"Dynamics of Conditional Stock Returns Volatility": An Empirical Analysis of the Nairobi Securities Exchange Limited for the period 2001 - 2014.

BY

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DECLARATION

I, the undersigned, declare that this proposal is my original work and has not been submitted to any other college, institution or university for the award of a degree or any other award.

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DEDICATION

To my guardian Gerald and Leah Gicheru

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I wish to state that the views expressed in this study are my own and do not represent the views of the University of Nairobi or any quarters.

ABSTRACT

This study analyzed the volatility in conditional stock returns at Nairobi Securities Exchange for the period 2nd January 2001 to 31st March 2014. The study adopted a purely econometric approach majorly using the ARCH – family econometric models with a blend of both the symmetric and the asymmetric models in attempt to ensure robustness of the results.

The study focused on the main aspects of daily returns with special attention on volatility clustering, leptokurtosis, long memory, market risk premia and the leverage effect. In addition, the study captured the day of the week as well as the effects of changes in policies and regulations on the daily stock returns at the NSE. The results are as follows: returns are predictable thus rejecting the weak form efficiency. On volatility, market volatility effects on stock returns are short lived and decay at a short interval in addition to them being not explosive. Market premium is priced at NSE hence acceptance of time – varying risk premium theory. For the day of the week, Tuesdays and Thursdays post negative significant returns. The implication is that announcements for sale of government securities mainly treasury bills on Thursdays and their actual sale on Tuesdays adversely affect equity market.

The ARCH – LM tests indicate that daily stock returns at NSE are generated by a stochastic rather than a chaotic process. Introduction of the new regulations on foreign investors with a 25% minimum reserve of the issued share capital going to local investors (in 2002), introduction of live trading, cross listing in Uganda and Tanzania stock exchange (in 2006) and change in equity settlement cycle from T+4 to T+3 (in 2011) significantly reduce volatility clustering, impact of bad news in market, volatility shocks and their persistence for the entire sample with the onset of US tapering increasing the daily mean returns significantly while reducing conditional volatility.

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CHAPTER ONE

BACKROUND INFORMATION

1.1 Introduction

Financial markets play a critical role in any economy mainly by facilitating financial intermediation with the aim of linking savers to investors thus supplementing the role of banking sector in economic development. A vibrant financial market is preferred in any economy given its economic contributions. In particular, a well-functioning security market is of great preference if investors' confidence, reduced transaction and information cost, price discovery and risk transfer are to be guaranteed. Moreover, beyond national frontiers, stock markets facilitate the inflow of foreign financial resources via foreign direct portfolios. Therefore, the contribution of stock market to economic development cannot be overstated.

However, volatility is an eminent feature in stock markets that disrupts the smooth functioning of any stock market. High volatility discourages investors from holding stock given that the expected returns have to be traded off for the risk exposure (volatility) thus leading to demand for high risk premium to leverage volatility risks.

In forecasting volatility researchers seek to ascertain the standard deviation that minimizes the error term. Following the October 19, 1987 stock market crash where the largest one – day decline of over 22 percent was registered (for example Dow Jones industrial average fell508 points[1]), there has been a great attempt towards empirically predicting stock return volatility. The crash was worsened by the inability of stock market trading system to process many transactions at once hence market inefficiency[2]. First, examining stock market volatility is important since volatility influence decisions with regard to saving and consumption by individuals mainly through substitution and income effects. Secondly and

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[1]The market Crash of October 19, 1987 was a shock in the stock markets worldwide that led to turbulence in prices of many financial assets. With the S& P 500 index falling by 20percent it presented stock market swiftness that has led to studies on stock market volatility worldwide both in developed and emerging stock markets.

[2]These market systems have gradually been upgraded overtime. Perhaps, the crash might have provided an impulse towards their upgrade

more importantly, such volatility influences pricing of various financial derivatives such options (Black and Scholes, 1973)

Moreover, understanding of volatility of stock returns is useful in determining the cost of capital and the evaluation of asset allocation decision. Policy makers mainly rely on market estimates of volatility as a barometer of the vulnerability of financial markets.The mere reporting on the stock market index is of no economic significance to investors and policy makers but of importance is the market volatility.

The reason as to why stock returns change over time still remains to be a puzzle ever since its first documentation in Schwert (1989). The main arguments advanced in theoretical literature being that (1) the leverage effect in (Black 1976 and Christie 1982) and (2) the volatility feedback by (French, Schwert and Stambaugh, 1987 and Campbell and Hentschel, 1992).

However these two strands in the literature do not fully explain the ever-changing stock market volatility. From the theoretical literature there arises a debate between the efficient market theorists and the proponents of behavioural finance theory globally on the long run behaviour in stock markets with the former upholding the random walk hypothesis while the later supporting mean reversion model.

Ever since the seminal work on meanvariance analysis by Markowitz (1952), the investigation of portfolio choice by financial economists has been one of the major attempts. However, the traditional mean variance analysis is based on the assumption of a single – horizon investment which is vague given that in reality investors portray a multi – period investment horizons in attempt to cushion themselves against potential adverse future eventualities in stock returns.

On the stock market returns, the relationship between stock returns and their volatilities is nonlinear and dynamic. From financial theory, stock returns and their volatilities are positively related. French et al (1987) documents that excess market stock returns are positively related to expected volatility and negatively related to unexpected volatility. However, we can argue that returns can be positively related to unexpected volatility since the higher premiums demanded by investors compensate the unexpected volatility.However, such relationships vary across stock markets depending on the market microstructures. Change in the trading rules, arrival of new information among other factors influence the dynamics of stock market returns which is manifested through stock price movements.

The Nairobi Securities Exchange can be categorised as a shallow developing stock market by international standards. It is characterised by information asymmetry, low local investor confidence and knowledge, vulnerability to shocks, over dominance by foreign investors[3], few number of traded instruments and low levels of capital – market liquidity.

A full blown bear run at the NSE in 2007 – 2009 period led to stock prices falling given the widespread pessimism of local investors.This made it difficult to know whether the market was bottoming out was just experiencing small - short term adjustments. However despite these demining features, the Nairobi Securities bourse is ranked as the fifth largest stock markets in Africa by market capitalisation (CMA, 2008).

A few studies have been conducted on behaviour of stock prices and returns at the NSE focusing mainly on how various factors influence stock price/ return volatility. There exists scanty work on what are the behaviour of stock returns volatilities at the NSE in terms of their distribution, persistence to shocks, risk premia, response to information asymmetry, tendency to converge or diverge in the long run among others. In addition, there is little evidence on anomalies at the NSE; - are there some days in a week or some months in a year that stock returns are very low or very high and if so is this trend consistent over a long period of time?. Oluoch and Oyugi (2012) investigated the market risk (beta) using the Capital Market Pricing Model (CAPM) for different market segments at the NSE. They conclude that various equity investments segments of NSE exhibit unique idiosyncratic factors that influence segmental market risk. Returns for agricultural segment are found to be the most volatile while financial and investment segment returns are the least risky for the period 2008 – 2011 using monthly data. However, the study is mute on what is the nature of these volatilities; – are they permanent or transitory over time? In addition, the period under review is biased given the post-election violence of 2007/2008 and the global financial crisisthat are likely to exaggerated such volatilities hence could not fully give a clear representation of the market. Muriu (2003) using ARCH type models investigated stock

[3]Ngugi(2003); the impact of foreign investors on the performance of the stock market is however not clear. It is for example observed that greater foreign participation in the market reduces price volatility. De Santis and Imrohoroglus (1997) explain that new investors broaden the market, dampening the effect of order flow shocks on prices and may also make prices efficient by increasing the precision of public information regarding fundamental values. Sellin (1996), however, regards foreign investors' participation as noise trading, therefore a source of excess volatility in the market. Moreover the general literature on capital flows indicates that when capital flows are push-factor driven then they are more volatile.

returns' volatility at NSE for 1992- 2003period. The study found presence of high volatility clustering, asymmetric volatility and positive relationship between conditional volatility and stock returns. Positive and significant volatility was also reported for Wednesday and Thursday. However, the study captures the entrance of foreign investors in 1991 and the change in trading system in 2001 which were the main reforms at NSE. In addition the study fails to explain reasons behind the day of the week anomalies of Wednesday and Thursday.

The study therefore sought to review dynamics in stock returns volatility for the period 2001-2014. The choice of this period was informed by the crucial development at NSE given major occurrences in the market. The period has seen the number of listed firms rise to 61. In addition, the period recorded massive IPOs, Additional Offers(AOs), Introductions, Right Issues, Bonus issuesand stock splits all of which have great influence on stock prices and ultimately stock returns (CMA, 2013). Moreover, cross listing, demutualization, dematerialization and global financial crisis occurred in this period and we expect them to influence returns' volatility.

With the upward surge at NSE index and bullish behaviour dominating the market till the end of 2013, this begs the question; for how long will the bullish run last? It is against this background that this study provides an empirical study on stock market returns volatility dynamics which improves our understanding on stock market volatility.

1.2 An overview of Nairobi Securities Exchange Limited

Shares and stock trading in Kenya dates back to 1920's during the British colonial rule. However, the trading was informal since there were no rules and regulations to govern the activities. In 1951, the first professional stock brokering firm was set up named Francis Drummond and in 1953 the London stock exchange officials recognized the setting up of Nairobi stock exchange as an overseas stock exchange. In 1954 the NSE was constituted as a voluntary association of stockbrokers registered under the societies act.

Year 1988 saw the first privatization take place at the NSE that saw the government successfully sell of 20% ownership of Kenya Commercial Bank. In 1990 the Capital Market Authority (Cap 485A) wasestablishedas a regulator in stock trading for promoting and facilitating development of an efficient stock market. In 1991, share trading moved from coffeehouse to floor based open cry system to enhance transparency and necessitate handling of the growing activity at NSE.

The NSE continued to thrive well and in February 18, 1994 the NSE 20 – share index posted a high of 5,030 points leading to the International Finance Corporation rating it the world's best performing market with a return of 179% in dollar terms. July 1994 saw the setting up of a computerised delivery and settlement system (DASS) that led to the number of registered stockbrokers increasing by 8 new stockbrokers. January 1995 saw the entrance of foreign investors into the market following the removal of restrictions that hindered inward portfolio investment in the past. However, foreign investors were permitted up to 20% of equity for inward portfolio investment. In 1996, NSE experienced the largest share issue following the Kenya airways privatization that was KLM acquire 26% stake.

The launch of CMA reform strategy on 8th May 2000 saw the establishment of three segments; - the Main Investment Markets (MIMs), the Alternative Investment Markets (AIMs) which targets the small and medium-sized companies with potential to grow, and the Fixed Income Securities' Markets (FISMs).

On 26 July 2002, new foreign investor regulations were established where a 25% minimum reserve of the issued share capital (during an IPO and Government of Kenya privatization) was for locals while the balance of the 75% was a free float for all classes of investors.Central Depository and Settlement Corporation (CDSC) was launched in 2004 to kick start dematerialization process. All the holders of share certificates were required to convert all of their shares into an electronic form by opening CDSC account by 2012. The reform aimed at boosting, safety of shares, efficiency in trading as well as cutting costs on paper work.

In May 2006, demutualization committee was formed to spearhead demutualization process. This would improve management listed firms by demutualizing 51 percent of the firms as well as raising the standards of NSE to international standards by delinking ownership from management. It would also promote foreign capital inflow into NSE. In September the same year ushered the live trading at NSE following the establishment of an Automatic Trading System (ATS). This also saw the number of daily trading hours increased to 1500hrs. ATS made it possible to trade all immobilized corporate bonds and treasury bonds. In addition there was the removal of block trades board. November, 2006 witnessed mass cross listing following the signing of memorandum of understanding between NSE and the Uganda stock exchange hence allowing dualism for companies listed in both exchanges.

In July, 2007 the NSE 20 – share index was reviewed to ensure that the index was a barometer for the market. In the same year, the Wide Area Network platform was introduced hence enabling trading to take place through easily and eradicating the need for stockbrokers to send their staff to the trading floor. In 2008, the NSE All Share Index (NASI) was introduced as an alternative index to NSE 20 – share Index to incorporate all the traded shares of the day. July 2011 saw the change of NSE and equity settlement cycle from T+4 to T+3meaning investors who sell their shares; get their money three days after the sale of their shares day as opposed to four days earlier on. By October 2011, the broker back office system commenced operations to facilitate internet trading thus necessitating greater access to securities market. As at 2012, there were 61 listed companies trading at the NSE. In January 2013, Growth Enterprise Market Segment (GEMs) was launched with Home Afrika being the sole company registered in the segment as at the end of 2013.Currently, in launching the NSE investment challenge 2014, the bourse plans to roll out Real Estate Investment Trusts (REITs) to enable direct investments in real estate through properties or mortgages. Exchange Traded Funds (ETFs) similar to unit trusts or mutual funds are also earmarked for listing.

1.3 Problem statement

The recent decade has been characterised by the debate between the efficient market theorists and the proponents of behavioural finance theory on the long run behaviour in stocks. The most controversial issue of the debate among others is the paradox as to whether stock prices revert to their mean in the long run. Efficient Market Hypothesis posits that stock prices cannot revert from the fundamental values since the onset of such deviations would trigger rational investors to trade it away. Instead, the rapid changes in the stock prices can be accounted for by the changes in the fundamental economic factors. Contrary to this proposition, the behavioural finance theorists are of the opinion that rationality does not hold and that changes in fundamental economic factors are inadequate in explaining the large variations in stock prices.

In the recent years, NSE has evidenced an upward surge in the market returns from the stock index hitting a high of 4970 points in the end of October 2013 from 4133 points in December 2012 thus outperforming the Dow Jones industrial average in this period. Market capitalization rose to Kes 1.8 trillion in by the end of October 2013 from 1.3 trillion in December 2012 a 41% increase rising further to Kes 2.003 trillion in March 2014 (NSE). In spite of this growth, stock prices remained very volatile between year 2001 and the first quarter of 2014 with bullish trends dominating 2010-2013 period after a turning point from a bumpy season in 2008-2009 that saw Kenyan economy hit its lowest.

Volatility disrupts smooth functioning of security market by reducing investors' confidence hence reduced investment that translates to slow economic growth. In order to boost investment at NSE, there is need to understand the characteristics of stock return volatility. Many questions regarding stock market volatility at NSE therefore remain unanswered. In particular, the following three pressing issues should receive more attention:does stock returns volatility at NSE change over time and if so, are these changes predictable? How frequent are the shocks in stock returns as evidenced by the statistical distribution of these returns and finally is there any relationship between market risks posed by reform at NSE and the expected returns?

A well-functioning stock market reduces uncertainty among the investors and contributes to development of an economy through two important channels; boosting savings and allowing for moreefficient allocation of resources. Given that from the liquidity preference theory of the term structure of interest rates risk averse investorsdominate the market, every investor will try to cushion him/herself from possible risks hence the importance of stock market volatility. At the NSE, only basic financial assets (equity and bonds) are traded hence there lacks instruments such as financial derivatives to hedge against market risks. Given this scenario, a deeper insight into the dynamics of stock prices and stock returns is of great importance towards development of a stable market.

For highly levered firms, high volatility cause a sharp decline in their share prices given the high risk that investors have to bear hence low returns[4]. This may lead to collapse of the market and ultimately impacting economy negatively.

The current U.S tapering[5] has seen the federal treasuries' interest rates rise by over 100 basis points following the reversal of monetary easing by federal government thus triggering capital flows reversal in developing market.

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[4]Black (1976) and Christie (1982) point; Stock price volatility is negatively correlated to stock price declines. As stock prices decline, stock returns volatility increases. Firms become more levered as relative value of debts rises relative to the value of equity. A fall in stock price will be almost entirely borne by equity thus increasing the debt- equity ratio that further raises future volatility.

[5]The action by the U.S federal government to adopt monetary tightening in attempt to build up on their reserves by reducing the size of bond buying programme after the global financial crisis.in December 2013 the government decided to taper its quantitative easing policy from

The announcement of Feds policy on tapering saw a stock surge signalling investors' approval of the modest tapering and the stronger pledge to keep short-term rates low for an extended time. Specifically, the Dow Jones industrial average rose more than 150 points minutes after the announcement. Therefore, since foreign investors dominate the NSE activities, U.S tapering is expected to affect volatility at NSE as investors liquidate their in favour for U.S federal treasuries.

NSE currently suffers from market microstructure risk that arises from a narrow range of financial products, high market concentration and low liquidity. High market concentration arises from the fact that 8 firms out of 61 listed companies account for 70 percent of total market capitalization (Financial Sector Stability Report, 2012). Further low liquidity aggravates market volatility and consequently liquidity risk. In attempt to mitigate these, CMA has spearheaded market diversification initiatives aimed at creating conducive environment for investments especially the SMEs.These initiatives include: plan to introduce financial market derivatives, establishment of hybrid OTC bond market, formal OTC equity market and market segment for Small and Medium Enterprises – Growth Enterprise Market Segment (GEMs). There are also plans to introduce margin trading, provide for securities borrowing and lending arrangements as well as short – selling and market – making (Capital Market Survey, 2013). However, these are only viable if in-depth knowledge on dynamics of stock returns volatility is available. Though few studies have been done on volatility at NSE there is very little coverage on the recent reforms. This study sought to fill this gap.

$75 to $85 billion per month. The consensus is that tapering will continue through 2014 and wind up by the end of 2014.Beginning in February 2014, the federal committee agreed to add holdings of agency mortgage-backed securities at a pace of $30 billion per month rather than $35 billion per month, as well as adding to its holdings of longer-term Treasury securities at a pace of $35 billion per month rather than $40 billion per month. This is expected to lead to massive outflow of capital from emerging markets with South Africa already experiencing the effects as evidenced in deterioration of the Rand's value.

1.4Objectives

The main objective of this study was to analyse the dynamics of conditional stock return volatility at the NSE.

Specifically the study sought;

- To determine the distribution, long memory and mean reversion in stock returns at NSE.
- To find out the persistence of shocks in stock returns over time or regimes - whether transitory or permanent.
- To determine the extent of risk premia.
- To find out effect of foreign investors' participation in the stock market performance
- To draw policy recommendations based on empirical findings.

1.5 Significance of the study

Thiscontributes to the existing literature and policy threefold. First, the study uses the most recent high frequency daily data series dating from 2001 to March, 2014. This aids in capturing the new developments at the NSE for the last 13 years. The new trading rules devised by the CMA, demutualization, change in trading system, cross listing in Ugandan and Tanzanian stock markets, the newly concluded general elections in 2013 among others are some of the developments at the NSE for the period covered in the study. More importantly is the recent 2013/2014 U.S tapering effects and the geopolitical developments involving Russia and Ukraine that adversely affect recovery of fragile Euro zone and their ultimate effects on the emerging markets financial markets. These are some of the developments that previous studies for example Muriu (2013) failed to address.

On the policy front, understanding dynamics of stock return volatility at NSE will guide Capital Market Authority in formulating policies that create conducive environment for investments. Currently there has been debate on the introduction of financial derivatives mainly futures at the NSE to leverage on market volatility (risks). Knowledge on dynamics of returns volatility will hasten this innovation as well as pricing of such financial products. Few instrument traded at NSE limits portfolio diversification by investors. There is need to increase the number of financial instrument traded in the market to leverage on risk of loss from some instrument. Moreover, this study captured the recent U.S tapering arising from monetary tightening and its possible effects on volatility via foreign investors' re-allocation of portfolios. The expectation is that foreign investors are likely to liquidate their portfolios from NSE in favour of U.S federal treasuries. However, the relevant issue would be how long such occurrences are likely to persist, a vital concern for CMA in market stabilization. Finally, the study will be beneficial to both domestic and foreigninvestors. The knowledge on stock price/return volatility is important to investors' portfolio selection decision. An investor will choose a portfolio mix that maximizes returns and minimizes risks. Theoretically investor will choose portfolio along efficient market frontier. However in reality high volatility may cause some stocks to be under-priced and others overpriced with reference to security market line. Information on how frequent and persistent such volatility shocks are will influence investors' portfolio choice as well as investment horizon. In a stock market, investors' investment horizons are classified into two: - short term and long term investment horizon. Investors usemarket volatility as a barometer for choosing investment horizon. High market volatility implies that a short term investor will demand for a higher market premium to invest in a long term financial assets. Therefore, the findings of this study would aid investors in choosing their investments horizons in addition to choosing efficient portfolio.

1.6 Organization of the research paper

This study wasorganized as follows; the next chapter covers both theoretical and empirical literature review. In chapter three we discuss the research methodology which covers data, salient features of financial data as well as the specification of models to be estimated. Chapter four presents empirical findings of the study as generated by different models. Chapter five concludes with policy recommendations and areas for further research.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter covers both theoretical and empirical literature on stock market volatility. It concludes with an overview of the literature highlighting the research gap that the study seeks to fill.

2.2 Theoretical Literature

Within the finance literature there exist robust literature on stock market volatility both for developed and emerging markets. Researchers in finance have been interested in the dynamic long run behaviour of stock prices. The literature addresses the causes of stock volatility overtime. Over the period several theoretical models have been devised on asset pricing.
Markowitz portfolio selection model (1952, 1956) – a single period model that illustrates investor forms asset portfolio at the beginning of the period and aims at maximising the expected return. The returns are subject to acceptable risk level depending on stock volatility which is the measure of risk. The model uses variance or standard deviation of expected stock returns as a measure of volatility. Depending on the volatility of expected returns (the investor therefore selects portfolio along the efficient frontier.

Sharpe (1964), Litner (1965), Mossin (1966) and Merton (1974, 1980) developed the link between asset's return to its own variance or to covariance between asset's return and the returns on market portfolio. However a strand in literature arises on whether such relationships are positive or negative.Poterba and Summers (1988) established that stock returns are positively autocorrelated over a period of less than one year and negatively autocorrelated over a period of three to eight years thus indicating transitory components in stock prices and in both the real and excess returns in the long run. However, a number of models in finance present an evidence of long tradition that stock returns volatility is negatively correlated to stock returns (leverage effect). Black (1976), Christie (1982) and Bekaert and Wu (2000) all subscribe to this principle.

Within the literature it is evident that the early models treated volatility in stocks to be a linear variable. However, the fact is that stock volatility is asymmetric rising more during bad times and falling more during good times. This is well explained by the leverage effect concept whereby volatility is negatively related to stock prices. Given this scenario, we expect investors to alter their future expectations in returns' volatility given volatility today. Unexpected rise in market volatility today could lead into an upward revision of expected future returns. As s result, investors will demand for higher rate of returns to cushion then against losses emanating from the revised future risk expectations. Higher rates of return translates into higher risk premium leading to higher discounting of expected future cash flows thus, lower stock prices today.

Campbell and Shiller (1988a) put it-present value decomposition, deviation of the dividends–price ratio from its long term mean signal in expected future dividends growth rates and/or expected future stock returns; changes in the latter represent time – varying discount rates and predictability of returns. We may therefore conclude that fluctuation in risk exposure that produces time – varying discount rates and return predictability is in line with the efficient market hypothesis.

Fama and French (1988) found out that there is large negative autocorrelation in stock returns for horizon period beyond one year hence the presence of mean reversion in real returns. They estimated that variations in predicting returns between three and five years due to mean reversion are 40 percent and 25 percent for small and large firms respectively. Further, they assert that the negative autocorrelation is attributed to a slowly decaying price component which strengthens as the return horizon increases from short to medium term. However, they are of the view that the random walk price component regains its influence on the variation of returns over long period horizons.

Contrary, Lo and Mackinly (1988) point out evidence of mean aversion in short – horizon stock returns which is inconsistent with the random walk hypothesis especially for the small capitalization stocks. However, its noteworthy that mean reversion can arise due to a small – sample bias. Richard and Stock (1989) posit that correcting for small – sample bias may reverse the evidence for mean reversion in favour of mean aversion.

From the investor's point of view, the investors' behaviour may contribute towards mean reversion in stock returns. Ceccheti, Lam and Mark (1990) demonstrate that negative serial correlation in long – horizon in stock returns may arise from the investor's moderate desire to smoothen consumption based on the hypothesis that asset prices are determined in equilibrium and assets returns rationally reflect market fundamentals. Using the S&P 500 index, they establish that the variance ratios and regression coefficients for 1 to 10 years horizons are within 60% confidence interval. They conclude that small – sample bias is responsible for much of the autocorrelation in historical stock returns although the concave utility function model proved to be a better fit for the evidence of serial correlation in stock returns.

Pagan, and William (1989) posit that stock return volatility can be broken down into predictableand unpredictable components, and research interest has largely been placed on the determinants of the predictable part; the conditional variance of that series thus ignoring the unpredictable component of stock returns. This is because investment in any financial assets is deemed to be a function of risk premium which is predictable.

In modeling stock volatility, the need to capture the non- linear properties in financial data is crucial if valid and reliable inferences are to be obtained. Engle (1982) developed the first outstanding ARCH model to model volatility in conditional returns which is valid to date. Later Bollerslev (1986) extended the model by generalizing it to come up with the Generalized ARCH (GARCH) which is crucial in capturing volatility in stock returns as well as shocks to stock returns and how persistent they are.

In the new economic error, developing economies have sought to liberalize their financial sectors thus encouraging an upward surge in the sector and the economy as a whole. However the effects of financial sector liberalization on stock market volatility has been keenly observed. McKinnon (1973) and Shaw (1973) – the proponents of financial liberalization theory are of the idea that it will raise savings and investments hence stabilizing economic growth. Contrary to their opinion, Keynesians argue that though financial liberalization may increase volatility in stock markets, this may not be damaging to the real economy. In addition Lamoureux and Lastrapes (1990) argue that financial liberalization leads to increased information flow thus marking the market more efficient. This can be explain from the simple logic of the Efficient Market Hypothesis that increased flow of information attenuates information symmetry thus no investor can outperform the market.It is noteworthy that the influx of foreign investors into a stock market and increased issuance of IPOs following financial sector liberalization may contribute towards market volatility through increased volume and pace of transactions.

Volatility in stock returns does not only affect investor's portfolio selection based on the efficient frontier as per the Markowitz hypothesis but also has a bearing on consumption and income levels hence its crucial link to economic business cycles. (Fama and French, 1989; Cochrane, 1999, 2007, 2011) in their analysis, if an agent becomes risk averse during economic depression given contraction in consumption and income, then such agents will demand for higher returns on stock in times near business cycle troughs for them to take the risks associated with stocks.

Although stock market volatility is a common phenomenon, from the efficient market hypothesis, anomalies do exist thus suggesting that some periods may be evidenced by high volatility than others year in year out. The most common anomalies are calendar anomalies whereby some days in a week or some months in the year are proved to exhibit high volatility or low volatility. Taylor (2005) point out that empirical studies have shown anomalies from calendar effects exist throughout for a long period in the history of stocks prior to the last thirty years. Jaffe and Westerfield (1985) introduced the day of the week effect in analyzing stock volatility in Canada, UK, Australia and Japan whereby the lowest mean returns were found to exist on Tuesday in Australia and Japan across different periods between years 1950 and 1983.

2.3 Empirical Literature

There is vast empirical literature on volatility of stock returns with a bias on the developed market. Though the early seminal works used the OLS in their analysis, a large proportion of these studies have used the Engle (1982) and the generalized ARCH model by Bollerslev (1986) in their analysis with a few employing the regime switching models.

Using EGARCH model, Rafagut and Afzal (2012) revealed that in both Pakistan and Indian stock markets, negative shock have pronounced impact on volatility compared to positive shocks hence asymmetric volatility. They assert that the global financial crisis of 2007/2008 cause mild-negative shock on stock returns thereby increasing market volatility. This affirms results Ahmed and Suliman (2011) and Adamu (2010) of asymmetric volatility at Khartoum Stock exchange and Nigerian stock market respectively. However this is in sharp contrast to Rousan and Al – Khaouri (2005) who find symmetric volatility at Amman Stock Exchange (ASE) implying that good and bad news of similar magnitude have similar degree of influence on market volatility level. Olowe (2009), using EGARCH model finds out that stock returns and volatility in Nigerian stock market during global financial crisis freed from severity of the crisis. This is unique as it suggests that during the crisis volatility improved hence contradicting financial theory. Though Adamu (2010) negates this, the disparity in their findings is due to econometric approach since the latter uses standard deviation and variance analysis.

Alsubai and Najand (2009) in studying the response of conditional variance to the available information posit that the intra-day overnight predicts conditional volatility in stock returns. In addition volatility spill over from large to small firms in Saudi Arabian marker is more pronounced. This is consistent with Pyun et al (2000) on the Korean stock market.Goudazi and Ramamarayan (2011) studied the effect of good and bad news on volatility in the Indian stock market using asymmetric ARCH model. They found the presence of leverage effect implying that bad news have a greater impact on stock returns volatility than good news.

Maheshchandra (2012) uses ARFIMA – FIGARCH model in analyzing daily returns Bombay stock exchange establishes presence of long memory in conditional variance of stock returns. Similarly, Mcmillan and Thupayagale (2008) using ARFIMA – FIGARCH model examine Johannesburg's securities exchange (JSE) efficiency. They establish that JSE all share returns portray long memory characteristic hence volatility in JSE could be efficiently forecasted in the long run. Their finding that past information can be used to improve predictability of future volatility at JSE implies that the largest African securities market is inefficient. The finding is in harmony with Kasman and Torun (2007) who establish strong evidence of dual long memory in both daily stock returns and volatility in Turkish stock market.
Bannerje and Sakar (2006) had earlier arrived to a similar conclusion that Indian daily returns posit long memory in conditional variance despite them being largely uncorrelated. Therefore we can conclude that negation of correlation between past and current daily stock returns does not necessarily rule out the presence of long memory in stock returns. However, Kilic (2004) and Kormaz*at al* (2009a) conclude that there is no long memory in stock returns in Istanbul stock exchange.

Ahmed and Suliman (2011) using GARCH (1, 1); GARCH - M (1, 1); PGARCH (1, 1) TGARCH (1, 1) and EGARCH (1, 1) investigated volatility at Khartoum Stock exchange (KSE) and found that the conditional variance process is highly persistent. In addition, the study revealed existence of risk premium implying that the mean of return sequence considerably depends on past conditional variance. Therefore, the risk of stock return is positively correlated to stock return. The study also concluded the presence of asymmetric volatility.Nam, Pyan and Kim (2003) analysed time varying volatility in weekly index returns using an asymmetric Non – linear Smooth Transition GAR (ANST – GARCH) who found that stock returns exhibit an asymmetric pattern of return reversals. On average, a negative return reverses more quickly with a greater magnitude into a positive return than a positive return reverting to a negative one. This assertion is directly linked to the unequal pricing behaviour on the part of the investors. Therefore, following a negative return shock, investors do not appear to demand for any additional premium to the leverage effect but they actually neutralize the risk inform of a reduced risk premium. Surprisingly, they point out that a reduced risk premium causes not only the current stock price to rise but also the realized negative return to revert faster with a greater magnitude.

These findings conquer with a past study by Koutmos (1999) analysed asymmetric price and volatility adjustments in the emerging Asian Markets and upon testing the hypothesis that returns in these markets adjust asymmetrically to past information the conclusion was in the favour of the hypothesis. Both the conditional mean and the conditional variance asymmetrically adjust to past information. The study also found that the faster response of stock prices to bad news offered an alternative interpretation for leverage effect[6] provided that the level of volatility rises with the speed of price adjustments.

Vlaar (2005) found that mean reversion in stock prices highly contributes towards attractiveness in equity investments for pension funds. Therefore mean reversion in stock returns may stimulate investments in stocks by pension funds after a stock market down fall since low returns are expected to be followed by higher returns in future.

Paresh and Russell (2004) studied mean reversion versus random walk in stock returns of the G7 countries. By allowing for structural breaks for movements in stock prices over time, they conclude that the second break in stock prices lead to detrimental effects on the movement in stock prices.

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[6]Black (1976) and Christie (1982) point; Stock price volatility is negatively correlated to stock price declines. As stock prices decline, stock returns volatility increases and vice versa. However, Duffe (1995) points out that in long run the use of daily highly frequency data may reverse the evidence for leverage effect in stock prices and consequently stock returns.

Using panel method with equal- weighted industry portfolios Gropp (2004) finds mean reversion for NYSE, AMEX and NASDAQ stocks for the periods 1926 – 1988, 1963 – 1998 and 1973- 1988 respectively.This confirms a previous study by Balvers et al. (2000) reports significant evidence of full mean reversion in national equity indexes with a reversion speed of 18% to 20% annually. He further states that mean reversion is equivalent to stationarity in mean; stock price shocks are temporary and stock returns are negatively autocorrelated at some horizons implying that stock returns can be predicted by lagged prices. Mukherji (2011) contrast the findings on mean reversion in stock returns by asserting that despite mean reversion is evident only in small company stocks. However, Chaudhuri and Wu (2003) posit that emerging markets may be subject to structural changes, and if a structural break is explicitly taken into account in the regression, mean reversion can be detected.

Campbell and Shiller (2001) indicate that in an economy comprising of both rational and irrational investors who freely interact, irrationality can bring about substantially long lasting effects on stock prices and any strategies adopted to address the anomaly arising from the irrational trading behaviour could be both risky and costly hence rendering them unattractive. Therefore it is possible for stock prices to deviate from their fundamental values due to trading behaviour of investors. However the complicated task would be to uphold the argument by behavioural theorists since fundamental values of stocks are unobservable.

Using Markov Switching model, Guidolin and Trimmerman (2007) estimated U.S stock and bond returns with the dividend yield as the return's predictor using a four- regime ("crash", "slow growth", "bull" and "recovery"). The study found out that the real time assets allocation essentially guided by Markov Switching model forecasts decisions of stock and bonds returns yields greater gains relative to asset allocation decisions based on constant expected excess returns forecasts. This confirms previous studies by Malik et al. (2005) and Susmel (2000) who concluded that switching volatility across regimes reduced significantly in Canada and in the US, Canada, United Kingdom and Japan respectively upon employing Switching ARCH (SWARCH) model.

2.4 Overview of literature review.

Despite the vast empirical literature on stock returns behaviour, analysis of developed stock markets dominate the studies with scanty research on emerging markets. The literature review in the preceding section reports mixed results, contradictory and also convergence in some studies. The reviewed empirical literature confirms earlier conclusions by Bekaert and Wu (2000) who posit that emerging markets' stock returns portray at least four distinguishing features; - high sample average returns, low correlations with developed markets' returns, more predictable returns and higher volatility. However, there is scanty evidence of empirical studies that present all these characteristics with majority of them citing the presence of one or two of these characteristics.

For example, a sizeable number of studies show that stock returns portray asymmetric conditional volatility overtime with negative shocks having a higher impact on volatility compared to positive shock of the same magnitude (Rafagut and Afzal 2012; Goudazi and Ramamarayan 2011 and Chiang and Doong 2001). This contradicts Rousan and Al – Khaouri (2005).Whereas some studies find evidence of long memory attribute hence possibilities of predicting future volatilities (Maheshchandra 2012, Ozun and Eifter 2008, Mcmillan and Thupayagale 2008, Kasman and Torun 2007and Bannerje and Sakar 2006), others finds no long memory (Kormaz*et al* 2009a, Kilic 2004). These divergent findings are perhaps due different econometric modeling.

There is likelihood that stock market volatility is largely determined by market's microstructure based on their setting – location, number of financial instruments traded, and changes in regulations over time among others. The strands in literature make it difficult to generalize volatility in stock markets either across different regionsand time periods. There is therefore the need to study the market of our interest and where possible use a combination of econometric techniques for comparison purposes if we are to have clear insight on dynamics of stock returns in such markets.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter discusses the research methodology that was used in the study. It encompasses theoretical framework, empirical model, definition and measurement of variables, sources of data and the econometric approach adopted by the study.

3.2 Theoretical framework

The ordinary least square method of econometric estimation assumes that the variance of the error term is constant across all observations; - homoscedasticity. However, in reality this assumption is often violated as the variance changes from time to time across observations especially when dealing with time series data hence more outliers than expected in the case of normal distribution. In our case, we are dealing with highly frequency financial data on stock prices and stock returns hence the need to model for heteroscedasticity.

Stock returns are highly volatile hence the need for a model that will appropriately capture volatility. In our case we assumed that the conditional mean is constant while the conditional variance is non – constant. In finance, the investor holds an asset depending on the expected mean return and the randomness or variance of the return (Jaffe and Westerfield, 2010). Therefore, the study used the Autoregressive Conditional Heteroscedasticity (ARCH) models introduced by Engle (1982) to model the conditional variance and asymmetry at the NSE. In these models, the volatility in stock returns at time *t* is a function of exogenous, lagged endogenous variables and the past error term.In order to be capable of selecting an appropriate time series model in this study a clear understanding of the empirical characteristics of financial data.

Leptokurtosis: this is a characteristic of financial time series data such as stock returns that is exhibited when its distribution tends to have flatter tails compared to normal distribution. Under the normal distribution the kurtosis is equal to 3 but in the case of leptokurtosis, the skewness is greater than 3. The concept of fat tails in financial data was first documented by Mandelbort (1963), Fama (1965) and others that afterwards led to vast literature on modelling stock returns.

Volatility clustering: this is a scenario whereby high stock returns are followed by high returns and low returns are followed by low returns. This phenomenon is evidence upon plotting stock returns over time whereby from the graph one can tell how persistent the shocks in the stock market have been.

Leverage effect: this refers to the phenomenon whereby changes on stock prices tend to be negatively related to changes in stock volatility. The concept of leverage effect was first mooted by Black (1976) and the concept has led to great improvements incorporating information asymmetry in modelling stock returns whereby good news increases asset price and lowers volatility while bad news lowers the price and increases volatility.

Long memory: this is a phenomenon in financial data where the observed stock returns are not independent over time. This implies that past stock returns can predict future stock returns.

Looking at the above characteristics, it is clearly evident that linear models cannot capture volatility since stock returns are non-normally distributed. Volatility cannot be observed hence must be estimated. Several models have been constructed to represent dynamics of stock return volatility in attempt to forecast it. These are Autoregressive Conditional Heteroscedasticity (ARCH) models introduced by Engle (1982).However there mere ARCH model is of little meaning in analysis volatility given that it has only one memory period. We therefore based our study on Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model developed by Bollerslev (1986). The study used both symmetrical and asymmetrical GARCH models to capture volatility in stock returns. The models introduce an explicit modelling of variance of stock return whereby the variance follows a specific temporal process. From the model we related stock returns such that given the historical information the conditional distribution of returns is normal with a mean of zero and a variance h_t which is a function of historical variance. However, we modified the model in incorporate the stock market anomalies; - the day of the week dummies and specific years' dummies.

3.3 Empirical models specification

Any inquiry into the stock returns volatility and the possible causes of such volatility ought to account for the complex non – linear dynamics in the variables at hand, failure to which could lead into misspecification of the conditional characterization of the data and consequently drawing of vague conclusions.

Given that stock returns are non-normally distributedAutoregressive Moving Average(ARIMA) Model may not appropriately capture stock volatility. Autoregressive Conditional Heteroscedasticity (ARCH) models developed by Engle (1982) could help modelling volatility in financial data. However, model has only one memory period hence unable to capture long memory periods.We therefore turn toGeneral Autoregressive Conditional Heteroscedasticity (GARCH) models that have proved to be very useful in modelling stock return volatility. This study therefore made use of the GARCH, TGARCH and the EGARCH model.

In specifying the model the study started with the simple random walk model defined as:

$$\mathbf{R_t = \mu + \alpha_1 R_{t-1} + \varepsilon_t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \mathbf{(1)}$$

Where $\mathbf{R_t}$ is the daily continuously compounded stock return at time ***t***

μ is the daily mean return

$\boldsymbol{\varepsilon_t}$ is the error term at period ***t***.

However, the random walk hypothesis does not hold especially in an inefficient stock marketthat is characterised by high information asymmetry implying that the random walk hypothesis may not hold.Poterba and Summers (1988), Fama and French (1988) and others posit that there is tendency for stock prices to revert back to their mean in the long run thus violating the principle behind the random walk hypothesis and the efficient market hypothesis in general. As a result, the variance of stock returns will not be constant hence that need to model for heteroscedasticity. To do so, we develop the GARCH model that assumes that the conditional mean is constant since it is independent of past information but the conditional variance depends on the past.

Before developing the GARCH model we highlight the Engle (1982) ARCH model that necessitates testing for the ARCH effect in the GARCH. The ARCH model is defined as:

$$h_t = \pm_t^2 = \mu + \sum_{i=1}^{p} \sim_i \pounds_{t-i}^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Where;ω<0, α_i..................α_p ≥0 – this is the non – negativity condition for parameters under the ARCH model. Also, α_i>α_j for i> j

$\sum_{i=1}^{p} \sim_i \text{£}_{t-i}^2$ measures the ARCH effect and $h_t$is the conditional variance. However, the Engle (1982) ARCH model has a major limitation in modelling volatility in that the model has only one memory period. Due to this shortfall, we extend the model and define the GARCH model.

GARCH Model

The Generalized ARCH (GARCH) model was introduced by Bollerslev (1986) to circumvent theshortcomings of Engle (1982) ARCH model. The model is based on infinite order ARCH model and as a result, the current stock return volatility depends on previous days' volatility. The model has two equations; the mean equation and the variance equation. The model is specified as follows:

$$R_t = R_{t-1} + \text{¦}_1 DMON + \text{¦}_2 DTUE + \text{¦}_3 DWED + \text{¦}_4 DTHU + \text{¦}_5 DFRI + \text{¦}_6 D2002 + \text{¦}_7 D2006 + \text{¦}_8 D2011 + D_9 2013 + \text{£}_t \text{.....(3)}$$

$$h_t = \pm_t^2 = \mu + \sum_{i=1}^{p} \sim_i \text{£}_{t-i}^2 + \sum_{j=1}^{q} {}_j h_{t-j} + \coprod \text{.......... ....} (4)$$

Equation (3) and (4) are the mean equation and the variance equation respectively where:
p>0, q> 0 while ω, α, β ≥ 0. If p=0 then the GARCH model collapses into the ARCH model. If p=q=0 then the error ε_t is a white process implying that: E[ε_t] = 0, Var [ε_t] = σ^2 and
E[ε_t, ε_s] = 0 Ɣt≠s. h_t is the conditional variance of the daily stock returns signifying the conditional stock returns' volatility.The day of the week anomaly, (seasonal effects) is captured in the Џ vector. Within the model the summation of α and β(∑α + ∑β) should total to unity. When ∑α + ∑β = 1 implies that the shock to the present stock returns volatility is more likely to be persistent for a long time in the future and the process is therefore referred to as the Integrated AGRCH (IGARCH). The implication here is that the current information still remains very important in predicting future stock prices and stock returns thus the market is a weak from efficient market. On the other hand, if ∑α + ∑β is very close to unity but not unity then there exists strong persistence of shock to stock returns and vice versa.In our case, we defined GARCH (1, 1) model which we estimatedas follows:

$$h_t = \pm_t^{2} = \mu + \sim\pounds_{t-1}^{2} + \quad {}_j h_{t-1} + \coprod \text{...}(5)$$

<u>GARCH – in Mean (GARCH – M)</u>

GARCH in mean model is used to model the relationship between conditional volatility and the expected stock returns. It is an extension of the GARCH model by Engle et al (1987) in which the conditional mean is expressed as an explicit function of the conditional variance. The GARCH in mean equation to be estimated wasgenerally expressed as:

$$\mathrm{R}_t = \Omega_t + \text{ª}_1 h_t + \text{ª}_2 DMON + \text{ª}_3 DTUE + \text{ª}_4 DWED + \text{ª}_5 DTHU + \text{ª}_6 DFRI + \text{ª}_7 D2002 + \text{ª}_8 D2006 + \text{ª}_9 D2011 + \text{ª}_9 D_{10} 2013 + \text{«}_t \text{...}(6)$$

$\varepsilon_t / \Psi_{t-1} \sim N(0, h_t)$ ....(7)

$$\mathrm{h}_t = \pm_t^{2} = \mu + \sum_{i=1}^{p} \quad {}_j h_{t-j} + \sum_{j=1}^{q} \sim {}_j \pounds_{t-j}^{2} + \text{¡} \coprod \text{...}(8)$$

Equation (6) is the mean equation while equation (8) is the variance equation. Equation (7) gives the distribution of condition variance. In the model:

Ω_t- The mean return conditional on past information (Ψ_{t-1})

R_t – stock return

λ_1 – The time varying risk premium

α_j – The ARCH effect (volatility clustering)

The model imposes restrictions; $\omega > 0$ α_j, $\beta_j \geq 0$ to ensure that conditional variance is non – negative. In addition, $\alpha + \beta$ measures the responsiveness of shocks to volatility over time. A sum greater that unity imply that shocks to stock returns are sustained over time while a sum less than unity imply that shocks decline over time.

Therefore, our GARCH - in – mean (1, 1) was defined as follows:

$$h_t = \pm_t^{2} = \mu + \quad {}_1 h_{t-1} + \sim {}_1 \pounds_{t-1}^{2} + \text{¡} \coprod \text{...}(9)$$

<u>Asymmetric GARCH Models</u>

These models have an added advantage compared to symmetric GARCH models in that they are capable of capturing information asymmetry. Given that leverage effect is eminent in financial data, asymmetric GARCH models are capable of capturing it in stock returns whereby a positive shock has less effect on conditional variance compared to negative shocks. The models therefore enable the analysis of the relationship between volatility and stock returns. The study therefore proceeded to estimate asymmetric GARCH models to determine the validity of the symmetric distribution of null hypothesis.

i. <u>E- GARCH Model</u>

ExponentialGeneral Autoregressive Conditional Heteroscedasticity (EGARCH) model was proposed by Nelson (1991).the general representation of EGARCH (p, q) model is specified as follows:

$$\mathrm{Ln}(\mathrm{h}_t) = \mathrm{Ln}\pm_t^2 = \mu + \sum_{j=1}^{p} {}_j Ln\left(\pm_{t-j}^2\right) + \sum_{i=1}^{q} \sim_i \left\{ \left| \frac{\pounds_{t-i}}{\pm_{t-i}} \right| - \sqrt{\frac{2}{\circledR}} \right\} - \yen_i \frac{\pounds_{t-i}}{\pm_{t-i}} \text{............................(10)}$$

Where: $\frac{\pounds_{t-i}}{\pm_{t-i}}$ is the standardized error term and ª is the asymmetric parameter.

From the general representation we specified our EGARCH (1, 1) as follows

$$\mathrm{Ln}(\mathrm{h}_t) = \mathrm{Ln}\pm_t^2 = \mu + {}_j Ln\left(\pm_{t-1}^2\right) + \sim_1 \left\{ \left| \frac{\pounds_{t-1}}{\pm_{t-1}} \right| - \sqrt{\frac{2}{\circledR}} \right\} - \yen \frac{\pounds_{t-1}}{\pm_{t-1}} \text{......................................(11)}$$

$h_t = \pm_t^2$ is the conditional stock variance while ω, β, λ are constant parameters. The term in parenthesis represents the magnitude effect. The main advantage of this model compared to the GARCH model is that it is capable of taking into account the asymmetric effect of volatility on stock returns which is measured by parameter ª. Since the model is in logarithms then this allows both the good and bad news to affect stock return volatility in similar manner thus the estimated conditional variance is always positive. The model also rules out the imposition of the non – negativity condition on the estimated model parameters as opposed to the GARCH model. The model therefore enabled us to determine the effect of idiosyncratic risk at the NSE that is posed by information asymmetry.

ii. <u>The Threshold GARCH (TGARCH) Model</u>

The threshold GARCH just as the EGARCH is ideal for capturing information asymmetry in financial data. This model was proposed by Zakoian (1991) and clearly indicates that bad news has a greater impact on true stock return volatility than good news do. It is mainly used to test whether the downward shifts in security market are followed by higher volatility compared to upward movements of the same scale. The general specification for conditional variance equation under TGARCH (p, q) model is given as:

$$h_t = \sigma_t^2 = \mu + \sum_{i=1}^{q} \left(\alpha_i + \gamma_i d_{t-i} \right) \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \quad \text{..}(12)$$

From the specification we specified our conditional variance equation TGARCH (1, 1) as follows:

$$h_t = \sigma_t^2 = \mu + \alpha_1 \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad \text{..}(13)$$

Where d_{t-1} is a dummy where

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

And γ is the asymmetry or leverage term of the model. If we set $\gamma = 0$, the model collapses to the standard GARCH forms. Otherwise, when the shock is positive (such as good news) the effect on volatility is given by α_1. However, in case of a negative shock (such as bad news) the effect on volatility is given by $\alpha_1 + \gamma$. Therefore, ifγ is positive and significant, this would imply that negative shocks have a larger effect on conditional stock returns volatility than the positive shock of the same magnitude hence we conclude there is evidence of leverage effect in stock returns.

3.4 Definition and measurement of variables

From our empirical models, stock returnsrefer to the continually compounded daily rate of returns on stocks. They are defined by the first difference of the logarithm of daily stock indices, computed as $R_t = \text{Log}\ (P_t/P_{t-1})$ where P_t represents the value of the NSE – 20 share index at time *t*.In this study the NSE – 20 share indices was used as a proxy for the entire market price since it is deemed to be the most appropriate yardstick for measuring the NSE performance. The index constitutes the “blue chip” companies that are viewed as representatives of the entire NSE performance and form the bulk of the entire market capitalization, market turnover and trade volume. Alternatively the study would have used the recently introduced All – share index and the FTSE index but this risks the problem of fewer data points that may not capture long memory volatility at NSE objectively.

DMON through DFRI are the dummy variables that capture the day of the week (anomaly) effect.D2002 captures the new regulations on foreign investors where a 25% minimum reserve of the issued share capital (during an IPO and Government of Kenya privatization) was for locals while the balance of the 75% was a free float for all classes of investors. D2006 captures the introduction of live trading upon the introduction of ATS as well as cross listing in Uganda and Tanzania stock exchange. D2011 captures the change in equity settlement cycle from T+4 to T+3. D2013 captures the onset of U.S tapering on the fourth quarter of 2013. Here we took December 2013 onwards as the period under tapering. The announcement was done on December 2013 and since stock market is driven by news we assume the announcement was immediately factored in the stock prices and ultimately returns.

3.5 Sources of Data.

This study used data consisting of daily closing prices. The study utilized daily data over a period of 2nd January 2001 to 31stMarch 2014 totalling to 3,313 data observations.The data was sourced from Nairobi Securities Exchange.

3.6 Econometric Approach

Eviews was used for estimation of empirical models. Upon collection of daily data on NSE–20 share index, we derived stock returns given by the formula $R_t = \text{Log}\ (P_t/P_{t-1})$. We also generate the respective dummies for the models. First we tested stationarity and autocorrelation before applying any ARCH type model to determine the order of integration for stock returns. We estimated GARCH (1, 1) model and tested for normality and serial correlation of the error term, and ARCH effect to determine normality, clustering volatility and long memory in stock returns. To analyse the investors' risk premia at the market with reference to time changes, we fitted the GARCH - in – mean (1, 1) model. However to fit the leverage effect and idiosyncratic risk and their effect on returns volatility we estimated the EGARCH (1, 1) and TGARCH (1, 1) models and compared the two on their efficiency to capture information asymmetry at NSE.

CHAPTER FOUR

4.1 Introduction

The chapter covers data analysis and discussion of the results. It gives the descriptive statistics of the daily stock returns as well as the summary statistics of the week days. In addition the chapter covers the regression results of different models estimated.

4.2 Empirical Results and Discussions

Table 1: Summary Statistics for StockReturns

	2nd Jan 2001 to 31st Dec 2001	2nd Jan 2002 to 31st Dec 2005	2nd Jan 2006 to 31st Dec 2010	2Jan 2011 to 31st Dec 2013	2Jan 2013 to 31st March 2014	Entire sample
Mean	-0.0006	0.0005	0.0000	0.0001	0.0003	0.0001
Median	-0.0004	0.0002	0.0000	0.0000	0.0003	0.0001
Maximum	0.0085	0.0202	0.1287	0.0913	0.0168	0.1287
Minimum	-0.0104	-0.0178	-0.1298	-0.0913	-0.0071	-0.1298
Std. Dev.	0.0025	0.0037	0.0077	0.0067	0.0028	0.0059
Skewness	-0.1904	0.4097	-0.0035	-0.0082	1.4258	0.0098
Kurtosis	6.20	8.25	136.97	142.48	9.84	188.09
Jarque-Bera	108.4	1164.0	935.5510	411.7928	636.3	467.91
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	-0.1498	0.4646	0.0501	-0.0304	0.0812	0.4157
Sum Sq. Dev.	0.0012	0.0135	0.0735	0.0225	0.0022	0.1132
Observations	250	991	1251	508	278	3278

Note: Table 1 is divided into six different parts. **The pre 2002** capture the period before the Introduction of the new regulations on foreign investors, **after 2002 but before 2006** captures the introduction of the new regulation, **after 2006 but before 2011** captures cross listing and the introduction of live trading, **after 2011 but before 2013** captures the change in equity settlement cycle from T+4 to T+3, **after 2013** captures the effects of US tapering

Table 1 shows that with the introduction of the new regulation the mean daily returns increased from -0.0006 to 0.0005 due to increased participation by local investors which reflects increased confidence in the market. This marginally rose upon cross listing and live trading coming into effect in 2006. The reduction in equity settlement cycle from T+4 to T+3 further surged the daily mean returns upwards. However, the news on monetary tightening policy in US affected the mean daily returns negatively. The mean returns were however positive returns compared to the negative returns in pre 2002 period. The daily returns for the entire sample averaged at 0.0001.

With regard to skewness of returns, the pre 2002, onset of cross listing, live trading and change in equity settlement cycle shows negative skews (extreme left tails) while the new regulation of 2002 and the US tapering effect posting positive skews (extreme right tails). This finding imply spill over volatilities from other markets as a result of cross listing which leads into negatively skewed returns. On the other hand, new regulation of 2002 increased participation by local investors thereby increasing market confidence hence the positively skewed returns.

The entire period shows that daily returns exhibited fat tails (leptokurtosis) as evidence by kurtosis greater than 3 with the introduction of live trading and cross listing in Uganda and Tanzania stock market yielding the fattest tails. This is perhaps due to the spill over volatilities from the Ugandan and the Tanzanian market into the NSE. Introduction of live trading increases the number of trading volumes which is likely to increases volatility through increased speculation.

Regarding volatility, introduction of live trading and cross listing post the highest volatility of 0.0077. This supports the evidence of spill over volatilities from cross listing and increased trading volumes from live trading thereby high volatility. Similarly, the new regulation of 2002 increased volatility of daily stock returns from 0.0022 to 0.0037. However, the change in equity settlement cycle lowers volatility from 0.0077 to 0.0067. On whether the daily returns are normally distributed, the significance of the Jarque-Bera statistics reflected by their respective probability values negates the null hypothesis of normal distribution.

Fig 1.0: Daily stock returns for period 2nd January 2001 to 31 March 2014

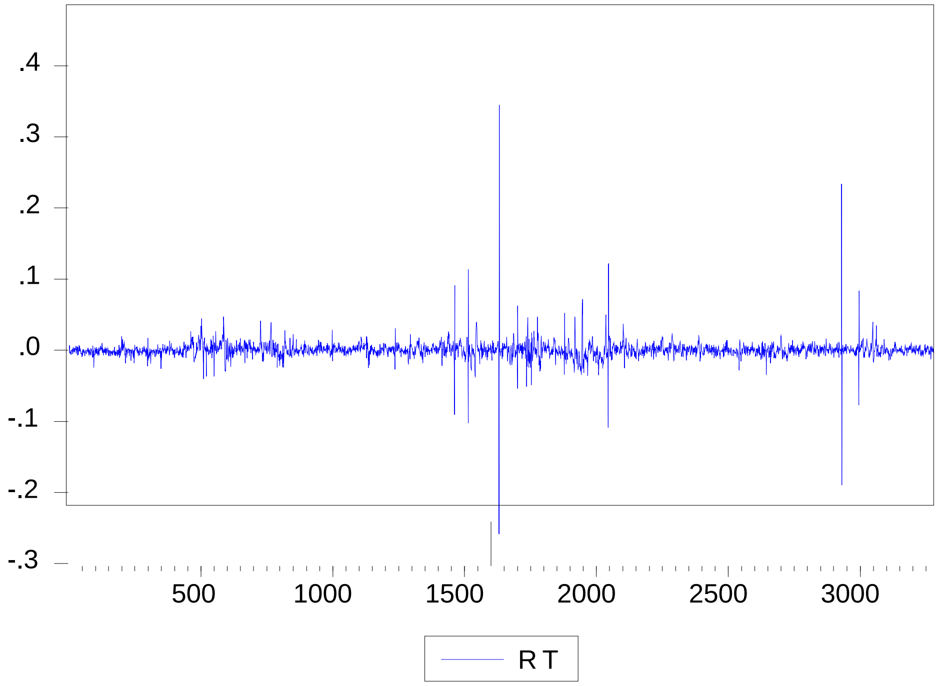

Table 2: Summary Statistics for Weekdays

	MON	TUE	WED	THUR	FRI
Mean	0.0001	-0.0008	0.0004	-0.0006	0.0001
Median	0.0002	0.0001	0.0001	0.0001	0.0001
Maximum	0.0913	0.0349	0.1287	0.0302	0.0469
Minimum	-0.0349	-0.1298	-0.0154	-0.0469	-0.0500
Std. Dev.	0.0059	0.0076	0.0063	0.0043	0.0046
Skewness	6.2505	-9.9672	13.0612	-1.4848	-0.0427
Kurtosis	101.9303	160.8043	259.6591	30.2609	40.6776
Jarque-Bera	271373.9	691521.9	1819205.0	20554.02	38743.53
Probability	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	0.0832	-0.0533	0.2942	0.0404	0.0512
Sum Sq. Dev.	0.0225	0.0383	0.0263	0.0121	0.0140
Observations	655	656	656	656	655

Table 2 shows day specific summary statistics. Wednesday has the highest positive daily mean returns of 0.0004 with fattest tails followed by Monday and Friday at 0.0001 and 0.00008 respectively. However, Tuesday and Thursday have negative daily mean returns with Tuesday having the largest negative returns. This perhaps explains the effects of announcements for auctions in government’s treasury bills on Thursdays and the actual trading taking place on Tuesdays. Tuesday has higher volatility in stock return relative to other days. Therefore, Tuesdays present a case of leverage effect; - a negative relationship between volatility and stock returns since it experiences the highest negative daily returns as well as highest volatility. On the contrary Thursdays have the lowest volatility.

Table 3: Unit Root Test (ADF)

	With Intercept		With Intercept and Trend	
ADF test statistics	Calculated Values	Critical Values	Calculated Values	Critical Values
R_t	-29.936	-3.432 (at 1%)	-29.931	-3.961 (at 1%)
		-2.862 (at 5%)		-3.411(at 5%)
		-2.567 (at 10%)		-3.127(at 10%)
AR 1	-29.932	-3.432(at 1%)	-29.928	-3.961 (at 1%)
		-2.862 (at 5%)		-3.411(at 5%)

The test for stationarity is based on the Box and Jenkins (1976). Following this test the daily stock returns should be stationary. The use of the dickey fuller test for unit root reveals that the daily stock returns are integrated of order zero implying the absence of unit root

Estimation of GARCH model variants

Table 4: GARCH (1, 1) Results

GARCH (1, 1) Results					
Mean equation					
	1	2	3	4	5
Constant	0.0000 (0.7568)				
Return (t-1)	0.4253 (0.000)	0.5504 (0.0000)	0.4881 (0.0000)	0.4719 (0.0000)	0.4022 (0.0000)
DMON		-0.0003(0.1201)	-0.0002 (0.4548)	-0.0005 (0.1374)	-0.0078 (0.0082)
DTUE		-0.0015(0.0000)	-0.0004(0.0241)	-0.0019(0.0000)	-0.0008(0.0000)
DWED		-0.0006(0.7285)	0.00034 (0.1507)	-0.0032 (0.3478)	-0.0006(0.1086)
DTHUR		-0.0003(0.0051)	-0.0002 (0.0703)	-0.0009(0.0041)	-0.0006(0.0264)
DFRI		0.0032(0.0000)	0.0001 (0.5810)	0.0021(0.0000)	-0.0005(0.0499)
D2002				0.0004(0.2247)	0.0009 (0.0001)
D2006				0.0012 (0.0000)	-0.0004(0.2814)
D2011				-0.00281 (0.0000)	-0.0001(0.8058)
D2013				0.0017 (0.0000)	0.0004 (0.2361)
Conditional Volatility Equation					
Constant	0.0002(0.0000)	0.0000(0.0000)	0.00053 (0.0000)	0.0001(0.0000)	0.0000 (0.0000)
ARCH (1)	0.1334 (0.0000)	1.8511(0.0000)	0.5696 (0.0000)	1.8662 (0.0000)	0.3312 (0.0000)
GARCH (1)	-0.0099 (0.6816)	0.0318(0.0000)	0.1458 (0.0000)	0.0534(0.0000)	0.1608 (0.0000)
DMON			0.0005(0.0000)		0.0000 (0.0000)
DTUE			-0.0001 (0.0000)		0.0000(0.0090)
DWED			0.0001 (0.0000)		0.0001(0.0000)
DTHUR			-0.0001(0.0000)		-0.0001(0.0000)
D2002					0.0001(0.0000)
D2006					0.0001(0.0000)
D2011					0.0002(0.0000)
D2013					-0.0002(0.0059)
R^2	-0.2777	-0.4653	-0.3516	-0.3770	-0.2529
Adjusted R^2	-0.2794	-0.4691	-0.3566	-0.3821	-0.2606
Log likelihood	12967.79	13058.15	13332.11	13155	13411.16
Durbin - Watson	2.9516	3.0492	3.0149	2.9679	2.9276
ARCH – LM TEST					
Constant	0.993 (0.0015)	0.999 (0.0000)	0.991 (0.0000)	1.0107 (0.0000)	0.9835 (0.0000)
Residual squared	0.0088 (0.6137)	0.0002 (0.9885)	0.0087 (0.6195)	0.0001 (0.9937)	0.0126 (0.4685)
Observed R^2	0.1549 (0.6135)	0.0002 (0.9885)	0.2467 (0.6195)	0.0006 (0.9937)	0.5260 (0.4683)
F - Statistics	0.2549 (0.6137)	0.0002 (0.9885)	0.2466 (0.6195)	0.0006 (0.9937)	0.5258 (0.4685)

The previous period returns are positive and significantly influences the current period return at the NSE as evidenced by the coefficients of Return (t-1) in all the models in the mean equation. This implies that NSE is not a weak – form efficient market. For the daily returns, virtually all days have negative returns with the exception of Friday in model 1 to 4. However, for the entire sample negative daily returns are reported for all week days. D2002 and D2013 post significantly positive daily returns implying introduction of the new regulations on foreign investors with a 25% minimum reserve of the issued share capital going to local investors and U.S tapering captured by D2013 positively influences daily stock returns in model 5 and 4 respectively. Thus a regulation promoting investment toNSE by local investors increases market confidence yielding positive returns.

For the conditional volatility, the ARCH effect is present and pronounced implying serial correlation in daily return. Similarly is the GARCH effect. Taking into account days of the week into the variance equation sums the ARCH **(0.5696**) and GARCH **(0.1458)**effect to **0.71** while inclusion of new policies and regulations captured by year dummies into the conditional volatility equation yields 0.049<1. Therefore introduction of new regulations and policies at the NSE lead to the tendency of mean reversion in stock returns which is a deviation from the random walk hypothesis. A sum of 0.49 and 0.71 rules out persistent volatility clustering in daily stock returns at the NSE. This implies that high returns are not followed by high returns and low returns are not followed by low returns. The findings are contrary to Muriu (2013) who report persistence of volatility clustering given the sum of ARCH and GARCH term close to unity.

Table 5: GARCH – M (1, 1) Results

Mean equation					
Constant	-0.0014 (0.0000)				
Return (t-1)	0.4197 (0.0000)	0.4809 (0.0000)	-0.1160 (0.0015)	0.4732 (0.0000)	-0.1185 (0.0043)
DMON		-0.0118(0.0268)	-0.0061(0.0060)	0.0002 (0.5661)	-0.0055(0.1019)
DTUE		-0.0028 (0.0000)	-0.0031 (0.0345)	-0.0010 (0.0034)	-0.0061 (0.0547)
DWED		-0.0018(0.0126)	-0.0048 (0.0081)	0.0007 (0.0502)	-0.0054(0.0832)
DTHUR		-0.0016 (0.300)	-0.0029 (0.0029)	-0.0001 (0.7415)	-0.0045 (0.1333)
DFRI		0.0009(0.1237)	-0.0048 (0.0087)	0.0029 (0.0000)	-0.0063 (0.0522)
D2002				0.005(0.1626)	0.0019 (0.4134)
D2006				0.0013 (0.0000)	-0.028 (0.0045)
D2011				-0.0028 (0.0000)	0.0007 (0.1901)
D2013				0.0015 (0.0000)	0.0025(0.1864)
Garch	0.2828(0.0000)	0.2278(0.0051)	0.4834(0.0024)	-0.1849(0.0000)	0.4906(0.0175)
Conditional Volatility Equation					
Constant	0.0002 (0.0000)	0.0000(0.0000)	0.0000(0.0000)	0.0000(0.0000)	0.0003(0.0000)
ARCH (1)	0.2694(0.0000)	0.5269(0.0000)	0.1496 (0.0000)	1.8289(0.0000)	0.1482(0.0000)
GARCH (1)	-0.0241(0.0214)	-0.0195(0.1595)	0.5972(0.0000)	0.0670(0.0000)	0.5942(0.0000)
DMON			0.0001(0.0000)		-0.0001(0.0594)
DTUE			-0.0001(0.0000)		-0.0001(0.0000)
DWED			0.0000(0.0001)		-0.0002(0.0140)
DTHUR			-0.0001(0.0000)		-0.0002(0.0000)
D2002					-0.0002(0.6275)
D2006					0.0003(0.2129)
D2011					0.0002(0.3602)
D2013					-0.0003(0.0000)
R^2	-0.2505	-0.3465	0.0291	-0.4866	0.0215
Adjusted R^2	-0.2524	-0.3503	0.0253	-0.4925	0.0151
Log likelihood	12946.98	12891.68	12591.38	13171.04	12334.65
Durbin - Watson	2.9448	2.9754	1.904	2.754	1.9236
ARCH – LM TEST					
Constant	0.8393(0.0011)	0.7235(0.0005)	0.4890(0.0000)	1.0083(0.0000)	0.4153(0.0000)
Residual squared	0.0120(0.4913)	0.0078(0.6573)	0.0264(0.1313)	0.0011(0.9484)	0.0275(0.152)
Observed R^2	0.4739(0.0492)	0.1970(0.6571)	2.2783(0.1312)	0.0042(0.9484)	2.4825(0.1151)
F - Statistics	0.4737(0.4714)	0.1969(0.6573)	2.2785(0.1313)	0.0042(0.9484)	2.4829(0.1152)

The GARCH –in- mean captures the effect of volatility on the daily stock returns thus revealing the risk premium in the market by allowing conditional variance in daily stock returns to enter the mean equation. For the entire sample the effect of volatility on the daily stock returns at the NSE is positive and significant as measured by 0.491 thus implying that the time varying risk premium is significant at the NSE. Therefore volatility at the NSE positively impact on the daily stock returns. Introduction of the conditional variance into the mean equation yields negative but insignificant days of the week returns. This is replicated for D2002, D2011 and D2013 though positive returns. However, D2006 posts significantly negative effect on the daily mean returns implying that cross listing, introduction of live trading as well as introduction of demutualization at NSE negatively impact on daily returns. Presence of risk premium confirms Pagan and William (1989) who asserts that investments in financial assets are a function of risk premium which is predictable. Study by Ahmed and Suliman (2011) affirms this findings too.

Analysis of the conditional variance equation reveals prolonged volatility clustering at NSE as evidenced by significance of ARCH 1 coefficients in all models. Summation of ARCH 1 and GARCH 1term for model 3 and 5 yield a total of 0.73. This shows that volatility shocks on daily returns at the NSE are transitory. However, exclusion of week days and policies and regulations from the mean variance equation sums up to 1.88 as presented in model 4. Therefore in the absence of regulations and policies, volatility shocks would persist for long. Introduction of new regulations and policies at the NSE have therefore shielded the market against volatility shocks. Tuesday and Thursday returns are negatively shocked by market volatility with Thursday being the most pronounced which is consistent with the summary statistics reported in Table 2. This can perhaps be traced to the Treasury bills trading whereby the auctions announcements are on Thursday with the sale being on Tuesday. Therefore upon the announcement equity holders' rush to offload their holdings in anticipation of purchasing bills come Tuesday. Presence of the day of the week anomaly is consistent with the Jaffe and Westerfield (1985) findings of lowest mean returns were found to exist on Tuesday in Australia and Japan markets. Similar findings are reported by Muriu (2003) who reports the highest volatility on Monday.

Table 6. Exponential GARCH (1, 1) Results

Mean equation					
Constant	0.0002(0.5745)				
Return (t-1)	0.4358(0.0000)	0.5366(0.0000)	0.4966(0.0000)	0.4198(0.0000)	0.4916(0.0000)
DMON		0.0023(0.0000)	0.0029(0.0000)	0.0014(0.0116)	-0.0009(0.0641)
DTUE		0.0014(0.0000)	0.0016(0.0000)	0.0003(0.6354)	-0.0009(0.0008)
DWED		0.0026(0.0000)	0.0028(0.0000)	0.0018(0.0020)	-0.0005(0.2375)
DTHUR		0.0025(0.0000)	0.0018(0.0000)	0.0012(0.0378)	-0.0067(0.0283)
DFRI		0.0047(0.0000)	0.0039(0.0000)	0.0034(0.0000)	-0.0001(0.9288)
D2002				0.0006(0.1974)	0.0007(0.0006)
D2006				0.0007(0.0014)	0.0001(0.9458)
D2011				-0.0025(0.0000)	-0.0011(0.0006)
D2013				0.0017(0.0007)	0.0011(0.0005)
Garch	-0.0348(0.6939)	-0.4367(0.0000)	-0.4883(0.0000)	-0.3941(0.0000)	0.0388(0.6094)
Conditional Volatility Equation					
Constant	-7.9646(0.0000)	-7.9627(0.0000)	-6.1987(0.0000)	-8.6310(0.0000)	-7.6218(0.0000)
ARCH (α)	0.4377(0.0000)	0.9864(0.0000)	1.0150(0.0000)	0.8960(0.0000)	0.6382(0.0000)
Asymmetry (γ)	-0.0518(0.0026)	0.0610(0.0094)	-1.1500(0.0000)	-0.0292(0.0966)	0.0220(0.0330)
GARCH (β)	0.3167(0.0000)		0.5080(0.0000)	0.2598(0.0000)	0.4240(0.0000)
DMON			1.3294(0.0000)		1.2907(0.0000)
DTUE			-0.8207(0.0000)		-0.8517(0.0000)
DWED			1.0452(0.0000)		0.9851(0.0000)
DTHUR			-0.4148(0.0000)		-0.3307(0.0000)
D2002					0.6472(0.0000)
D2006					0.9614(0.0000)
D2011					-0.3679(0.0000)
D2013					-1.1559(0.0000)
R^2	-1.6616		-384291.8	-2597859.89	-0.2356
Adjusted R^2	-1.6632		-384996.96	-2605814.15	-0.2394
Log likelihood	12947.67	13067.25	13321.53	13119.77	13492.74
Durbin - Watson	2.7719	2.0002	1.9937	2.005	2.9796
ARCH – LM TEST					
Constant	0.9952(0.0018)	1.0219(0.0002)	1.0327(0.0000)	1.0899(0.0001)	1.0031(0.0000)
Residual squared	-0.0003(0.9848)	-0.0012(0.9439)	-0.0031(0.8578)	-0.0013(0.9398)	-0.0019(0.9137)
Observed R^2	0.0004(0.9848)	0.0049(0.9439)	0.0321(0.8578)	0.0057(0.9398)	0.0117(0.9137)
F - Statistics	0.0004(0.9848)	0.0049(0.9438)	0.0321(0.8578)	0.0058(0.9398)	0.0117(0.9137)

The Exponential GARCH captures the asymmetry at the NSE which is measured by coefficient γ. From the mean equation, the market risk premium measured by Garch is negative and significant for models 2 to 4 with the entire sample showing a positive effect albeit insignificant. Thus, the NSE volatility negatively impacts on the daily stock returns.

Looking at the days of the week, the mean daily returns are positive and significant for all days with Friday posting the highest mean returns followed by Wednesday and Monday.

Tuesday records the lowest mean returns followed by Thursday. This manifests the pronounced effects of trading in government's securities Tuesdays and Wednesdays on daily mean returns. The results are consistent with those of GARCH and the GARCH – in Mean. The previous day's results positively and significantly influence the following day's stock returns as evidenced by coefficient of Return (t-1) in the mean equation.

Turning on the conditional variance equation, Monday and Wednesday have positive and significant volatility while Tuesday and Thursday have negative and significant volatility. The Arch (1) term (α) is positive and significant throughout the models signalling the presence of volatility clustering hence positive daily returns are followed by positive daily returns and negative daily returns are followed by negative daily returns at the NSE. The Garch term (β) measures the persistence of the volatility shocks in the market. For the entire sample, $\beta = 0.42$ implying that present volatility at NSE does not last for long in future. Therefore, volatility shocks at the NSE are transitory rather than permanent. Since $\beta<1$ then our GARCH model is not an Integrated GARCH (IGARCH). The findings are in conformity with Muriu (2013) and Koutmos (1993) implying that investors at the NSE perceive market booms as not being supported by economic fundamentals and market returns portray speculative bubbles behaviour. On asymmetry, $\gamma=0.22$ for the entire sample. Its significance reveal presence of asymmetry at thus, bad and good news drive the daily stock returns outcomes at NSE. This implies that the asymmetric response of conditional variance enters the evolution of stock returns at the Nairobi Securities Exchange with a further implication of presence of idiosyncratic shock. The finding confirms Muriu (2003) findings. However, the finding differs from the previous study in that it reports a higher level of asymmetry of 0.22 as opposed to 0.0454 reported by Muriu.

Table 7.Threshold - GARCH (1, 1) Results

Mean equation					
Constant	-0.0002(0.4069)				
Return (t-1)	0.4669(0.0000)	0.3749(0.0000)	0.4879(0.0000)	0.4764(0.0000)	0.4018(0.0000)
DMON		-0.0005(0.3635)	-0.0003(0.3678)	-0.0010(0.0058)	-0.0007(0.0151)
DTUE		-0.0003(0.5997)	-0.0004(0.0317)	-0.0023(0.0000)	-0.0008(0.0011)
DWED		0.0003(0.5083)	0.0003(.2114)	-0.0061(0.0667)	-0.0005(0.1503)
DTHUR		0.00008(0.8832)	-0.0002(0.1229)	-0.0012(0.0002)	-0.0005(0.0297)
DFRI		0.0016(0.0000)	0.00010(0.6230)	0.0017(0.0000)	-0.0005(.00477)
D2002				0.0005(0.5191)	0.0009(0.0002)
D2006				0.0012(0.0000)	-0.0003(0.4360)
D2011				-0.0028(0.0000)	-0.0002(0.6488)
D2013				0.0017(0.0000)	0.0004(0.2488)
Conditional Volatility Equation					
Constant	0.0005(0.0000)	0.00003(0.0000)	0.0000(0.0000)	0.0000(0.0000)	0.0000(0.0000)
ARCH (1) (α_1)	0.1174(0.0000)	0.2215 (0.0000)	0.5281(0.0000)	1.522(0.0000)	0.3467(0.0000)
(RESID<0) ARCH (1) (α_2)	0.1224(0.0003)	0.1279 (0.0000)	0.0584(0.3110)	1.4275(0.0000)	-0.0303(0.5250)
GARCH (1) (β)	-0.0055(0.0000)	-0.0533(0.0000)	0.1484(0.0000)	0.0657(0.0000)	0.1588(0.0000)
DMON			0.0005(0.0000)		0.0000(0.0000)
DTUE			-0.0001(0.000)		-0.00001(0.000)
DWED			0.0002(0.0000)		-0.00003(0.0000)
DTHUR			-0.0004(0.000)		-0.00003(0.0000)
D2002					0.00002(0.0000)
D2006					0.00002(0.0000)
D2011					-0.00002(0.000)
D2013					-0.00002(0.000)
R^2	-0.2600	-0.2338	-0.3477	-0.3751	-0.2525
Adjusted R^2	-0.2604	-0.2357	-0.3498	-0.3789	-0.2559
Log likelihood	12532.62	12785.49	133332.26	12176.43	13411.03
Durbin - Watson	2.9272	2.8911	3.0117	2.9676	2.9275
ARCH – LM TEST					
Constant	0.4489(0.0005)	0.6085(0.0005)	0.9904(0.0000)	1.0045(0.0000)	0.9795(0.0000)
Residual squared	0.0402(0.0215)	0.0169(0.3339)	0.0086(0.6225)	-0.0006(0.9742)	0.0131(0.4536)
Observed R^2	5.2817(0.0216)	0.9342(0.3339)	0.24258(0.6225)	0.0011(0.9742)	0.5621(0.4534)
F - Statistics	5.2870(0.0215)	0.9339(0.3339)	0.024245(0.6225)	0.0010(0.9742)	0.5619(0.4536)

The Thresh-hold GARCH captures the leverage effect at the NSE with α_1 and α_2 measuring the impact of bad and good news on the daily stock returns respectively. In overall the sum (α_1+α_2) gives the impact of bad news.β measures the degree of persistence in conditional variance while the sum (α + β) gives the persistence in volatility shocks. α_2 =1.4275 for model 4 implying that bad news have greater impact on stock returns volatility than good news of the similar magnitude;-leverage effect. This is in conformity with Black (1976), Christie (1982) and Bekaert and Wu (2000) models. Empirical studies by Goudazi and Ramamarayan (2011) yield similar results for the Indian stock market. Previous study by Koutmos (1999) showed market adjustments to past information is asymmetrical hence a confirmation of leverage effect. However, inclusion of new policies and regulations into the conditional variance equation nullifies the presence of leverage effect implying that introduction of policies and regulations trades-off market information symmetry at NSE.

CHAPTER FIVE

5.1 Introduction

This study analyzed the volatility in conditional stock returns at Nairobi Securities Exchange for the period 2ndJanuary 2001 to 31st March 2014. The study adopted a purely econometric approach majorly using the ARCH – family econometric models with a blend of both the symmetric and the asymmetric models in attempt to ensure robustness of the results.

The study focused on the main aspects of daily returns with special attention on volatility clustering, leptokurtosis, long memory, market risk premia and the leverage effect. In addition, the study captured the day of the week as well as the effects of changes in policies and regulations on the daily stock returns at the NSE.

5.2 Conclusion

From the data analysis the following conclusions are deduced

Nairobi Securities Exchange is not a weak – form efficient market as evidenced by the significant coefficients of the previous day's returns in determining the present day's returns. Since the one day lag returns significantly influence the current day's returns, then the random walk hypothesis is invalid for the NSE rather daily stock returns at NSE follow a martingale process. Therefore, the day-to-day stock prices are dependent of each other, meaning that price "momentum" generally exist and past earnings growth predict future growth at the NSE

Volatility clustering is evident at the NSE as portrayed by the significance of the coefficients of the ARCH (1) terms implying that high returns are followed by high return and low returns are followed by low returns upon using the asymmetric GARCH for estimation. However, the shocks to the daily stock returns are transitory rather that permanent. Therefore, the market volatility effects on stock returns are short lived and decay at a short interval. In addition, the shocks are not explosive given that $\alpha+\beta < 1$ and not close to unity at all.

For the day of the week, Tuesdays and Thursdays post negative significant returns. The implication is that announcements for sale of government securities mainly treasury bills on Thursdays and their actual sale on Tuesdays adversely affect equity market. Therefore we cannot reject calendar anomalies at NSE.

The market risk premia is priced at the NSE. This is consistent with the portfolio theory implying that in case of high market volatility investors demand a higher return (additional premium) to leverage against any possible losses. Therefore during high market volatility at the NSE, the risk averse investors who mainly dominate the market demand a higher compensation for every shilling invest ed. This will in turn influence the cost of capital for the listed firm and eventually feeds into the firm's capital structure mix between equity and debts.Lastly, the leverage effect is present at the NSE signifying that bad news has high impact on the daily stock returns compared to good news of the similar magnitude.

In addition NSE has witnessed a number of structural reforms mainly through new policies and regulations arising from the capital markets authority. Introduction of the new regulations on foreign investors with a 25% minimum reserve of the issued share capital going to local investors (in 2002), introduction of live trading, cross listing in Uganda and Tanzania stock exchange (in 2006) and change in equity settlement cycle from T+4 to T+3 (in 2011) significantly reduce volatility clustering, impact of bad news in market, volatility shocks and their persistence for the entire sample. However, they increase the market risk premium leading to demand for higher returns by investors. On the other hand, the onset of US tapering effect increases the daily mean returns and significantly reduces conditional volatility in daily stock returns. This contradicts existing theories on the effects of exchange rates on stock returns since such tapering lead to devaluation of local currency which imply increased market volatility and ultimately adverse shocks on the stock returns. However, the findings of the study are consistent with Olowe (2009) who found out that crisis volatility in stock returns for Nigerian stock market during global financial crisis the improved.

5.3 Policy implications

The findings of this study have a number of policy implications. For instance the negative daily returns and high volatility on Tuesdays and Thursdays shows the effects of open market operations mainly through the sale of government securities (treasury bills) on the daily stock returns and volatility. Therefore in the scenario whereby the date for books closure for a firm falls on a Tuesday or Thursday investors holding equity for such a firm would lose upon making the sale on such a date in addition to selling cum dividend.

The positive relationship between the market risk premium and market volatility is in tandem with the portfolio theory implying that the risk averse investors dominate the NSE. Thus in order to make the market efficient, dissemination of information to shareholder and investors at large would help in reducing information asymmetry and thereby enhancing better performance for the listed firms.

The presence of volatility clustering effect indicates the volatility in daily stock returns is time varying and is not constant over time. In other words, portfolio managers and equity investors should adjust their portfolio management practice in response to the traditional risk measure of unconditional variance.

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