone at the same time. Moreover, a higher level of stock market development is often associated with greater market transparency, better accounting standards, and improved investor protection laws which NSE might be lacking.

Further, the fact that all the sampled stocks exhibits a similar trend as the index implies that the sample chosen was a true representation of the whole population and the results obtained can be used to generalize on the characteristics of the population. In addition, the results obtained with regard to volatility asymmetry and persistence is consistent for most of the companies during the two phases and the market index even though some sampled companies do not form part of the index.

5.2 Recommendations

5.2.1 Implications for investors

The empirical results would be beneficial to investors as it provides indication of behaviour of stock market volatility during the market phases in the Kenyan stock market. Investors endeavor at maximizing profit at moderate risk. Consequently, they need to study and examine stock market volatility, among many other factors, before making investment decisions. For both the 10 sampled stocks and the index, bearish phase exhibits highest volatility. This suggests that, during the bear phase, the conditional volatility tends to upsurge that might be explained by a lot of speculations going on and investors 'buy on rumours.' After the bear phase regime, investors

liquidate their stakes in expectations of high returns. The investors otherwise should not take a reverse position on their portfolios immediately after the bearish phase as the bullish phase will last for a long period of time than the bear phase. Furthermore, the bullish phase offers a high positive return at a relatively low volatility and therefore offers good opportunity to the investors to make safe returns. In-addition, during bullish phase positive news drives the market upwards and the shock tends to slowly die out.

5.2.2 Implications for policy makers

The implications for investors given above are also significant for the stock exchange administrators and policy makers. The surveillance regime during bearish phase should be stricter to keep excessive volatility under check. The policy makers should also work on possible ways of enhancing market efficiency particularly during bull phase.

5.3 Further research

Further research can be done to ascertain whether the Nairobi Stock Exchange market efficiency has improved overtime dividing the market into bull and bear phases.

5.4 Research limitations

The research lacked qualitative aspects from the Nairobi Securities exchange participants. Further the model employed was sensitive to missing data points, share splits and reversals.

5.5 Ethical consideration

The research used secondary data and all the terms and conditions for data acquisition and usage were followed to the later. The data used was obtained from the authorized data vendors hence reliable and valid for analysis.

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Appendices

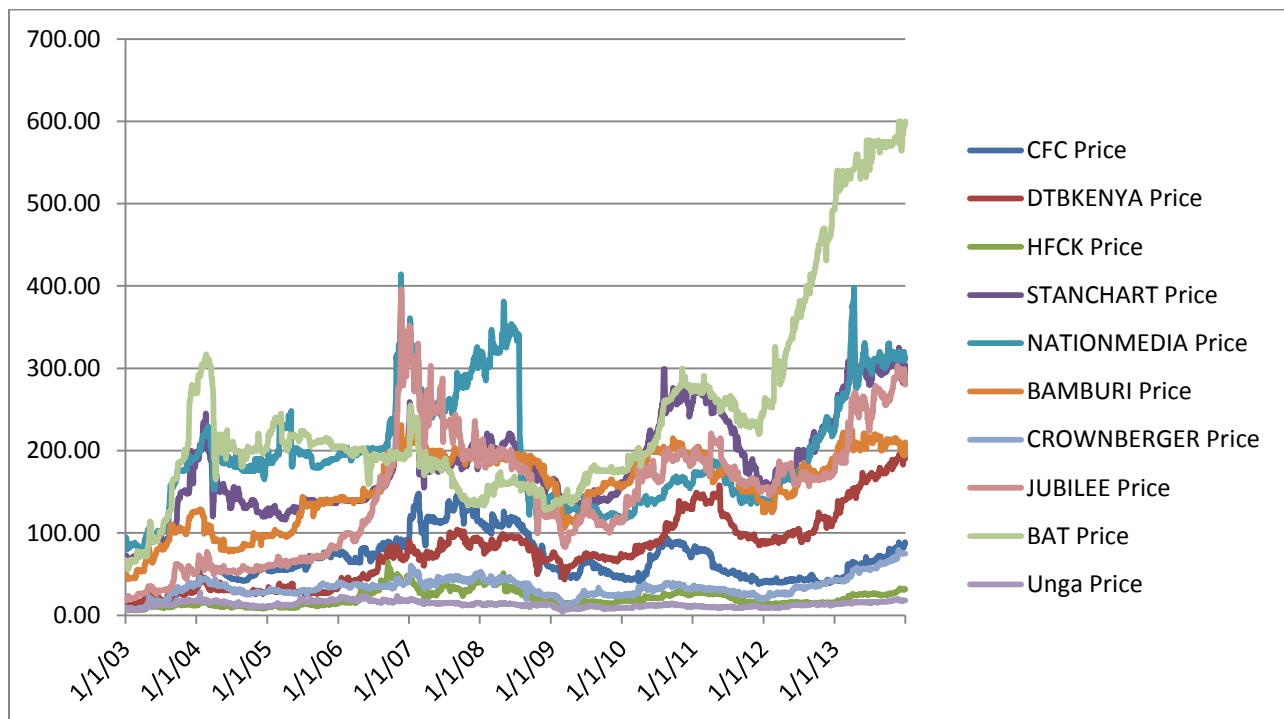
RESULTS OF PREVIOUS STUDIES ON THE MEASUREMENT OF STOCK MARKET VOLATILITY.				
Author	Journal	Market	Volatility Model	Results
French, Kenneth R. (1987) Schwert, G. William Stambaugh, Robert F.	Journal of Financial Economics	S&P Composite portfolio	GARCH-in-mean	Positive relationship between risk and return.
Aggarwal, Inchan, and Leal (1999)	The Journal of Financial and Quantitative Analysis	10 emerging market	GARCH China	Political, social and economic event are main cause of change in volatility
Rousan Raya and Al-khoury Ritab(2005)	International Journal of Applied Econometrics and quantitative studies	Amman Stock Exchange	ARCH, GARCH, EGARCH and the GJR-GARCH	ASE returns are volatile and that positive and negative shocks (good and bad news) of the same magnitude have the same impact and effect on the future volatility level, volatility response to a shock tend to persist
Frimpong Joseph Magnus and , Oteng- Abayie Eric Fosu,(2006)	American Journal of Applied Sciences	Ghana stock exchange	GARCH , EGARCH, TGARCH	GARCH model outperformed the other model.
Kang, Sang Hoon and Yoon, Seong-Min (2006)	Asia-Pacific Journal of Financial Studies	Japan, South Korea, Hong Kong and Singapore	FIGARCH, FIEGARCH	Volatility of stock index returns exhibits the long memory properties with asymmetry.
Rajni Mala and Mahendra Reddy, (2007)	International Research Journal of Finance and	Fiji stock market	ARCH & GARCH	7 out of 16 firms listed on Fiji were volatile.
Chiaku Chukwuogor and Mete Feridun, (2007)		15 emerging and developed European market	STANDARD DEVIATION	Emerging market had higher volatility and higher return.
Sami Khedhiri and Naem Muhammad, (2008)		UAE stock market	ARCH & TGARCH	Presence of leverage effect.
J. Cunado, L. A. Gil- Alana and F. Perez de Gracia, (2008)	Journal of Money, Investment and Banking	US stock market	GARCH	Volatility is more persistent in bear market than bull market.
Bahadur Surya (2008)	Journal of Nepalese Business Studies	Nepalese stock market	GARCH(1,1)	Strong evidence of time-varying volatility, a tendency of the periods of high and low volatility to cluster and a high persistence and predictability of volatility in the Nepalese stock market
Christos Floros,(2008)		Egypt & Israel stock market	GARCH, EGARCH, TGARCH, CGARCH, PGARCH.	Increased risk will not necessarily lead to a rise in the returns.
Kasman, Adnan (2009)	Applied Economics Letters	BRIC countries	ICSS, GARCH	Ignoring structural breaks could lead one to significantly overestimate the degree of volatility persistence
Jayasuriya S., Shambora W. and Rossiter R. (2009)	Journal of Emerging Markets	International	Power-GARCH	Many mature markets exhibit large magnitudes of asymmetric volatility and several emerging markets do so as well
Sabur Mollah and Asmam Mobarek,(2009)		Developed & Emerging markets	GARCH	Longer persistent shock in emerging market than in developed market.
Mishra Banamber and Rahman Matiur (2010)	International Business & Economics Research Journal	India and Japan	TGARCH-M	These markets are impacted asymmetrically by bad news and good news. The return volatility persists in both countries.
Hojatallah Goudarzi C.S. and Ramanarayanan,(2011)	International Journal of Business and Management	BSE 500	EGARCH & GARCH	Presence of asymmetric effect.
Ahmed Ahmed Elsheikh M. and Suliman Suliman Zakaria (2011)	International Journal of Business and Social Science	Khartoum Stock Exchange (KSE)	GARCH(1,1), GARCH-M(1,1), exponential GARCH(1,1), threshold GARCH(1,1) and power GARCH(1,1)	Conditional variance process is highly persistent (explosive process), positive correlation hypothesis between volatility and the expected stock returns, symmetric volatility effect.
Oskooe Seyyed Ali Paytakhti and Shamsavari Ali (2011)	International Journal of Economics and Finance	Iran Stock Market	ARIMA - GARCH (1, 1), TAR, EGARCH and PAR	No asymmetric effect in the volatility dynamic
Amir Rafique and Kashif-Ur-Rehman,(2011)		Karachi stock exchange.	ARCH & GARCH	Variance structures of high frequency data were dissimilar from low frequency of data.
Koutmos, Dimitrios (2012)	Accounting and Finance Research	Shanghai Stock Exchange	EGARCH	Investors demand higher returns in the presence of higher market risk, volatility persistence, volatility symmetry

Suleman, Muhammad Tahir (2012)	Asian Journal of Finance & Accounting	Karachi stock exchange 100 index	Univariate asymmetric GARCH model	Bad news have more effect (almost double) effect on the volatility than the good news
Maheshchandra, Joshi Prashant (2012)	Asian Journal of Finance & Accounting	BSE and NSE stock indices	ARMA-GARCH(1,0,1), ARMA-IGARCH(1,1,1), ARMA-FIGARCH(1,d,0) and ARMA-FIGARCH(1,d,1)	The long memory property of the BSE market is revealed to be stronger than NSE.
Kalu, Emenike and Friday, Aleke Stephen (2012)	European Journal of Business and Management	Nigerian Stock Exchange	GARCH (1,1), EGARCH and GJR-GARCH	Strong evidence that positive shocks have higher effect on volatility than negative shocks of the same magnitude
Kumar, Dilip and Maheswaran, S (2012)	IIMB Management Review	Indian stock market	GARCH and GJR-GARCH	Asymmetry and persistence in volatility are reduced significantly when regime shifts are accounted for in the volatility models
Iyegbuniwe Willi, Ezike John E. and Amah Peter N. (2012)	International Journal of Business and Management	Nigerian Stock Exchange Index	AR(3) EGARCH (1, 1)	Long memory and slow auto-correlation decay rate, not exhibit 'leverage effects
Mittal Anil K. and Goyal Niti (2012)	International Journal of Research in IT & Management	Indian Stock Market	GARCH (1, 1), PARC (1, 1)	Volatility clustering, heteroskedasticity & excess peakedness
Al-Rjoub Samer AM and Azzam Hussam (2012)	Journal of Economic Surveys	Jordan	GARCH-M	High persistence in volatility and strong reverse relationship between stock return and its volatility before and after the crises
Boubaker Adel and Makram Beljid (2012)	The Journal of North African Studies	North African stock markets	Joint ARFIMA-FIGARCH	long memory in return series
Abdalla Suliman Zakaria Suliman and Winker Peter (2012)	International Journal of Economics and Finance	Khartoum Stock Exchange, Cairo and Alexandria Stock Exchange	GARCH(1,1), GARCH-M(1,1), exponential GARCH(1,1), threshold GARCH(1,1) and power GARCH(1,1)	Conditional variance (volatility) is an explosive process for the KSE index returns series, while it is quite persistent for the CASE index returns series, a positive correlation, asymmetry in stock returns in the two markets between volatility and the expected stock returns
Yaya, O S, Shittu, O I and Tumala, M M (2013)	European Journal of Business and Management	Nigerian and Foreign Stock Markets	Smooth Threshold Parameter Nonlinear Market model	Stocks returns are found to stay longer in the up-market than in the down-market
Nkoro, Emeka Uko, Aham Kelvin (2013)	International Journal of Financial Research	Nigerian Stock Market	GARCH-M	Volatility clustering, moderately persistent

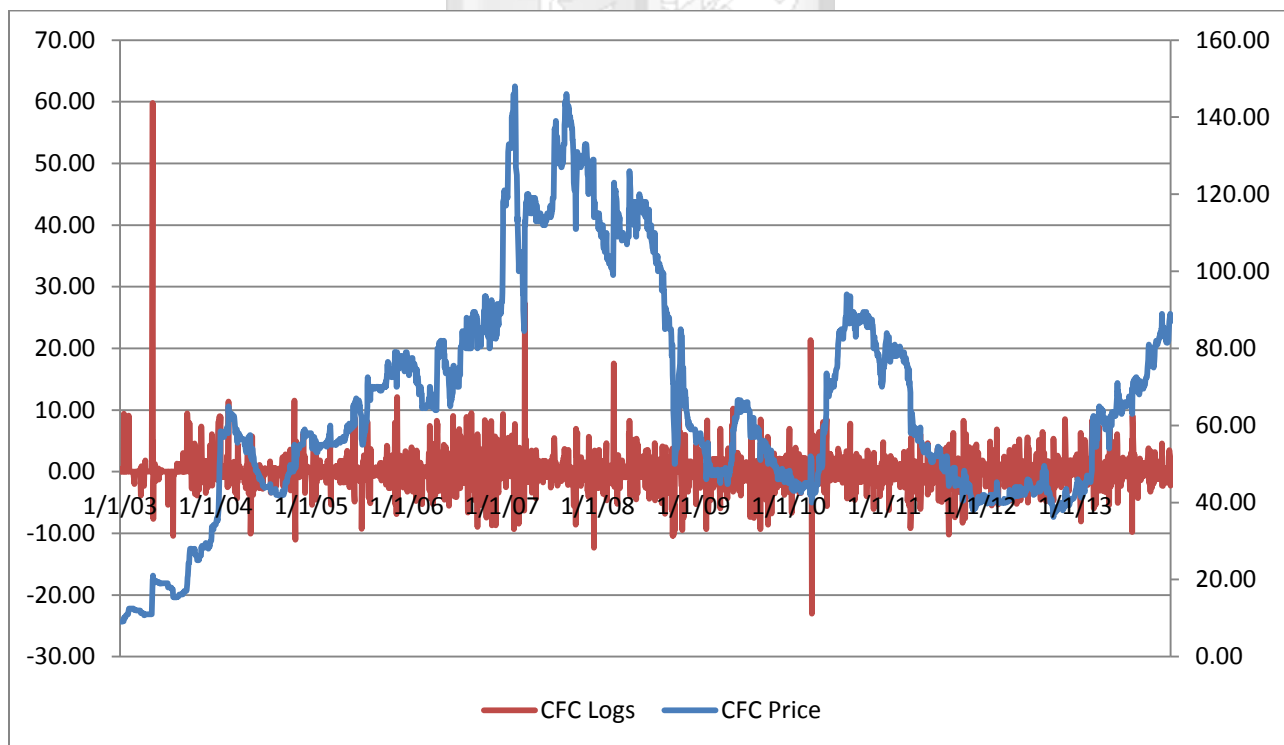
Studies on Stock Return Volatility In Kenya

Author	Journal	Market	Volatility Model	Results
Ogum George, Beer Francisca and Nouyriqat Genevieve (2005)	Journal of African Business	Kenya and Nigeria	EGARCH	Asymmetric volatility (Nigeria), asymmetric volatility coefficient is significant and positive (Kenya), volatility persistence
Nyamongo, Morekwa Esman Misati, Roseline (2010)	African Journal of Economic and Management Studies	Nairobi Securities Exchange	GARCH(1,1), TGARCH(1,1) and EGARCH(1,1)	A high level of persistence of volatility, the impact of news on volatility is insignificantly asymmetric with negative news impacting volatility more than positive news.
Olweny, Tobias and Omondi, Kennedy (2011)	Economics and Finance Review	Nairobi stock exchange	TGARCH, EGARCH	The equities returns are symmetric but leptokurtic and thus not normally distributed; volatility of returns is not highly persistent; the leverage effects are significant
Wagala Adolphus, Nassiuma Dankit K. Islam, Ali S. Mwanqi, Jesse W. (2012)	International Journal of Applied Science and Technology	Nairobi Securities Exchange	GARCH (p,q), IGARCH(p,q), EGARCH (p,q) and TGARCH (p,q)	The volatility increases more with the bad news (negative shocks) than the good news (positive shocks) of the same magnitude for the NSE Index
Tah, Kenneth A (2013)	Business and Economics Journal	Kenya and Zambia stock indices	GARCH-M	Volatility clustering, Nairobi Stock Exchange is vulnerable to external shock.

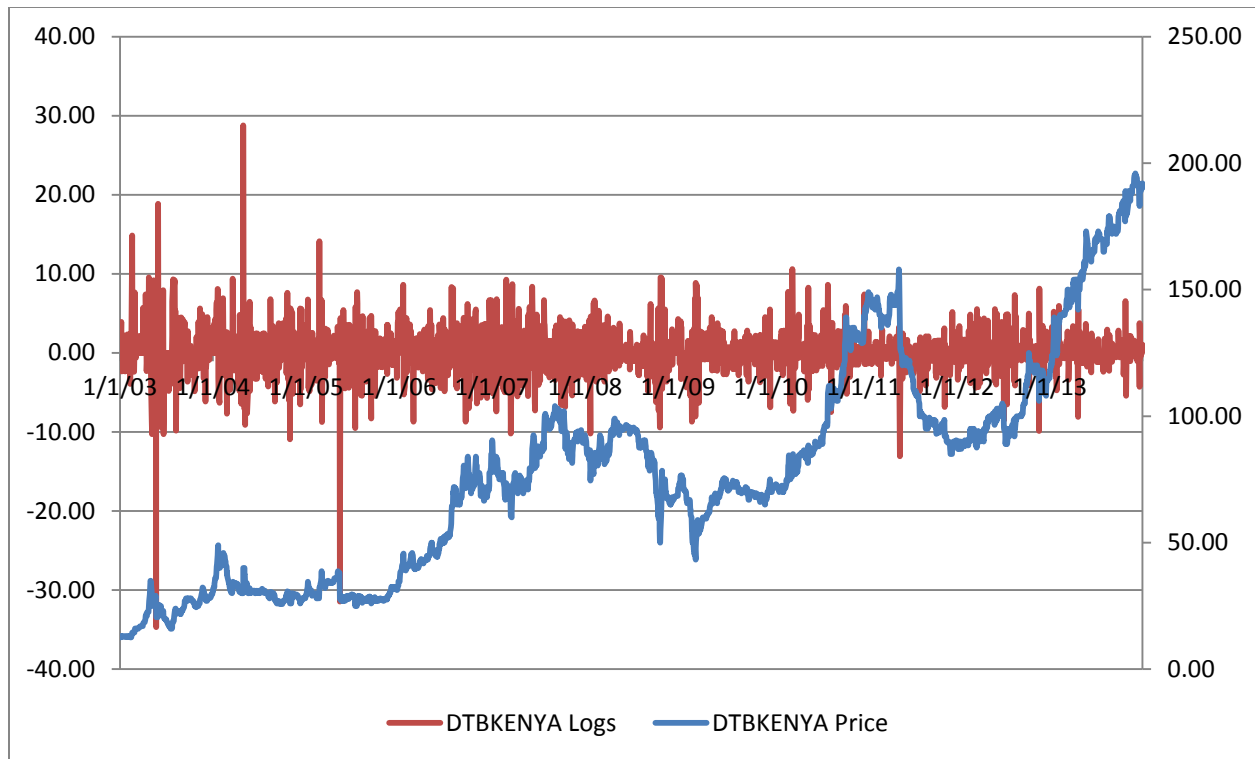
Appendix 2.1: Empirical Analysis Summary (Source, Author 2013)



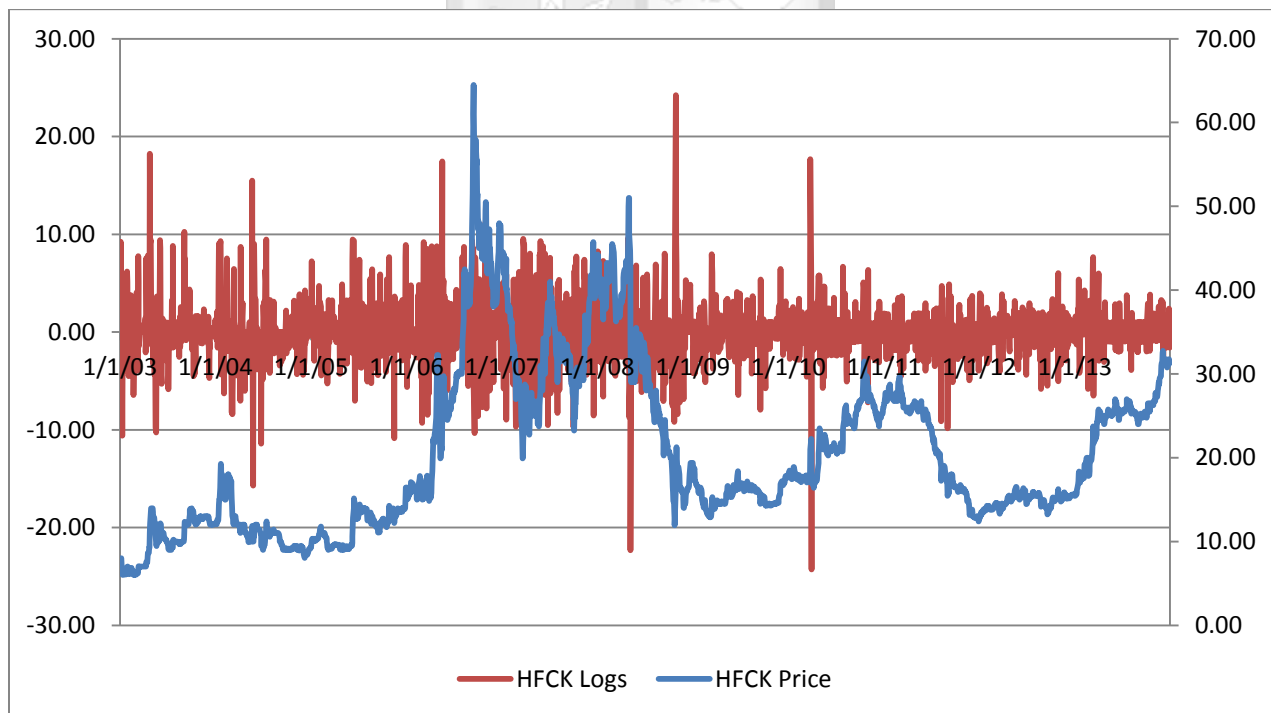
Appendix 4.1: 10 sampled Price trend (Source: Author 2013)



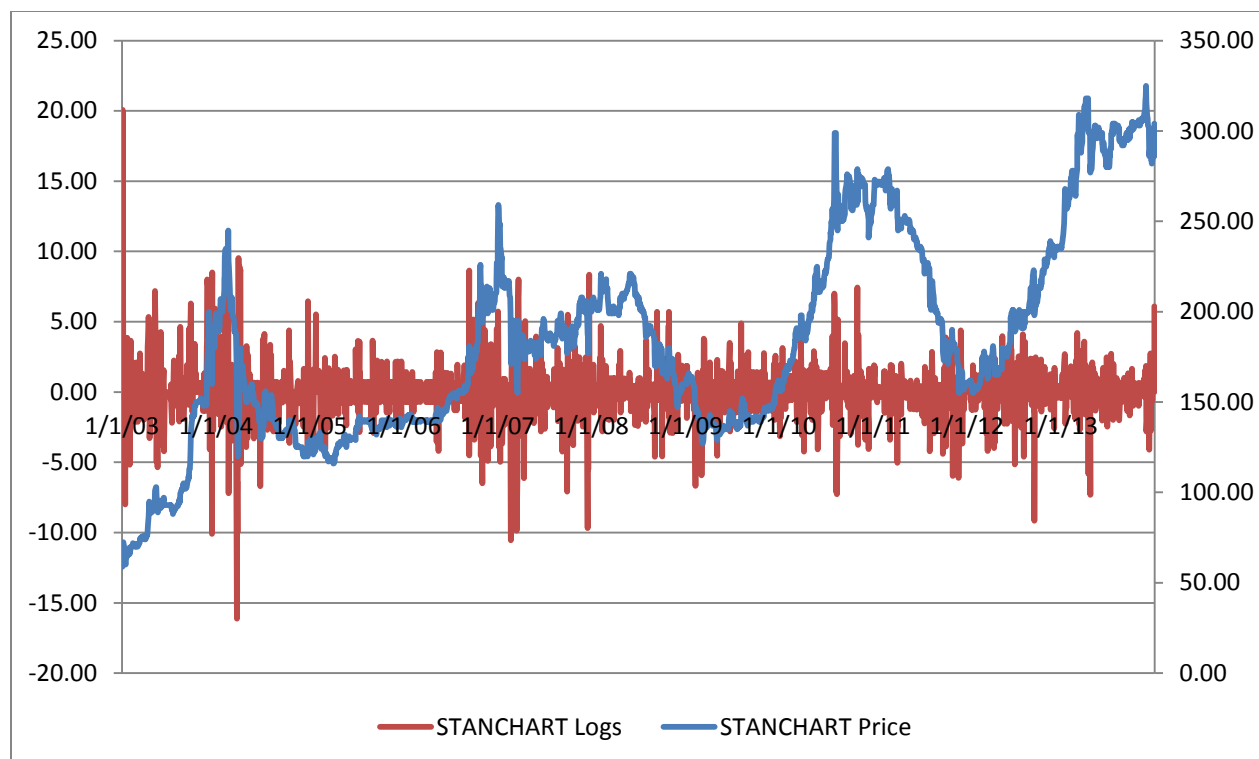
Appendix 4.2: CFC (Source: Author 2013)



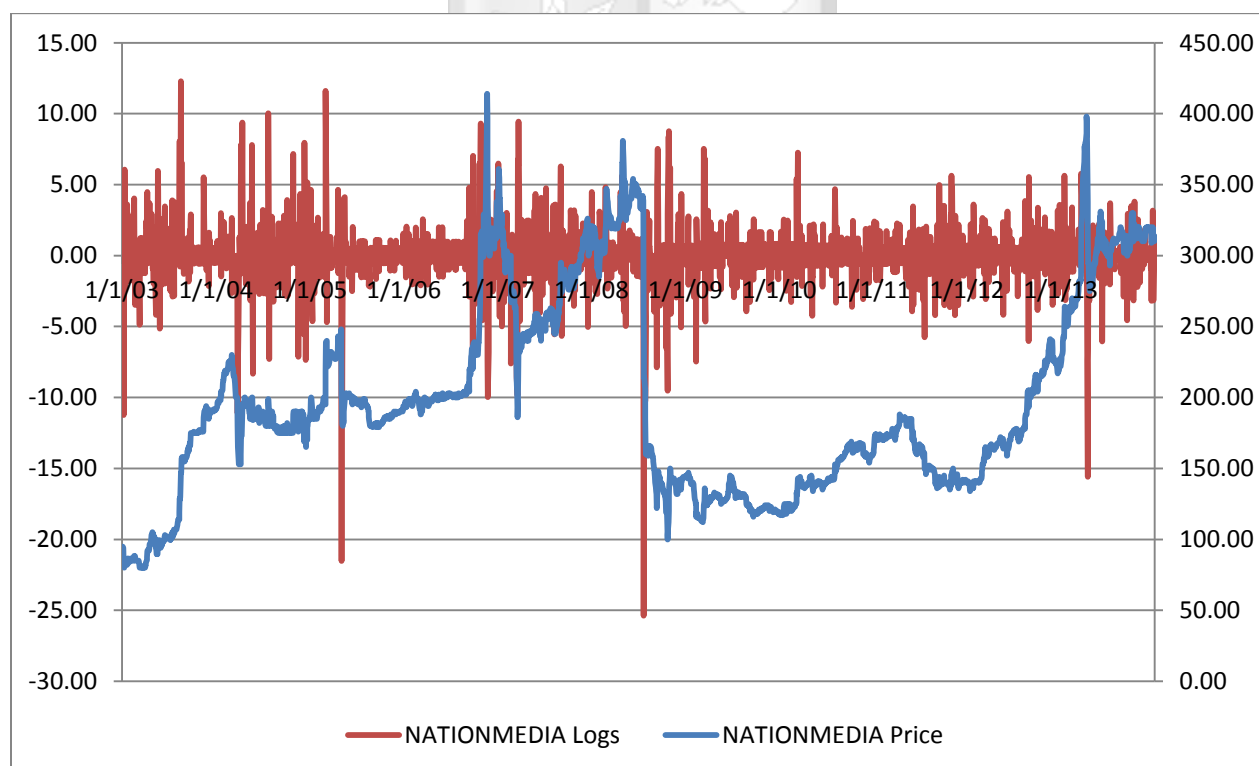
Appendix 4.3: Diamond Trust Bank (Source: Author 2013)



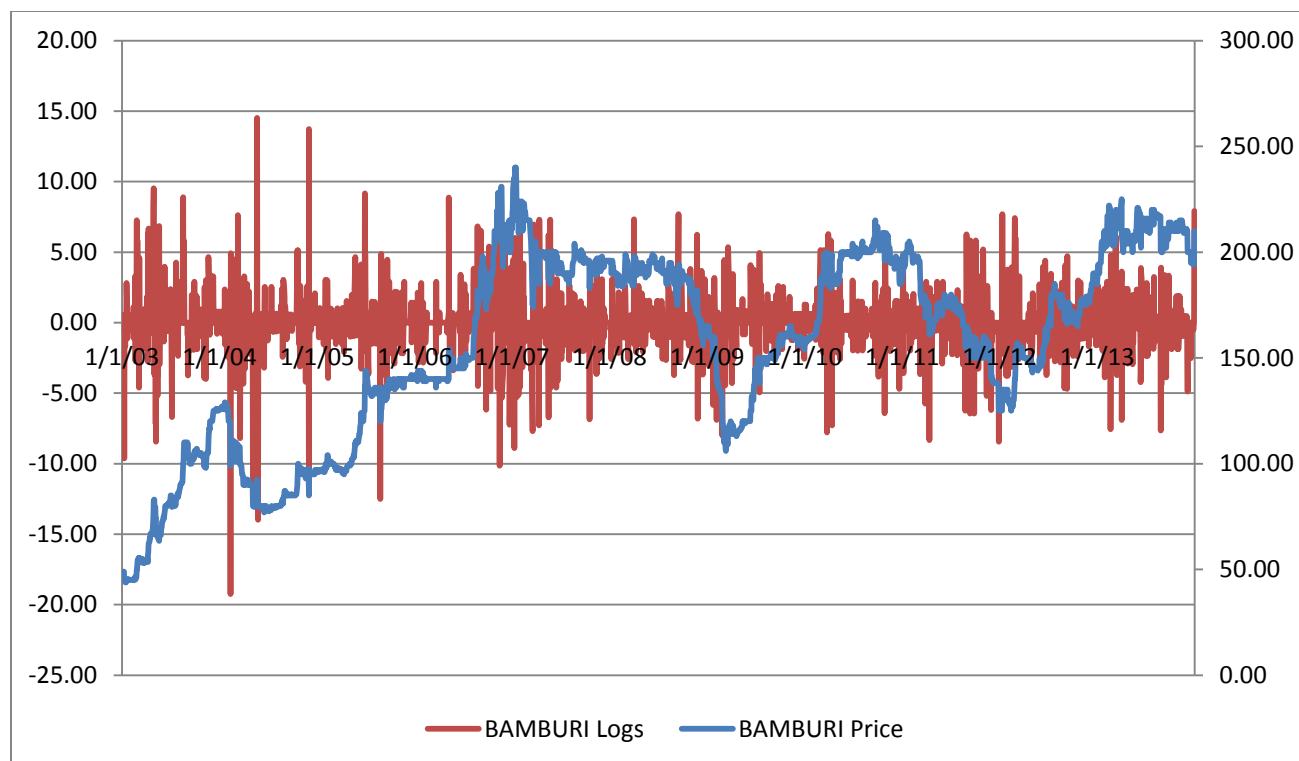
Appendix 4.4: Housing Finance Corporation of Kenya (Source: Author 2013)



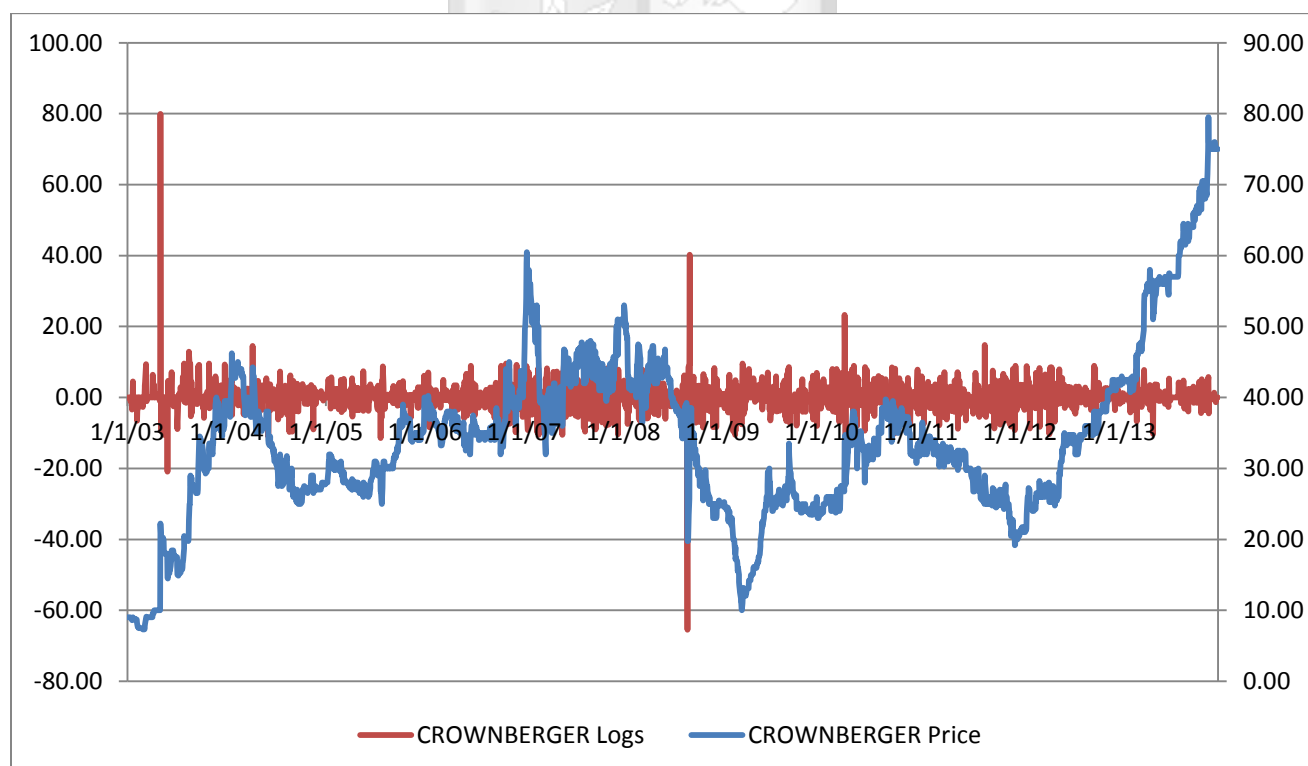
Appendix 4.5: Standard Chartered Bank Kenya (Source: Author 2013)



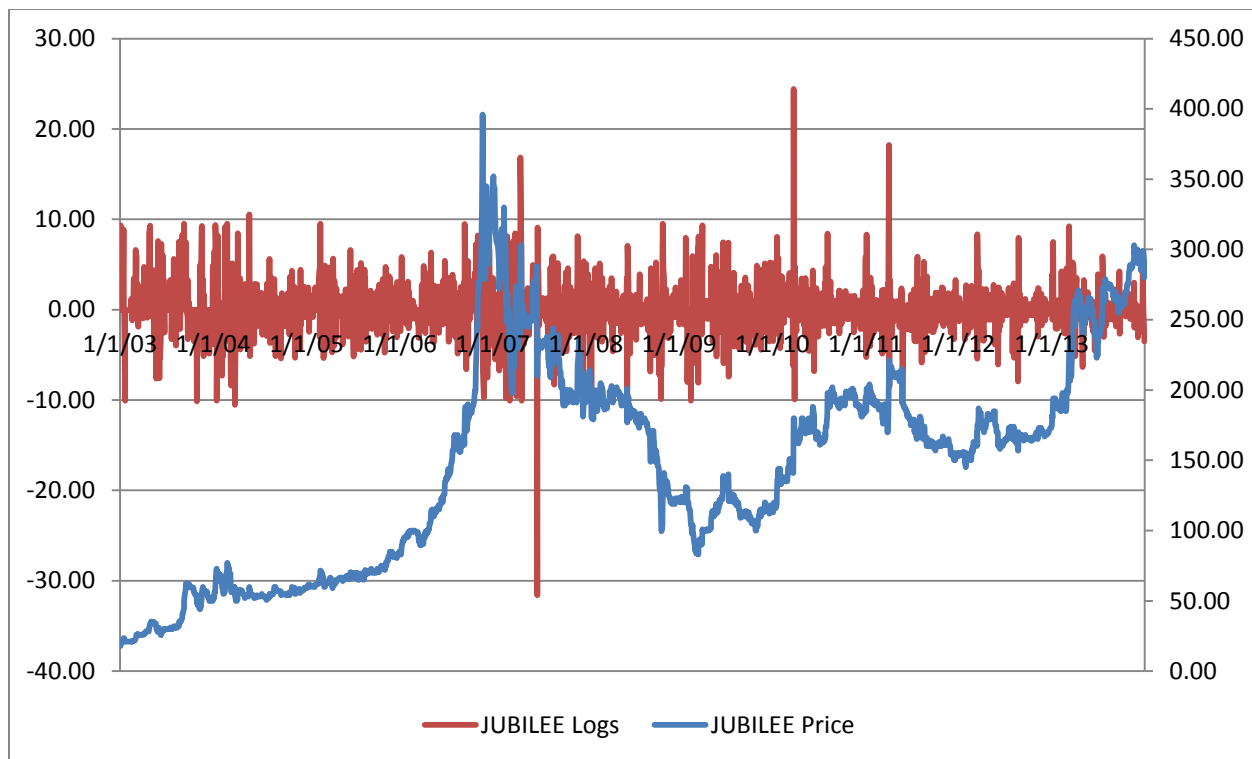
Appendix 4.6: Nation Media Group (Source: Author 2013)



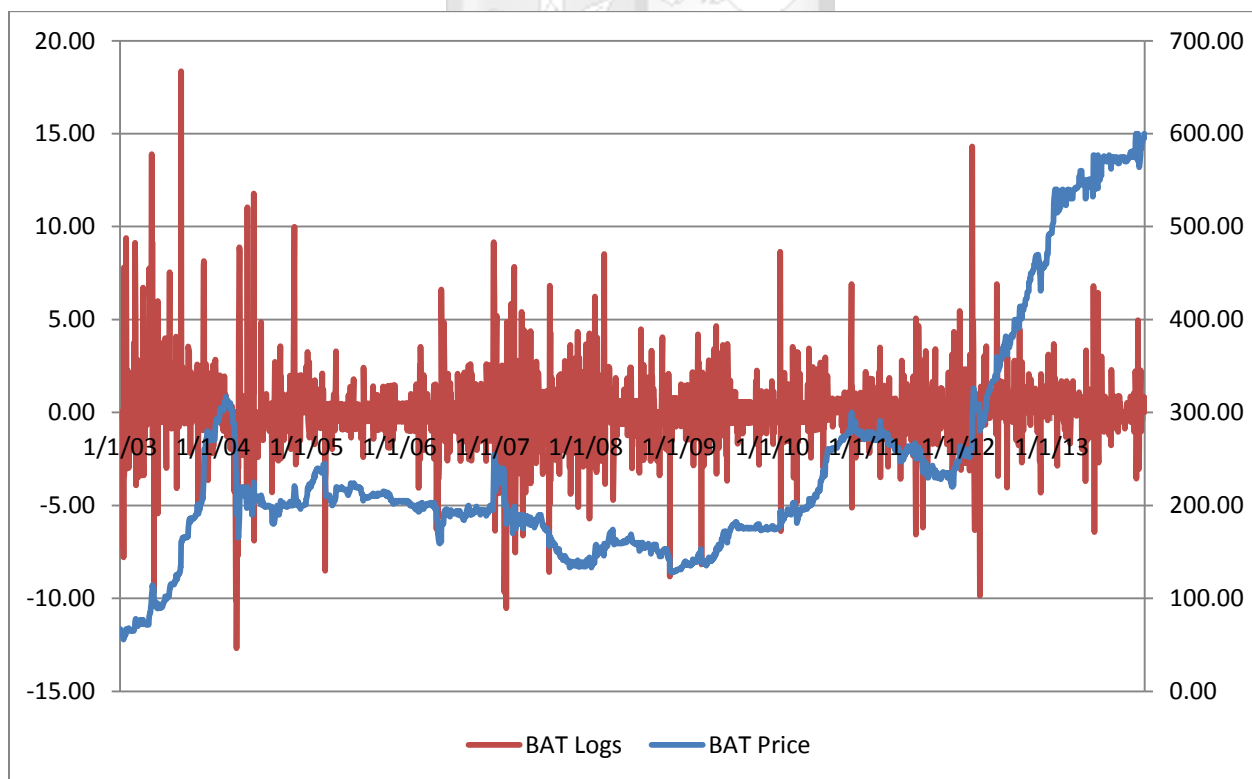
Appendix 4.7: Bamburi Cement (Source: Author 2013)



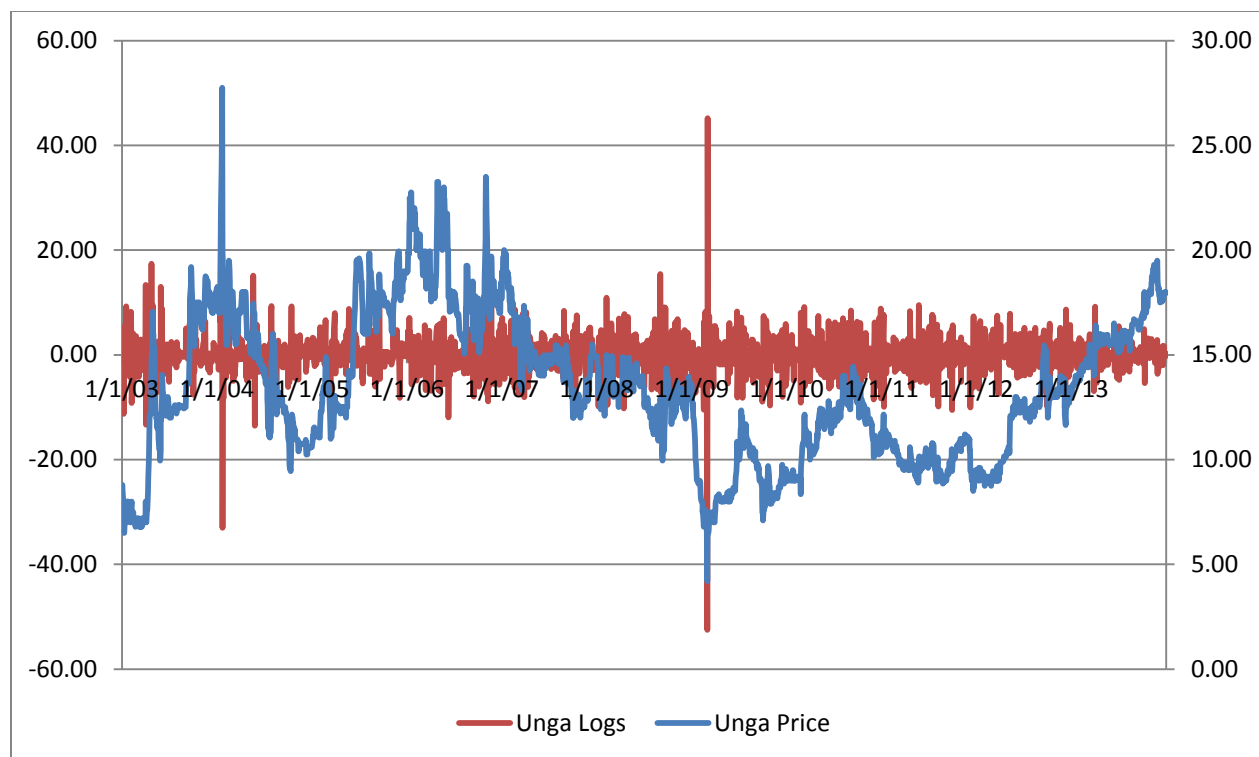
Appendix 4.8: Crown Berger LTD (Source: Author 2013)



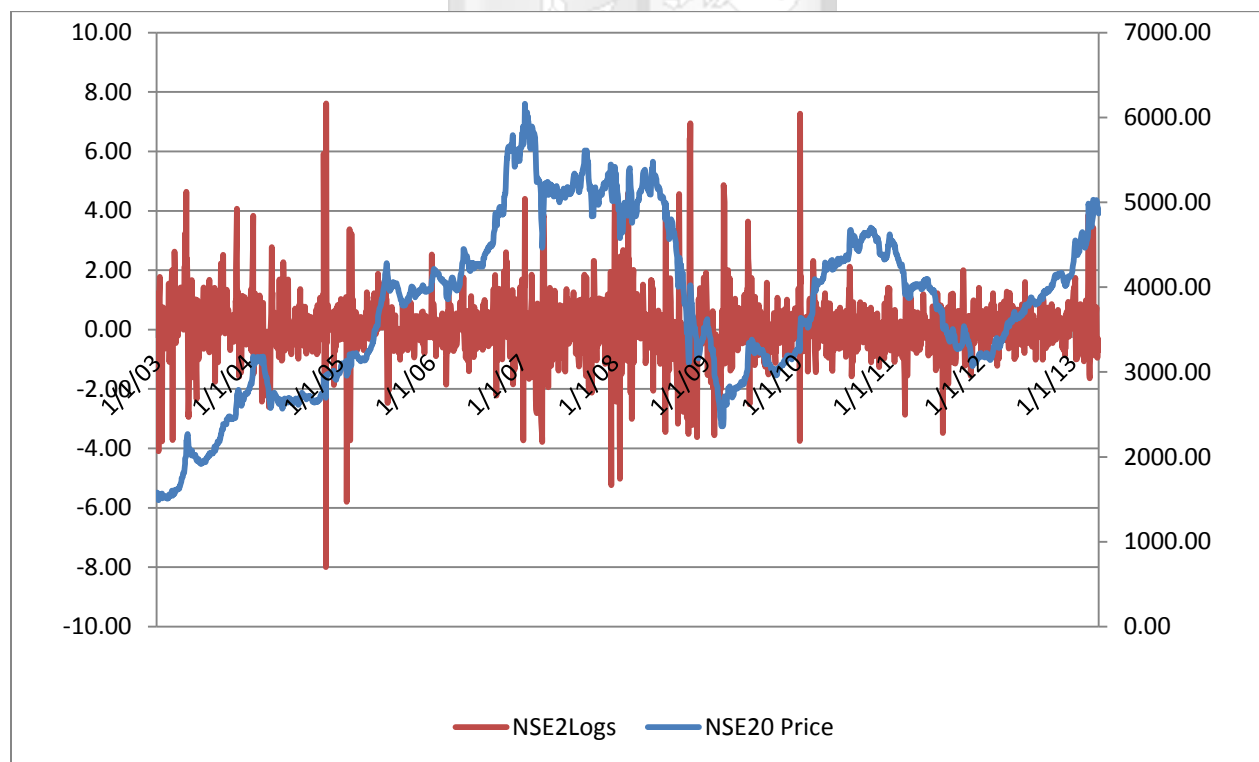
Appendix 4.9: Jubilee Insurance (Source: Author 2013)



Appendix 4.10: British American Tobacco (Source: Author 2013)



Appendix4.12: Unga Group LTD (Source: Author 2013)



Appendix 4.13: Nairobi Securities Exchange 20 Share Index (Source: Author 2013)

BEARISH	BAMBURI	BAT	CROWNBERGER	DTBKENYA	HECK	CFC	JUBILEE	NATIONMEDIA	NSE20	STANCHART	UNGA
Mean	-0.081511	-0.0643	-0.162405	-0.053773	-0.205209	-0.10071	-0.208932	-0.192003	-0.13493	-0.08047	-0.15657
Median	0	0	0	0	0	0	0	0	-0.10467	0	0
Maximum	7.696104	9.156719	40.22236	9.531018	24.22646	27.30405	16.83353	9.445218	6.947677	8.338161	15.41507
Minimum	-8.894749	-10.5361	-65.44327	-10.20493	-22.31436	-12.3614	-31.58529	-25.38461	-5.23397	-10.53605	-10.5361
Std. Dev.	1.849394	2.101465	4.878775	2.591376	3.857297	2.944205	3.231061	2.558613	1.32733	1.81351	3.222317
Skewness	-0.025778	-0.12724	-3.299627	0.219172	0.189732	1.609149	-1.667445	-2.046178	0.652229	-0.483816	0.191163
Kurtosis	8.391814	8.035767	67.33828	5.775451	7.513492	20.43366	21.01373	22.41208	7.687539	10.83617	4.908763
Jarque-Bera	674.7664	590.0418	97079.64	183.2361	476.133	7294.145	7795.316	9134.248	549.4487	1446.849	87.94915
Probability	0	0	0	0	0	0	0	0	0	0	0
Sum	-45.40183	-35.8134	-90.45947	-29.95165	-114.3012	-56.0975	-116.3752	-106.9456	-75.1548	-44.82163	-87.2085
Sum Sq. Dev.	1901.664	2455.382	13234.16	3733.668	8272.579	4819.597	5804.504	3639.855	979.5629	1828.583	5773.128
Augmented Dickey-Fuller test statistic	-28.42938	-25.3332	-13.53918	-22.21789	-13.26096	-21.0741	-25.15436	-12.55437	-14.6938	-20.90187	-28.0562
Prob. *	0	0	0	0	0	0	0	0	0	0	0
Test critical values:											
1% level	-3.441882	-3.44188	-3.441989	-3.441882	-3.441946	-3.44188	-3.441882	-3.441903	-3.44188	-3.441882	-3.44188
5% level	-2.866519	-2.86652	-2.866566	-2.866519	-2.866547	-2.86652	-2.866519	-2.866529	-2.86652	-2.866519	-2.86652
10% level	-2.569482	-2.56948	-2.569507	-2.569482	-2.569497	-2.56948	-2.569482	-2.569487	-2.56948	-2.569482	-2.56948
Observations	557	557	557	557	557	557	557	557	557	557	557
Kwiatkowski-Phillips-Schmidt-Shin test statistic	0.324674	0.073077	0.268626	0.099692	0.130207	0.266016	0.040445	0.18165	0.268826	0.136353	0.13972
1% level	0.739	0.739	0.739	0.739	0.739	0.739	0.739	0.739	0.739	0.739	0.739
5% level	0.463	0.463	0.463	0.463	0.463	0.463	0.463	0.463	0.463	0.463	0.463
10% level	0.347	0.347	0.347	0.347	0.347	0.347	0.347	0.347	0.347	0.347	0.347

Appendix 4.14: Bear period statistics (Source: Author 2013)

Bullish	BAMBURI	BAT	CROWNBERGER	CFC	DTBKENYA	HECK	JUBILEE	NATIONMEDIA	NSE20	STANCHART	UNGA
Mean	0.084694	0.1592	0.137871	0.105228	0.168086	0.142401	0.133041	0.07355	0.107328	0.140002	0.104678
Median	0	0	0	0	0	0	0	0	0.070539	0	0
Maximum	6.28479	8.654046	23.24459	21.35741	10.60182	17.66235	24.4197	7.534944	7.269002	7.438372	45.19851
Minimum	-8.004271	-8.1678	-22.49437	-23.05237	-8.701138	-24.3002	-9.920665	-4.652002	-3.74728	-7.268973	-52.501
Std. Dev.	1.562677	1.340015	3.544536	2.850213	2.238268	2.407628	2.531323	1.279098	0.882591	1.491583	4.423116
Skewness	-0.501704	0.054984	0.137293	-0.159999	0.162975	-1.38906	2.083955	0.967087	1.727783	-0.014334	-1.39902
Kurtosis	9.548104	13.15525	10.48495	20.18448	7.931925	32.58673	23.13133	10.45182	16.06647	8.837011	69.79432
Jarque-Bera	821.0058	1929.599	1049.535	5526.607	457.0469	16521.19	7906.923	1108.855	3417.516	637.4213	83613.34
Probability	0	0	0	0	0	0	0	0	0	0	0
Sum	38.02749	71.48087	61.90392	47.24758	75.47051	63.93808	59.73561	33.02417	48.19021	62.86087	47.00036
Sum Sq. Dev.	1093.997	804.4473	5628.554	3639.424	2244.409	2596.908	2870.604	732.969	348.9773	996.7188	8764.652
Augmented Dickey-Fuller test statistic	-18.20336	-23.764	-16.91544	-18.36501	-24.10518	-19.6238	-18.48516	-20.82031	-10.7388	-18.98619	-28.7647
Prob. *	0	0	0	0	0	0	0	0	0	0	0
Test critical values:											
1% level	-3.444757	-3.44472	-3.444757	-3.444757	-3.444724	-3.44472	-3.444757	-3.444724	-3.44479	-3.444724	-3.44472
5% level	-2.867786	-2.86777	-2.867786	-2.867786	-2.867772	-2.86777	-2.867786	-2.867772	-2.8678	-2.867772	-2.86777
10% level	-2.570161	-2.57015	-2.570161	-2.570161	-2.570153	-2.57015	-2.570161	-2.570153	-2.57017	-2.570153	-2.57015
Observations	449	449	449	449	449	449	449	449	449	449	449
Kwiatkowski-Phillips-Schmidt-Shin test statistic	0.114194	0.095744	0.079383	0.20935	0.188479	0.04649	0.064302	0.073603	0.086256	0.241098	0.112651
1% level	0.739	0.739	0.739	0.739	0.739	0.739	0.739	0.739	0.739	0.739	0.739
5% level	0.463	0.463	0.463	0.463	0.463	0.463	0.463	0.463	0.463	0.463	0.463
10% level	0.347	0.347	0.347	0.347	0.347	0.347	0.347	0.347	0.347	0.347	0.347

Appendix 4.15: Bull period statistics (Source: Author 2013)

Variable	NSE	20	STANCHART	NATION	MED	DTB	HFCK	BAT	BAMBURI	JUBILEE	UNGA	CROWN	CFC
μ_1	0.233746167	0.094996743	0.13059461	0.1839272	0.0993925	0.0698962	0.019928274	0.31898275	0.283618906	0.311128	0.244860149		
	0.00000001	0.00079369	0.00722633	0.0222745	0.09000479	0	0.75369602	0.0000024	0.00079992	0.001276	0.00119076		
μ_2	0.208631098	-0.31275608	-0.1712101	-0.180024	0.04663874	-0.06825	-0.19333506	-0.0985215	-0.35048135	-0.14917	-0.0650732		
	0.0010643	0	0.00046321	0.0005472	0.20706264	0	0.00001176	0.00666828	0	0.014866	0.04765017		
μ_3	-0.00069703	-0.02098499	-0.0712385	0.007464	0.05870537	-0.102681	-0.10660772	-0.0715918	-0.10545427	-0.174921	-0.05892625		
	0.99085657	0.03188209	0.1057916	0.8202525	0.17463099	0	0.01196714	0.06084508	0.04022172	9.61E-05	0.12652544		
μ_4	-0.04054665	0.04905478	0.01930971	0.000278	0.02709627	-0.02947	0.005158526	0.04256931	-0.11573656	-0.031421	-0.13905868		
	0.45704072	0.00103102	0.64860486	0.9863879	0.52716031	0	0.86117115	0.14212559	0.01768068	0.550971	0.00000007		
ω, Ω	2.926609044	0.340910532	0.22125014	2.0339553	0.92174417	1.8372721	1.158255213	3.28499381	-0.09604128	-0.078453	-0.05480506		
	0.00082547	0.05148068	0.03773966	0	0.00000003	9.52E-05	0	0.00000001	0.78591253	0.471884	0		
δ	-0.10094648	-0.11399733	-0.2499993	-0.07408	-0.2059163	-0.192598	-0.12090158	-0.0369666	-0.47909871	0.690304	-0.13018945		
	0.15141523	0.02369819	0	0.2184415	0	0	0.04135006	0.48643019	0.01128833	0.026164	0.52111428		
ψ, Ψ	0.402196031	-0.67142602	0.86568554	0.0940543	1.88647162	0.0722588	0.055795428	1.09943096	0.116912665	0.649779	1.053538722		
	0.1202403	0.00002032	0.00000015	0	0.00000037	0	0.8432494	0.00002104	0	0	0		
ϕ, Φ	-0.83381388	0.848433327	-0.3752653	-0.209747	0.47858788	0.5677009	0.425022258	-0.6250972	0.326789814	0.542888	1.011288947		
	0	0	0.00121033	0	0.00000084	3E-08	0.00000631	0.00149285	0.11644766	0	0		
Θ, θ	0.314214091	0.085550254	0.07645602	0.1035309	0.02062834	-0.000159	0.082705045	0.1092669	-0.0657	0.05229	0.14501		
	0	0.03811113	0.04189589	0.101262	0.07559211	0.0223794	0.00434875	0.0079322	0	0.0125	0.0347		
Γ, Υ	0.308547732	0.515277739	0.5997173	0.5339448	0.02153295	0.0005234	0.447377961	0.26181671	0.1686	0.2301	0.1534		
	0.0023221	0	0	0	0.0535172	4.192E-05	0	0.00008016	0	0	0		
D	0.769869301	0.402752046	0.52115589	0.1242615	0.73447945	0.5053089	0.631779397	0.39728543	0.113963203	0.243255	0.451413846		
	0	0	0	0	0	0	0	0	0.07485925	0	0		

Appendix 4.16 FIEGARCH Bull period results (Source: Author 2013)

Variable	HFCK	NATIONMEDI	BAMBURI	CROWNBERG	ENSE20	DTB	JUBILEE	STANCHART	UNGA	BAT	CFC
μ_1	-0.2765105	-0.3870151	-0.19599555	-0.5858027	-0.0806513	-0.186501	2.02068174	0.3067493	-0.195985	-0.03623875	-0.1840894
	0.03427557	0	0.00007799	0	0	0.0798019	0	0	0.0326173	0.40482307	0.0056574
μ_2	0.24558809	-0.3739935	-0.20434881	-0.18568785	0.39825239	-0.1901096	-0.6099306	0.05370002	-0.138012	-0.26574312	-0.130411
	0.00000011	0	0.00000001	0	0	6E-08	0.00000889	0.2315146	1E-08	0.00000461	0.0002942
μ_3	0.0122677	0.03166085	-0.09884496	-0.05876525	0.09622852	0.0676809	-0.3285646	0.3313438	-0.068477	-0.08764311	0.074842
	0.76884934	0.24538428	0.00416671	0.00110666	0.00837294	0.0001324	0	0	0.0175147	0.14092318	0.4178149
μ_4	-0.0153758	-0.1323509	-0.06149538	-0.02320178	-0.03058955	-0.0046675	-0.4915025	0.11011805	-0.000927	-0.10027851	-0.2865659
	0.59796388	0.00006963	0.05905251	0.00099008	0.35140253	0.9157624	0	0.03568472	0.9715109	0.03775012	2.05E-06
ω, Ω	0.35429889	1.61452746	0.311323159	0.050938401	1.31613227	1.9541052	0.58430274	0.19487527	4.5430484	0.050399256	0.3740252
	0.16067544	0	0.0000976	0	0.00132725	0	0	0	0	0.0000005	0.0888053
δ	0.05002533	-0.3336249	-0.0356314	-0.02197599	-0.16800982	0.443784	-0.3201185	-0.4999993	0.2804987	-0.03931942	-0.0891556
	0.498161	0	0.56001991	0.00015903	0.00001856	0.0658611	0	0	1E-08	0.31283437	0.4113099
ψ, Ψ	-0.48462	0.2026944	1.358114775	-1.03236596	1.01464952	-0.2264803	-0.9128431	-0.756646	1.6294936	-0.67002	3.2441256
	0.01646978	0.0822919	0.11401198	0	0	0	0	0	0	0	0.1312747
ϕ, Φ	0.8663572	-0.713749	0.868151473	0.977285949	-0.97773893	-0.3013787	0.81655843	-0.0859164	-0.393438	0.187462148	0.8235704
	0	0	0	0	0	0	0	0	0	0	0
Θ, θ	-0.0308206	0.57747744	-0.03606147	0.027229439	-0.0454145	-0.2883944	-0.263117	-4.2457996	-0.14741	-0.1458	-0.0002217
	0.53579435	0	0.01465095	0.00000648	0.26842017	0	0	0	4.05E-06	0	0.4831468
Γ, γ	0.50000133	-0.2901203	0.015212946	0.319702613	0.54951836	0.048047	0.69827345	0.3541468	0.4494248	0.785702585	0.0024805
	0.00000011	0.00000739	0.02064366	0	0	0	0	0	0	0	0.1793112
D	0.0677151	0.15022071	0.455937218	0.672342497	0.46258989	0.1424161	0.1082595	0.07413	0.3748411	0.999999989	0.2187047
	0.04385415	0	0	0	0	0	0	0	0	0	0.0109415

Table 4.5: FIEGARCH Bear results