TEST OF EXISTENCE OF LONG TERM MEMORY IN STOCK MARKET RETURNS AT NAIROBI SECURITIES EXCHANGE

JOLEEN MUMBE MUTINDA

D63/80473/2012

A RESEARCH PROJECT SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF MASTER OF FINANCE, SCHOOL OF BUSINESS, UNIVERSITY OF NAIROBI.

NOVEMBER, 2018

DECLARATION

I, **Joleen M. Mutinda**, do hereby declare that this research project is my original work and has not been presented for a degree in any other University

Signed;

Signed …………………………….. Date………………………………

Joleen Mumbe Mutinda

D63/80473/2012

This project has been submitted for admission with our approval as the appointed University supervisors.

Signed …………………………….. Date………………………………

Mr. Dominic Murage

Supervisor, Lecturer Department of Finance and Accounting

School of Business

University of Nairobi

Signed …………………………. ….Date……………………………….

Dr. Cyrus Iraya,

Co-Supervisor, Senior Lecturer Department of Finance and Accounting

School of Business

University of Nairobi

ACKNOWLEDGEMENT

I am sincerely grateful and Thankful to God for provision throughout my studies and all those who supported in one way or another. Special mention to my supervisor Mr. Dominic Murage who literally burnt the midnight oil to ensure I was on track and the numerous consultations may you never doubt the good work you do and I am forever indebted to your commitment to making learning a smooth and interesting process.

To my Co. Supervisor Dr.Cyrus Iraya, who put perspective into my study may God shower you with blessings and May you never lack for you are truly committed to this noble profession.

To the staff members of department of Finance and Accounting, I wish to express my sincere gratitude for their coordination and timely communication on the progress of the research documents left in their care.

To my loving and supportive Husband, thank you for your endearing support and being my supervisor at home. You have selflessly given your time, finances and knowledge to making this project a reality.

DEDICATION

I dedicate this project to my Husband Robert Thuku, my baby girl Natalia Thuku, and all students of finance who are intrigued by the market. May God bless you and guide you in pursuit of Finance.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ARCH- Autoregressive Conditional Heteroskedasticity

ASM- African Stock Markets

CMA- Capital Markets Authority

EMH- Efficient Market Hypothesis

FIEGARCH- Fractionally Integrated Exponential GARCH

FMH- Fractal Market Hypothesis

GARCH- Generalized Autoregressive Conditional Heteroskedasticity.

GFC- Global Financial Crisis

NSE- Nairobi Securities Exchange

ABSTRACT

Long term memory in stock market returns has received considerable attention among academicians and finance practitioners. This paper explores the applicability of Fractal market hypothesis and Chaos theory in explaining market behaviour. The rationale of both theories that markets patterns can be studied for the possibility of predictability of returns to inform investment decisions motivated this research subject. The study embarked on the objective to test for existence of long range dependence in stock market returns in Nairobi securities exchange. Based on the fact that post automation the market is expected to have improved efficiency. The study employed a non parametric test; classical rescaled range analysis to examine long term memory which is measured by the Hurst exponent developed by Hurst (1951). The stock market returns were considered using secondary data. The daily NSE-20 share index was collected for a period of eight years from January 2010 to December 2017.A longitudinal research design was employed for the research. The data was analyzed using E-views financial software. The results show that there is long term memory in stock market returns in NSE with an H-value of 0.7 from the rescaled range analysis. It is further observed that market returns are not normally distributed for the test of normality with a negative skewness of -0.067 and the autocorrelation denoted by P-value <0.05 showing the market does not follow a random which actually invalidates the efficient market hypothesis. This indicates that there exists a chance to predict market returns and make above market profits. The research recommends factoring in long term memory properties in investment decisions.

CHAPTER ONE: INTRODUCTION

1.1 Background of the Study

A proper functioning market and its ability to provide efficient allocation of resources for development is the focal point of modern finance. Globalization and market integration has attracted a significant number of investors to emerging markets and especially African stock markets (Sugimoto, Matsuki & Yoshida, 2014). The key attraction being better returns compared to developed markets where the level of efficiency erodes arbitrage opportunities (Hull & Mc Groarty, 2014). Given that the NSE has experienced both bullish and bearish swings in the recent past, investors are keen to find arbitrage opportunities amidst the cycles (Ogega, 2014). The desire of high returns has prompted market participants to employ technical trading techniques in a bid to achieve higher returns. In Kenya, there is lack of general consensus among researchers on whether NSE is weak form efficient or in efficient. For instance, Anyumba (2010) finds evidence in favour of weak form efficiency while Njuguna (2016) against weak form efficiency. In this regard, there seems to be an existent a chance to predict returns.

According to EMH, informational efficiency is achieved if securities prices display all the available information, Fama (1965). This implies a random walk in stock prices i.e. each change in price is completely independent of previous price. Lo (1991), asserts that when stock returns have strong long range dependence properties they fail to portray a truly random walk process. Mandelbrot (1971) proposes that if long memory properties exist in asset returns then new information is not immediately portrayed in prices and events in the remote past are correlated with events in the foreseeable future. This could be due to limits to arbitrage, irrationality and illiquidity among other factors. It's not surprising that alternative models such as Chaos theory and Fractal Market Hypothesis (FMH) have emerged to better explain the behaviour of stock returns. According to Chaos theory, financial markets are complex and dynamic which cannot be easily modelled by linear models of EMH. The complexity may stem from heterogeneous expectations by investors who are not fully rational, that is, they apply available information differently, invest at different investment horizons and react gradually to information (Peters, 1994). The Fractal market hypothesis attempts to put structure on Chaos theory. FMH considers liquidity and investment horizon to be crucial for market stability. Prices changes in the market occur due to differences in interpretation of the same information by investors (Nyamute, Oloko, & Lishenga, 2017).

Nairobi securities exchange has undergone several reforms in the last decade which have attracted significant number of foreign investors with a participation of 65% in the market at the end of 2017(NSE, 2017). This raises the questions whether there opportunities of making above market returns which could indicate presence of market anomalies such as Long term memory. Barkoulas et al. (2000) suggests that Long range dependence in asset market prices contradicts the weak form of EMH. In addition, market returns in developing markets tend to have nonlinear behaviour and this is attributed to the fact that investors have a degree of irrationality and the influence of speculators may drive prices off the equilibrium (Saadi, Gandhi & Dutta (2006).Given this background this study seeks to determine whether long term memory exists in Nairobi Securities Exchange.

1.1.1 Long Term Memory

Long term memory or Long range dependence can be defined as events in the distant past being highly correlated with events in the foreseeable future (Lo, 1991). Cajuerior and Tabak (2010) describes long range dependence in stock returns to be a stylized fact. Mandelbrot (1971) was among the first to study Long term memory and used Hurst ‘rescaled range ’statistics to examine Long memory behaviour in stock market returns. Mandelbrot &Wallis (1968) coined the term the ‘Joseph Effect’ referring to a prophet in the bible who foretold a cycle of seven years of plenty would precede seven years of famine. In a time series data, this implies events happening in the present have an impact on events that will happen in the future i.e. infinite memory.

Long memory generally suggests nonlinear dependence in average asset returns.A stationary process that possesses long term memory has qualitative features such as: existence of certain persistence both high and low. Possible periodic cycles in short time periods and overall the process described looks stationary (Beran, 1994). It is debatable whether asset prices display Long memory properties. According to Peters (1989) on testing the long memory hypothesis found that capital markets do not immediately reflect new information as assumed by EMH.

There several methods that can be used to measure long range dependence in time series data. These methods can be grouped into parametric, semi-parametric and non-parametric. The parametric methods which are linear in nature include AFRIMA. The semi-parametric are like Wavelet method which was introduced by Jensen (1999) but works better in combination with other methods and lastly the non-parametric approach are the classical Rescaled range analysis and Modified rescaled range analysis developed by Lo (1989). There is no consensus among researchers on the best method to use to examine long term memory.

1.1.2 Stock Market Returns

Stock markets returns as defined by Alagidede and Panagiotidis (2010) are a reflection of cash flow valuations into the future. Basically, investors are driven by profit and returns are the compensation expected from investment. According to Wang (2012) Stock market returns indicate how much profit/loss a company is making and investors realise positive returns in form of capital gains and dividends. Hamrita and Trifi (2011) defines returns as economic and financial signal of development in a country in current and future state.

Individuals or institutional investors consider several factors in purchase of stocks such as price earnings ratios, the return on equity, and the earnings per share and governance structure among other factors (Wang, 2012). In addition, markets are expected to be efficient and information available to all market participants. This is not always the case, proponents of behavioural finance emphasize that investors are normal and make decisions at times based on emotions, market trends and how they perceive the effect of the new information (Stanman, 2014).

As a collection of returns from different companies in different sectors in the economy that are listed in stock exchange, an index is used to give measure of market performance.

Stock exchange index is the weighted average of selected stocks of companies listed in Stock market the selection is based on capitalization, outstanding company performance among other variables (Daferighe & Sunday, 2012.). The NSE has three market indices which are calculated from the 64 listed companies for Trading. The three indices are the NSE-20 Share index which is derived from weighted prices, the NSE-25 Share index which is a recent addition that is arrived at by calculating the weighted market capitalization of the 25 companies reviewed and NSE All Share Index (NASI) the weighted market capitalization of all listed companies The indices are reviewed periodically in line with world best practices to capture the accurate market performance (NSE, 2017).

1.1.3 Long Term Memory and Stock Market Returns

Long term memory presence in asset returns is important in testing for market efficiency. According to Lo (1991) Stock markets do not always adhere to random walk this means that future returns are not independent of past returns. Stock market returns are non linear and portray Stochastic behaviour. Otieno (2017) emphasizes the importance of stock market returns in depicting market performance and risk levels of investors due to the stochastic nature of returns. When Returns possess long range dependence then weak form efficiency is violated since it provides that given historical asset returns future prices cannot be predicted.

Empirical evidence shows returns pricing models in support of random walk like Capital asset pricing model and Arbitrage pricing theory which is mostly used in determining stock market returns would be irrelevant in presence of long memory (Mandelbrot, 1971).

Furthermore, FMH emphasizes the need to have stable markets as opposed to an efficient one since everyday randomness and anomalies in the market are reflected in the price changes (Thomas, 2002).

According to EMH, investors who have invested the same amount in the market should receive the same amount of return and none can expect more since markets are efficient. This however, is refuted by development of Chaos theory where insignificant factors can cause a major impact in the market which affects stock prices and eventually return to the investor (Peter, 1994). Therefore, it is important to put into consideration that a market does not exist in a vacuum and investors make decisions based on many factors other than just facts and numbers presented by analysis and this in turn will affect market performance (Statman, 2014).

1.1.4 Nairobi Securities Exchange

Capital markets serve a crucial role in the economy of a country and stock market indices represent the economic well being. The NSE 20 Share index was introduced in 1964 as a measure of market performance and has significantly improved overtime to a record 6060 points in February 2007. Nairobi Stock Exchange was established in 1954 and has since had several transformations to date including a name change to Nairobi securities exchange in the year 2011. Some of the key significant changes since inception include reduction of trading days to T+3 in 2011, demutualization in year 2009 which is basically separation of ownership, automation of trading from open outcry system in 2006, and introduction of Central depository System (CDS) in 2004 which has facilitated real time ownership of securities(NSE, 2017).

These changes have improved market efficiency, liquidity and have attracted more local institutional and foreign investors (Onyuma et al., 2011). Additionally, Waithiru (2015) notes that the microstructure changes to NSE has improved informational efficiency over time especially after automation of trading. This is not to say that NSE has been immune to the political changes in the country and the Global Financial Crisis (GFC). As suggested by Otieno (2017) changes in inflationary pressures and swings in exchange rates have had an unfavourable effect on stock market returns and especially post GFC.

1.2 Research Problem

The ability of capital markets to perform their role depends on market efficiency. Over the past years, there has been mounting evidence that capital markets may not be efficient due to factors such as irrationality and limits to arbitrage. The existence of inefficiencies such as long range dependence implies that investors may earn above market returns. Empirical evidence on emerging markets suggests that majority of Sub-Saharan markets are weak form inefficient (Jefferis & Smith, 2005); Magnusson & Wydick 2002). This can largely be attributed to the size of the market. However, these markets are negatively correlated with developed markets which present an opportunity for portfolio diversification and increased returns (Bekaert & Harvey, 2003).

NSE has been classified as an emerging market with great potential of growth being ranked the 4^{TH} in Africa in terms of market size, liquidity and product diversification (Rachael & Moses, 2017). As an emerging market it has had its fair share of ups and downs. It has experienced both bullish and bearish cycles coupled with political shocks in the last eight years begetting both market winners and losers (Ogega, 2014). The behavioural patterns of NSE warrant a closer look to determine if market returns can be predicted given historical prices.

Empirical evidence from global studies shows that developed markets have weak or no traces of long memory properties and suggest that most markets are efficient. For instance, Tolvic (2003) found weak proof of Long range dependence in the Finnish stock exchange. Vougas (2004) found inconclusive indication of long term memory in the Athens Stock Exchange. Similarly, Hiemstra and Jones (1997) supported by Sadique and Silvapulle (2001) found absence of Long term dependence in the US common stock. This could be attributed to technological advancement in trading as well as stocks in developed markets are affected more by fundamentals as compared to emerging markets (Hull & McGroarty, 2014).

There are numerous efficiency studies on NSE for instance; Dickinson and Muragu (1994), Anyumba (2010) and Mlambo and Biekpe (2005) established that efficiency at NSE was of the weak form. On the contrary, Parkinson (1987) and Njuguna (2016) concluded that NSE was weak form inefficient. Most of these studies are equivalents to testing for short range dependence and linear dependence the absence of which may not necessary imply that the market is efficient. The reviewed have alluded to the fact that few studies that have given attention to existence of long term memory in NSE and those that tested for it included it as a component amongst other variables with the assumption that market returns are linear. This study seeks to answer the question do stock returns in Nairobi Securities Exchange exhibit long term memory?

1.3 Research Objective

To test the existence of long term memory in stock market returns at Nairobi securities exchange.

1.4 Value of the Study

The existence of random walk has a lot of implications on finance theory and investment strategies and so plays an important role to academicians, investors and regulatory authorities. The observations of this research paper will provide immensely to literature on long term memory in NSE and build on other areas scholars can test in regard to the same subject.

Regulatory authorities like CMA can encourage cross border listings to improve liquidity of NSE this will in turn increase trades and activity in the market. Companies will also benefit from wider shareholder base and this reduces risk and builds on improved corporate governance structure. CMA should also expand on its programmes of investor education to minimise noise trading which influences prices in the exchange.

Investors will gain knowledge and a better understanding of emerging markets like NSE and adopt strategies that will encourage balanced and profitable portfolios given the understanding how the market operates.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

The chapter provides the discussion on the foundational theories to understanding the study, literature review related to long term memory which is relevant to this study as well as discusses the determinants of stock market returns. The chapter concludes with the review of literature provided.

2.2 Theoretical Review

This section discusses the theories informing this study. The review begins with the Efficient Market Hypothesis followed by Chaos Theory and finally Fractal Market Hypothesis. These theories explain the relationship between Stock market returns, market efficiency and Long term memory.

2.2.1 Efficient Market Hypothesis (EMH)

An efficient market is one whereby the prices of securities are reflective of the available information according to Fama (1965) who is the originator of Efficient Market Hypothesis. EMH categorises market efficiency into three with respect to information available, that is, weak- form, semi- strong, and strong- form of efficiency. In weak form, all market prices bear all historical news on stock prices and arbitrage approaches cannot be employed to beat the market. The semi-strong EMH suggests that the current asset prices incorporate all public information and investors cannot make above average risk adjusted returns (Fama, 1970).

Finally, the strong form holds prices reflect all information, both private and public information (inside information). The implication is that company insiders cannot consistently derive above-average risk adjusted returns.

In a nutshell, EMH holds that investors make rational decisions while markets are efficient and investors cannot make above average returns (Lo, 1991). Anomalies in the market like Calendar effect, Days of the Week and January effect invalidate EMH. The presence of long term memory in financial data implies that stock market do not immediately reflect new information as assumed by EMH (Peters, 1994). Peter's conclusion is further backed by Armachie (2017) who also using the R/S test observed evidence of long range dependence in Ghanaian stock exchange both in the squared and absolute returns tested. This relates to this study because it forms the basis upon which efficiency in related to long term memory.

2.2.2 Chaos Theory

Chaos theory was formulated by Lorenz (1960), a metrologist working to predict weather patterns developed Chaos theory. The theory has been used today in explaining financial markets which are considered to be complex systems. The theory claims flapping of a butterfly wings can cause weather changes elsewhere which is an attempt to explain how insignificant occurrence can influence major outcomes in factors that are not related (Konard, 2006). This concept has been applied in Finance to predict stock market behaviour. Proponents of Chaos theory believe that investor's behaviour may influence activities in the markets greatly as opposed to the traditional supply and demand forces driven purely by price. It also assumes that market expectations are rational (Wang, 2012). Market participants react differently to information and can sometimes read too much into events that lead to panic selling for instance and this may result in a dramatic change in stock prices.

According to EMH, investors who have invested the same amount in the market should receive the same amount of return and none can expect more since markets are efficient (Fama, 1970). This however, is refuted by Chaos theory where insignificant factors can have a significant impact on the market which affects share prices and eventually return to the investor (Konard, 2006). Therefore, it is important to put into consideration that a market does not exist in a vacuum and investors make decisions based on many factors other than just facts and numbers presented by analysis and this in turn will affect market performance.

The swings of positive and negative feedback affect a chaotic system such as financial markets where chaos is not just lack of order but a composition of both order and disorder (Konard, 2006). This brings about the bullish and bearish market conditions where good news in a bull market results in strong stock purchase and bad news in bear market stock dummying. The swing between order and disorder creates a pattern that can lead to prediction of events in the future. This theory is significant to this study for examining long term memory because it is concerned about patterns and market behaviour is not a random walk process but exhibits some structural and systematic pattern that can aid in prediction of returns.

2.2.3 Fractal Market Hypothesis

The Fractal market hypothesis (FMH) was developed by Edgar Peters (1994, 1996) to demystify the behaviour of market participants with respect to investment and time horizons. FMH emphasizes the need to have stable markets and a market is deemed to be stable when participants hold portfolios with different timelines given the same information. Investors who hold portfolios for longer assume more risk as compared to those who hold for a shorter period (Thomas, 2002).

For investors to realize market liquidity, FMH assumes investors attach different values to the securities to be traded and react differently given the same information. To maintain balance in the market FMH proposes rules that govern trading and rest time between trades to encourage holding periods in portfolios. A clash in investing time horizons will cause crisis in the market (Thomas, 2002). Adverse changes in information in the market will result in market instability and shift in liquidity position to the worst. Therefore, stable markets equal high liquid stocks.

The fractal structure of markets actually shows that financial markets can be considered a non linear system because prices according to FMH are determined by fundamentals in trading by investors and non linear market forces. Therefore, technical trading strategies can be used in predicting future returns (Vácha & Vosvrda, 2005). This theory is significant to this study because it supports the prediction of market returns and puts emphasizes on markets being stable as opposed to efficient which is an emphasize of

EMH and allows room for irrationality which depicts a true representation of market participants.

2.3 Determinants of Stock Market Returns

Stock returns can be affected directly by how firms are managed or indirectly by the economic conditions in which companies operate.

2.3.1 Company News

Company news is a factor that affects stock market returns because the news concerning company performance is paramount to investors. Sometimes the news could be genuine news or rumours. Good news and bad news receive shareholders reaction in their buy and sell decisions. The profits made by the company affects dividend payments and given that return can be in form of capital gains and dividends; this influences the buy, hold or sells moves (Wang, 2012). Changes in management in company's especially key positions like Chief executive officer can be perceived positively or negatively by investors. This definitely affects share price movements as market participants react to the news. Aduda and Chemarum (2010) found evidence of abnormal returns in NSE after earnings announcement by listed companies.

2.3.2 Industry Performance

Industry performance affects stocks prices in the sense that companies in the same industry are prone to the same challenges and mostly likely are affected in the same way by changes in the industry for instance legislative requirements (Otieno, 2017). However, in certain instances one company may thrive when a competitor in the same industry is facing a down fall and this makes investing in such a company more profitable to investors. On the other hand, investors in the company facing difficulties may experience share dummying in the market and this affects the price at the end of the day. Layoffs for instance what happened in Kenya's banking industry between years 2016-2017 may cause investors to shy away from buying from those counters yet not all listed banks laid off their staff (Mbua, 2017).

2.3.3 Investor's Confidence

Investor's confidence can cause price volatility in the market as they react to arrival of information. A bullish market receives over reaction to good news and bearish market conditions receive over reaction to bad news. For instance, Sinha (2016) found evidence of under reaction to news among large cap stocks in New York stock returns. Strong market conditions attract investors and improve on their confidence and market activities while weak market conditions turn investors to pessimistic modes and dampen their confidence this happens especially in periods of high inflation, unemployment and financial crisis like GFC (Otieno, 2017).

2.3.4 Economic and Political Stability

Economic and Political stability in a country has an impact on stock returns. When a country has high interest rates the cost of capital goes up and companies have to pay more when they acquire credit from financial institutions and this affects their profits (Ogega, 2014). Given that investors analyze stocks to buy based on measures such as earnings per share, return on investment among other variables, then in such instances the economy has a negative impact on returns. Political instability affects development and in turn the stock market and puts investors off. This is evidenced in market index during the post-election violence in Kenya (2007) when the NSE 20 share index was its lowest (Waithiru, 2015).

2.4 Empirical Studies

This section highlights both global and local studies reviewed that are relevant to this research topic.

2.4.1 Global Studies

Oprean and Tanasescu (2013) studied the application of chaos theory and fractal theory in 8 emerging markets which are: India, Romania, China, Russia, Brazil, Czech Republic, Hungary and Estonia. The study employed rescaled range analysis in investigating presences of long term memory and concluded with Hurst exponents of 0.5 and above which is consistent with long range dependence presence in asset returns. The study also found the indices daily returns portrayed persistent behaviour that invalidates EMH.

Consequently, Hull and McGroarty (2014) used Hurst Wallis -Mandelbrot rescaled range i.e. classical rescaled analysis in testing whether emerging markets became efficient over time and long memory persistence. They sampled 22 countries in a span of 16 years .As from the above studies they find evidence of volatility clustering in returns. They equally argue that markets do not necessarily improve in efficiency with time. They as well advocated for classification of emerging markets in terms of being secondary or advanced.

In ranking capital markets by efficiency, Baciu (2014) examined 20 stock markets in Europe. The markets were ranked in accordance to, fractal dimension, efficiency index and long term memory. Using rescaled analysis the study found developed markets are most efficient especially UK which showed no features of long range dependence and fractal dimension. Emerging like Greece, Czech Republic and Bulgaria and markets were least in efficiency. The study focused on emerging markets in Europe and with some relatively more developed and with different trading systems compared to African markets.

Hiremath and Kumari (2015) examined the Indian stock market for long memory which is an emerging market. The study used Andrews and Guggenberger (2003) test for existence of Long term memory. They examined 29 daily return indices of the exchanges nine years (2003-2012). The findings of the study show strong long range dependence in mean returns under investigation. The findings also imply that capitalization and liquidity contribute to long memory properties in prices and microstructure changes in India have not yielded the desired informational efficiency.

In conclusion, there are studies that do not support presence of long memory in returns such as Kormaz et al. (2009a) analyzed existence of long memory by verifying structural breaks variance in Istanbul Stock Exchange (ISE) for a period of 20 years for the period 1988-2008. The study employed ARFIMA-FIGARCH model to daily closing prices .The researchers found non existence of long memory in asset returns, but found volatility in the data tested. This concludes that ISE was inefficient.

2.4.2 Local Studies

There are limited local studies that have examined stock returns for long term memory in NSE from the reviewed studies. However, these studies provide mixed evidence of the same. Alagidede and Panagiotidis (2009) in modelling returns for the seven biggest stock markets in Africa using GARCH and Smooth transition regression ranked on capitalization and liquidity which included: Tunisia, Egypt, Morocco, Kenya, Nigeria, South Africa, and Zimbabwe concluded stock market returns have shown non linearity from the volatility observed and they rejected the Random walk hypothesis. This study used a linear model in statistical analysis of long term memory stock market returns.

In support of the above studies, Thupayagale (2010) explored aspects of long memory behaviour in 11 ASM which include: Mauritius, Tunisia, Nigeria, Ghana, Namibia, Morocco, Kenya, Egypt, Zimbabwe, South Africa, and Botswana. Using GARCH and ARMA which are linear models found that ASM generally found evidence of asymmetric and long memory components in stock returns. These findings are a deviation from EMH and show a delay in processing new information. The study used a parametric test while this research paper used a non parametric test and focused on Kenya only.

Ogega (2014) in analysing NSE for volatility, persistence and asymmetric and in returns volatility in Market while using FIEGARCH model, found evidence of persistence in bullish phases where unexpected positive returns resulted in more volatility compared to negative returns of the same intensity as well as unexpected negative returns in bearish phases were more volatile than unexpected positive returns of the same intensity. This alludes to information asymmetric and market inefficiency.

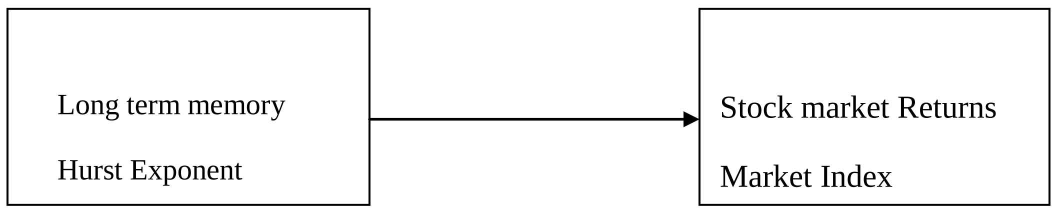
Balparda et al. (2015) using unit root test and fractional integration tested for Long term memory, inefficiencies, persistence and anomalies on stock returns in NSE for a period of 8 years for years 2001-2009 and found long range properties in returns as well as day- of- the -week anomaly an indication of possible non-linearity. The use of linear models in testing returns like unit root used in the study above may fail to give a true presentation of data since returns portray non linearity (Lo, 1991).

Market efficiency and Long memory go hand in hand. Provided that long memory can be detected in returns then a market is deemed inefficient. Njuguna (2016) tested the weak form efficiency of NSE using unit root, serial correlation test and run test. The findings show that NSE 20 and NASI index to be weak form inefficient. In support, Jefferis and Smith (2005) investigated whether emerging markets were becoming efficient with time and found that the NSE to be weak form inefficient. In efficient market presence of anomalies is an indication of arbitrage opportunities.

In conclusion, Gichana (2009) in a comparison of Linear and Nonlinear models in Predicting stock returns at Nairobi securities exchange while using ARMA and ARCH models concluded that stock returns are nonlinear and ARCH model was the best nonlinear model in predicting returns. On the other hand, Ndigwa and Murui (2016) in examining volatility in stock return of emerging markets a case study of NSE applied

GARCH models and found no evidence of volatility persistence and asymmetric effect in stock market returns. This signifies absence of long memory because of lack of volatility in returns.

2.5 Conceptual Model



Source: Researcher 2018

Figure 2.1 Conceptual Model

2.6 Summary of Literature Review

It is evident from the reviewed literature that developing markets are considered to have low efficiency levels compared to developed markets. The conclusion is drawn from studies of emerging markets not just in Africa. Predictability seems to be a common feature in equity returns in emerging markets a reason why ASM are sort for portfolio diversifications. The testing of many markets together could be factor that contributes to lack of proper focus on findings and a deeper understanding of the behaviour of the market under study.

The studies done on Kenya although limited in number, examine it for long term memory among other markets (Thupayagale, 2010, Alagidede & Panagiotidis, 2009). This could influence the findings and fail to paint the real picture. The study that focused on long memory tested it among other variables and both used parametric models to test while this study proposed to use a non parametric model. Gichana (2009) probed the question which models were best suited to test for predictability and from his conclusion; nonlinear models were suitable since returns are nonlinear. The efficient studies used linear methods to test for efficiency and given that stock returns have nonlinear features; forms the basis of this research to use nonlinear model to test for existence of long range dependence in stock returns in NSE.

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the research design for the study, the population and the sampling procedure that was used. The methods of data collection and data analysis are captured alongside the model to be used for analysis.

3.2 Research Design

A longitudinal research design was adopted for this research paper. This is because the study involved taking repetitive measures overtime for the purpose of comparing returns. This design is also suitable in analysing and comparing the behaviour of returns in the period of the study.

3.3 Population

The population considered for this study includes all listed companies in the Nairobi Securities Exchange. There were 64 listed companies trading at NSE as at December 2017 (Appendix I)

3.4 Sample Design

The study used the NSE-20 Share index. The NSE-20 Share is a value weighted index consisting of the 20 most actively traded and highly capitalized companies from the various market segments of the listed companies. The study used a predetermined sample and therefore no sampling procedure was required. (Appendix II)

3.5 Data Collection

Daily data collected on the NSE-20 share index was for a period of 8 years, that is, 4th Jan 2010-29th Dec 2017. Daily secondary data on the NSE-20 share index was obtained from NSE Database and Capital Markets Authority (CMA) statistical bulletins.

3.6 Data Analysis

This section addressed the Stationarity test on the NSE daily return index followed by the analytical model for examining Long term memory in stock returns. EViews financial econometric software was used for calculation of returns on the index and modelling. The return on the index (R_t) at period t was computed as continuously compounded as per below equation

$$\mathbf{r_t = Inp_t - Inp_{t-1}} \qquad 3.1$$

R_t = Daily returns for NSE 20-share index for period $_t$

P_t= NSE 20-share index for day t.

P_{t-1} = NSE 20-share index for day $_{t-1}$.

In= Natural Logarithm.

A key assumption underlying the use of logarithms is that returns are likely to have normal distribution which is a pre-condition for normal statistical techniques.

3.6.1 Diagnostic Test

Stationary time series has the data mean, variance and auto-correlation constant over time. Augmented Dickey Fuller (ADF) unit root test was used to determine stationary of the returns. It is important for the time series is data to be stationary for testing, to obtain relevant results. Normality test was also carried out using Eviews on the returns to determine if stock prices were independent and normally distributed.

3.6.2 Analytical Model

First, An Autocorrelation test was carried out in the data using Ljung Box Q test preceding the examination of long term memory properties in the stock market returns. This was done to check for randomness in the overall time series data.

Second, Rescaled Range (R/S) analysis technique which is designed to detect data randomness in a time series was used as the analytical model. This model was first used by Harold Hurst in 1951 in handling of non periodic cycles at River Nile dam project and later in financial markets data by Mandelbrot (1972), Lo (1991) and Peters (1991).The Rescaled Range Analysis does not impose any prior assumption on the underlying distribution since it is a non-parametric technique. According to Mandelbrot (1972) and thereafter Peters (1994), and recently Armachie (2017) the Rescaled Range Analysis (R/S) is robust to standard statistical techniques in detecting non-random behaviour of returns especially where returns are not normally distributed and are not independent and identically distributed.

The R/S analysis method is as outlined below:

1. Choose the range; the rescaled range is computed for multi lengths of time chosen arbitrarily. For instance, if there are 10,000 daily returns, the first range would contain the entire 10,000 daily returns, the second range would contain two ranges of 5,000 daily returns, the third range would contain four ranges of 2,500 daily returns and so on.

2. Determine the mean value for the each chosen range

$$m = \frac{1}{n}\sum_{i=1}^{n} X_i$$

   Where:

   m = mean calculated for each range n = the range size X_i = the value of a point

   the in the range.

3. Create deviations series for each chosen range; A new time series will be created from the deviations using the mean for each range

$$Y_t = X_t - m, t = 1,2, \dots, n$$

   Where: Y_t= the new time series adjusted for deviations from the mean, X_t= the

   value of one element in the range, *m* = the mean for the range calculated in Step 2 above.

4. Derive another series which is the sum of the mean deviations.

$$Z_t = \sum_{i=1}^{t} Y_t , t = 1,2, \dots, n$$

Where: Z_t = the sum of the mean deviations for each series, Y_t= the adjusted time series for deviations from the mean.

5. Find the range series R

   Find the maximum and minimum values in the series of deviations for each range.

   $$R_t = \max(Z_1, Z_2, \dots, Z_t) - \min(Z_1, Z_2, \dots, Z_t), t = 1,2, \dots, n$$

   Where R_t = the largest spread in each range, Y = the value of one point in the mean deviations range

6. Calculate standard deviation series S for chosen range

   $$S_t = \sqrt{\frac{1}{t}\sum_{i=1}^{t}(X_i - u)^2}, t = 1,2, \dots, n$$

   Where u is the mean from X_1 to X_t.

7. Calculate the rescaled range series (R/S) for each range series.

   $$\left(\frac{R}{S}\right)_t = \frac{R_t}{S_t}, t = 1,2, \dots, n$$

Where:

$\left(\frac{R}{S}\right)$ = The rescaled range for each range in the time series

R_t = The range series calculated above.

S_t =Standard deviation of the range under consideration.

If given the same time series, an increase the number of observations, will increase the rescaled range as well. Hurst found that (R/S) scales up as time increases (proportional tot^H). The increase of the rescaled range can be shown by plotting the logarithm of $\left(\frac{R}{S}\right)$ vs. the logarithm of$t$. The slope of this line gives the Hurst exponent, H. Hence

$$\left(\frac{R}{S}\right)_t = C * t^H$$

Where C, is a constant and H is the Hurst exponent. By taking the logarithms, the Hurst exponents can be transformed from a power exponent to a linear form. The Hurst exponent (H) is obtained by estimating the following equation through ordinary least squares approach;

$$\log\left[\left(\frac{R}{S}\right)_t\right] = \log[C] + \mathrm{H}\log[\,t] \qquad 3.2$$

3.6.3 Test of Significance

The value of the Hurst exponent provides crucial information that can be used to infer on the predictability of a time series. It indicates how strongly times series data regresses from the mean and usually it is a value between 0 and 1. When the value of 'H' is between $0 < 0.5$ it signifies that the future point in a time series is likely to go back to historical point (mean reverting). When $H = 0.5$ it indicates that events are not correlated at all (random behaviour). When the value of H is between $0.5 > 1$ it indicates the presence of a trend in the series (long term memory).

CHAPTER FOUR: DATA ANALYSIS, RESULTS AND DISCUSSIONS

4.1 Introduction

This section presents, data analysis and discusses the results of the statistical tests carried out using E-views and Ms-Excel. The descriptive statistics are presented first, followed by the stationarity test, autocorrelation test and lastly the test for long term memory. These tests were carried out using daily index data from 4th Jan 2010 to 29th Dec 2017.

4.2 Descriptive Statistics

A preliminary analysis of the daily return on the index and the NSE 20 share index was done. The results are presented in the table 4.1.

Table 4.1: Descriptive Statistics

	Daily returns on the index	**NSE 20 share index**
Mean	0.007%	4147.27
Median	0.004%	4037.99
Maximum	6.071%	5499.64
Minimum	-5.903%	2789.64
Std. Dev.	0.684%	661.070
Skewness	-0.0672	0.044
Kurtosis	12.1979	1.893
Jarque-Bera	6999	101.9171
Probability	0.00	0.00
Observations	1985	1985

Source: Researcher (2018)

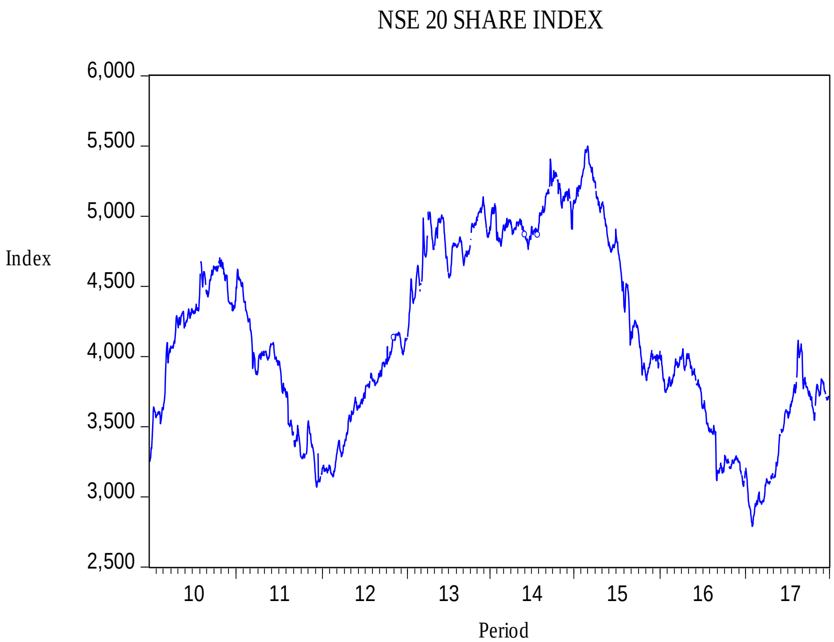
The daily returns have a mean of 0.007% (Table 4.1). The positive return implies that given a holding period of 8 years, investors would have gained on their investment. This could be attributed to the bullish ran that lasted for four years i.e. 2012 to 2015 after a period of depression (figure 4.2). This also explains why the mean of the NSE 20 share index is quite high for the period under study. The standard deviation for the daily return is 0.684% while that of the index is 661. The high standard deviation of the index is expected especially with the introduction of changes such as automation, the volatility of prices should be higher they adjust quickly to new information.

Both the daily returns and NSE 20 share index for the period show a departure from normality. This is evidenced by the negative skewness of value -0.067 and positive skewness value of 0.044 for the daily returns and index respectively. Daily returns have a high positive kurtosis value of 12.197 indicating that the distribution has fatter tails. The significant p-values for Jarque-Bera test further suggests that daily returns and index are non normal. Although, Finance theory posits that stock returns follow a normal distribution, empirical evidence has shown that returns exhibit certain stylized facts such as non normality, skewness and volatility clustering (Opong et al., 2010).

4.3 Trend Analysis

A plot of the NSE 20 share index shows that there is an upward trend from 2012 to 2015 followed by a downward trend (figure 4.2). This could suggest that NSE 20 share index is not stationary. The presence of a trend could imply predictability of prices.

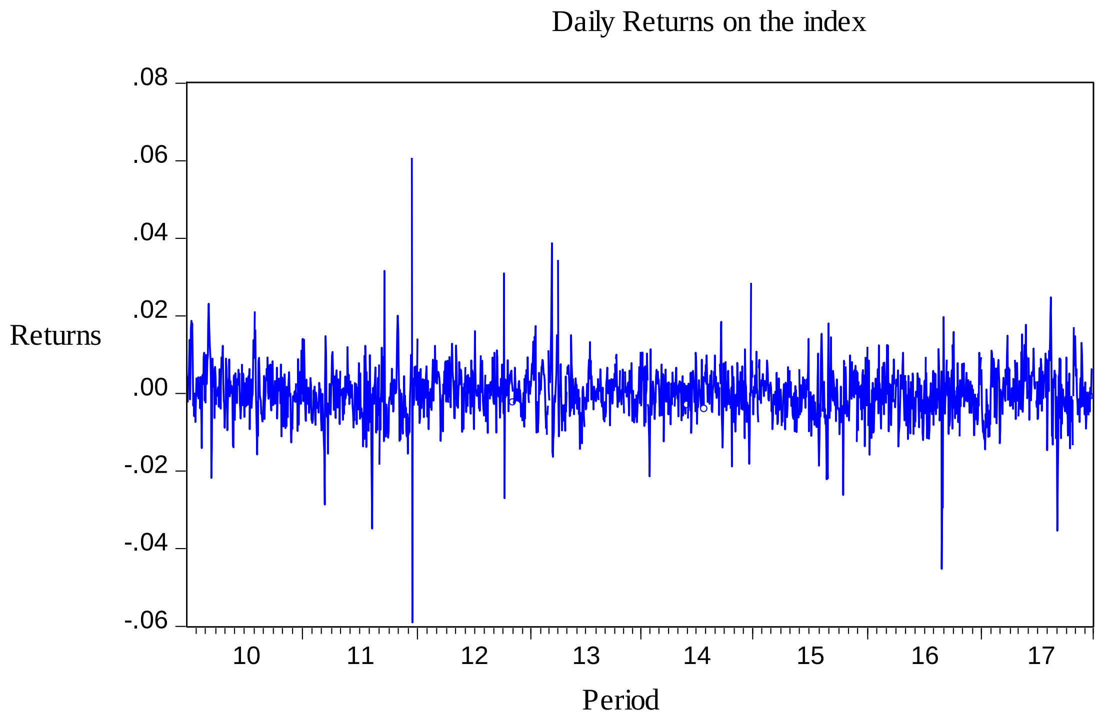
Figure 4.2: Time series plot of the NSE-20 share index



Source: Researcher (2018)

The time series plot for the daily returns show no particular trend and the mean is constant an indicator of a stationary process (Figure 4.3).

Figure 4.3: Time series plot of the NSE-Daily returns



Source: Researcher (2018)

4.4 Diagnostics Tests

The diagnostic test was carried out to ensure that time series data was stationary for testing to obtain relevant results.

4.4.1 Stationarity Test

The Augmented Dickey Fuller test (ADF) was used to test for the presence of non stationarity in both the NSE 20-index and the daily returns. The null hypothesis for the ADF test was; the series has a unit root (non stationary) while the alternative hypothesis was the series has no unit root (stationary). The Optimal lag length for the ADF test was selected with Schwartz information criteria and maximum lag was set to 25. The test was conducted under the specification of level series with trend and intercept.

Table 4.2: Stationarity test for NSE-20 share index

Null Hypothesis: NSE -20 index has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 2 (Automatic - based on SIC, maxlag=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.794934	0.7071
Test critical values:	1% level	-3.962678	
	5% level	-3.412077	
	10% level	-3.127952	

Source: Researcher (2018)

Table 4.3: Stationarity test of the NSE-Daily returns

Null Hypothesis: NSE daily return has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 1 (Automatic - based on SIC, maxlag=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-24.13805	0.0000
Test critical values:	1% level	-3.962676	
	5% level	-3.412076	
	10% level	-3.127951	

Source: Researcher (2018)

The ADF results in Table 4.2 indicate that the null hypothesis of non stationarity cannot be rejected at all levels. This is also supported by the significant this P value (P >0.05). . The mean of the index varies overtime therefore making it non stationary. However, the null hypothesis of unit root is rejected (P-value <0.05) for the returns (Table 4.2). The results imply that the returns in the eight year period are integrated in order I *(1).*

4.4.2 Autocorrelation Test

Before embarking on the test of long term memory, the autocorrelation test was carried out on the daily returns to determine whether there is a trend in time series data. The autocorrelation test was conducted using the Ljung Box Q test. Further, by looking at the autocorrelation function, a trend can be detected. If the autocorrelation function decays slowly to zero it may signify presence of long term memory. If the autocorrelation function decays quickly to zero it may indicate short memory. The autocorrelation test was conducted for up to 24 lags.

The autocorrelation function shows significant positive autocorrelation between lag 1 and lag 5 which quickly disappear. This is indicative of a short memory process. The positive autocorrelation from the 12^{th} lag to the 22^{nd} lag means that momentum strategies may be applied. The Q statistic is high at all lags with significant P-values (P-value <0.05). The null hypothesis of no serial correlation was therefore rejected implying that the market does not follow a random walk.

Table 4.4: Autocorrelation Test of the NSE Daily Returns

Sample: 1/04/2010 12/29/2017
Included observations: 1985

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
|** |	|** |	1	0.265	0.265	139.25	0.000
|* |	|* |	2	0.175	0.112	199.90	0.000
| |	| |	3	0.068	-0.003	209.12	0.000
| |	| |	4	0.027	-0.008	210.59	0.000
| |	| |	5	-0.006	-0.020	210.67	0.000
| |	| |	6	0.000	0.005	210.67	0.000
| |	| |	7	0.000	0.004	210.67	0.000
| |	| |	8	-0.018	-0.020	211.32	0.000
| |	| |	9	-0.003	0.005	211.34	0.000
| |	| |	10	0.009	0.015	211.51	0.000
| |	| |	11	-0.025	-0.032	212.75	0.000
| |	| |	12	0.029	0.042	214.43	0.000
| |	| |	13	0.036	0.029	217.07	0.000
| |	| |	14	0.003	-0.021	217.09	0.000
| |	| |	15	0.004	-0.002	217.12	0.000
| |	| |	16	0.029	0.030	218.78	0.000
| |	| |	17	0.015	0.004	219.23	0.000
| |	| |	18	0.008	-0.002	219.35	0.000
| |	| |	19	0.020	0.014	220.13	0.000
| |	| |	20	0.015	0.007	220.56	0.000
| |	| |	21	0.011	0.005	220.81	0.000
| |	| |	22	0.007	-0.003	220.91	0.000
| |	| |	23	-0.021	-0.026	221.82	0.000
| |	| |	24	-0.031	-0.020	223.76	0.000

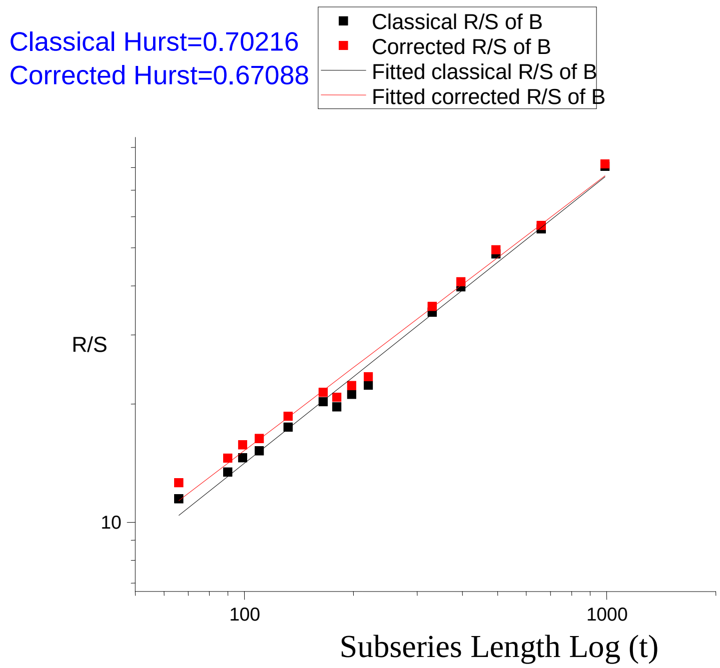
Source: Researcher (2018)

4.5 Test of Long Term Memory

4.5.1 Rescaled Range Analysis

The Hurst exponent was obtained by plotting the log of Rescaled range versus the log of observation. A regression line was fitted and the slope of the regression line is the H-value. The plot and the regression line for the time period is shown in figure 4.4.

Figure 4.4: Plot of Log R/S vs. Log (t)



Source: Researcher (2018)

Table 4.5: Hurst component of the NSE-Daily Returns

	Hurst
Classical Hurst exponent	0.70216
Corrected Hurst exponent	0.67088
N	1985

Source: Researcher (2018)

The table 4.5 above shows the estimated H- values for the period. When the Hurst exponent value 'H' is between $0 < 0.5$ it signifies that the future point in a time series is likely to go back to historical point (mean reverting) that is if prices increase the past then they will decrease in the future and vice versa. When $H = 0.5$ it indicates that events are not correlated at all and portray random behaviour. When the value of H is between 0.5 > 1 it indicates a pattern in the series. A price increase in the past equals an increase in the future and a decrease in the past equals a decrease in the future. The classical H-value from the test carried out is 0.70 while the corrected H value is 0.67 indicating the presence of a long term memory. Therefore, there is Long Term Memory in Stock Market Returns at Nairobi Securities Exchange.

4.6 Discussion of Research Findings

The objective of the study was to test for existence of Long term memory in stock market returns in Nairobi securities exchange. The Hurst exponent was used to measure long term memory in stock returns while the daily NSE 20 share index was used to measure stock market returns for the period between January 2010 and December 2017. One of the advantages of Rescaled range analysis is its ability to depict cycles in time series data (Gayathri, Murugesan & Gayathri, 2012). The findings show H value of 0.7 which indicates presence of long range dependence in NSE and signifies that current prices are more likely to be influenced by events in the past and a possibility of arbitrage opportunities. Long term memory should be considered in trading strategies for instance, Gayathri, Murugesan and Gayathri (2012) illustrates the 10 day Hurst exponent index where the value of H is <0.43 influence a sell decision and a value > 0.66 influences a buy decision within an average 10 days of a trading cycle.

The results of the study are in agreement with Thupayagale (2010) who investigated NSE among other ASM for a period between 1996 and 2007 using the NSE-20 index found long range dependence to be present in stock market returns in NSE using GARCH model presented by strong persistence levels in volatility of equity returns. The results rejected EMH which is also in agreement with the results of this study.

In regard to market efficiency, the results suggest that the market is weak form inefficient denoted by the autocorrelation test which rejects the the null hypothesis of no serial correlation (Table 4.4).These findings are supported by the study results of Jefferis and Smith, (2005) who investigated emerging markets for improved efficiency with time and found NSE not to be weak form efficient. Njuguna (2016) backs up the findings when she tested for weak form efficiency of NSE and found it to be inefficient.

CHAPTER FIVE: SUMMARY, CONCLUSIONS AND RECOMMENDATION

5.1 Introduction

This chapter covers the summary of research findings, the conclusion drawn from the study, suggestions for further research and the recommendations to policy makers and finance practitioners.

5.2 Summary of Findings

The study examined the existence of long memory in daily index returns for a period of eight years. From the results of descriptive analysis the mean return of the period is positive albeit negatively skewed with high kurtosis. The results of Jacque-Bera test further indicate that returns do not follow a normal distribution. The result should not be surprising since studies have shown that returns exhibit certain characteristics such as non normal distribution and volatility clustering (Ogega, 2014).

Unit root test was conducted to determine whether daily returns on the index are stationary using the ADF test. The ADF test concluded that daily returns are a stationary process and integrated in order I *(1).* The autocorrelation test does not show any significant trend aside from lag 1-lag 5. Further the test indicates that the market does not follow a random walk.

The Hurst exponent computed has a value of 0.7 which is greater than 0.5 suggesting the presence of long term memory. This is in line with studies of Balparda et al. (2015) who found presence of long memory in the NSE using unit root test and fractional integration. The results are also consistent with research findings of other emerging markets around the world as conducted by Oprean and Tanasescu (2013) using rescaled range analysis found Hurst exponent of above 0.5 which indicates long range dependence in assets returns. The generalization that emerging markets seem to have long term memory properties seems to hold given the results (Thupayagale, 2010).

5.3 Conclusions

The objective of the research was to determine existence of long term memory in stock market returns and based on the findings, there does exists long term memory in the daily returns of the NSE. This is further supported by the results of autocorrelation test that indicate that the market does not follow a random walk. The presence of the long term memory is evidence against the EMH. This implies that investors can study the patterns in NSE and develop strategies to earn higher returns.

5.4 Recommendations

The implication of this study is that the stock market returns can be predicted and investors can take advantage and benefit from high returns. Investors can use the findings in developing risk and portfolio management strategist because of the underlying factor of forecasting returns. Investors can also employ already developed trading algorithms to guide their buy and sell decisions as opposed to behavioural modes such herding.

Capital markets authority should consider investor education and awareness of the investment products available by working in tandem with stock brokerage firms to drive liquidity by increasing market participation. Adelegan (2008) finds that encouraging cross-listings can foster development and improve liquidity among integrated markets compared to those not integrated. Therefore, NSE and CMA can encourage cross listing of companies to achieve the same.

Given that market integration is happening to ASMs to other markets in the world it is important for NSE and CMA to ensure proper structure and policy to cushion the market in times of market crashes in light of recent global financial crisis.NSE should also have a mechanism to avail data to students conducting research at no fee to encourage more research that will eventually lead to improvement in NSE for instance increase market participation and efficiency.

5.5 Limitations of the Study

The study was based on eight year period and recommends use of longer period as well as used the NSE 20 share index perhaps carrying out a test on the NSE 25 and NASI can be explored to be known with certainty that the results reflect the entire market. It will also be beneficial in capturing all economic swings of booms and recession. The extent to which the findings of this research can be generalized to other periods is unknown but can be determined by further research capturing longer frequency beyond the frequency selected for this research.

The quality and accuracy of data used in research is important. Secondary data was used for this research and at times this data may not be as accurate as primary data and therefore it is a limitation that can affect the outcome of the study. In addition, obtaining the data was expensive since NSE has let out handling of data to vendors yet they are the primary generators of the daily trading data. This can limit the period of study since the larger the data the more one has to pay.

Even with the various studies indicating possible presence of long memory in the stock market returns, the R/S test has faced its fair share of scrutiny overtime with some researchers arguing that test is biased in the sense that presence of long memory is frequent, when applied. Some authors believe that stock market returns usually follow a biased time paths that could potentially be difficult to distinguish from random behaviour using statistical tests such as the R/S analysis method which could lead to erroneous conclusion that the stock market has long term memory.

5.6 Suggestions for Further Research

Further test can be carried out and for a different sample period to determine whether this phenomenon has been in existence as well as determine the relationship between investor's behaviour and long range dependence. This will shade light on how significant a determinant of stock market returns investor's behaviour is. The study recommends using the same analytical model for purposes of result comparisons with other African markets. Monthly data can be used in comparison to the daily data used for this study to determine the robustness of Hurst exponent given different data frequency.

This study used a nonparametric model Rescaled range analysis and found presence of long term memory and proposes using other nonparametric models such as Rescaled variance statistic, modified rescaled range analysis to mention a few which can be applied to the same data set to determine if the same conclusion will be arrived at. This will also provide insight on the shortcomings of the method used and reveal which is the best model to be used in future research on the same topic.

A comparison of parametric, semi-parametric and nonparametric models on the same data set will be an interesting factor to consider which models are best in testing the phenomena since there is no consensus among researchers. The test can also be carried on a larger data set than the one used for this study. The results obtained can show which method best captures the varying time and stationarity process in the data and which works with large sample of data effectively to inform future researchers interested in the same area of study.

REFERENCES

Aduda, J.O. & Chemarum, C.S. (2010). Market Reaction to Securities Splits; Empirical Evidence from NSE, *African Journal of Business Studies*, 1 165-185.

Alagidede, P. (2009). Modelling stock returns in Africa's emerging equity markets. *International Review of Financial Analysis*, 18(1-2), 1-11.

Anyumba, A.P. (2010). An Empirical Test of the Random Walk Model for the NSE. Unpublished MBA Project, University of Nairobi.

Armachie, J. (2017). Arbitrage Opportunity in the Ghanaian Stock Market an Arfima Approach. (Doctoral dissertation, University of Ghana).

Baciu, O. A. (2014). Ranking capital markets efficiency: the case of twenty European stock markets. *Journal of Applied Quantitative Methods,* 9(3). 24-45

Balparda, B., Caporale, G. M., & Gil-Alana, L. A. (2015). The Kenyan stock market: inefficiency, long memory, persistence and anomalies in the NSE-20. *African Journal of Economic and Sustainable Development*, *4*(3), 254-277.

Bekaert, G., & Harvey, C. R. (2003). Emerging markets finance. *Journal of Empirical Finance*, *10*(1-2), 3-55.

Daferighe, E. & Sunday, C. S. (2012). The Impact of Inflation on Stock Market Performance in Nigeria. *American Journal of Social and Management Sciences*, 3 (2), 76-82

Damodaran, A. (2007). Valuation approaches and metrics: a survey of the theory and evidence. Foundations and Trends® in Finance, 1(8), 693-784.

Dickinson, J. P. & Muragu, K. (1994). Market Efficiency in Developing Countries: A Case Study of the Nairobi Securities Exchange, *Journal of Business Finance and Accounting*, 133-149.

Fama, E. (1965). Random Walks In Securities Market Prices. *Selected papers No.16*, 1-16.

Fama, E. (1970). Efficient Capital Markets: A Review of Theory and Empirical work, *Journal of Finance,* 383–417.

Gayathri, M., Murugesan, S., & Gayathri, J. (2012). Persistence and long range dependence in Indian stock market returns. *International Journal of management and business studies*, *2*(4), 72-77.

Gichana I. M. (2009). A Comparison of Linear and Non-Linear Models in Predicting Stock Returns at the Nairobi Stock Exchange. Unpublished MBA Project, University of Nairobi.

Greene, M. T., & Fielitz, B. D. (1977). Long-term dependence in common stock returns. *Journal of Financial Economics*, *4*(3), 339-349.

Hamrita, M. E., & Trifi, A. (2011). The relationship between interest rate, exchange rate and stock price: A wavelet analysis. *International Journal of Economics and Financial Issues*, *1*(4), 220-228.

Hiremath, G. S., & Kumari, J. (2015). Is There Long Memory in Indian Stock Market Returns? An Empirical Search. *Journal of Asia-Pacific Business*, 16(2), 128-145.

Hull, M., & McGroarty, F. (2014). Do emerging markets become more efficient as they develop? Long memory persistence in equity indices. *Emerging Markets Review*, 18, 45-61.

Jefferis, K. and Smith, G. (2005). The changing efficiency of African securities markets, *South African Journal of Economics,* 54–67.

Korkmaz, T., Cevik, E. I., & Özataç, N. (2009). Testing for long memory in ISE using ARFIMA-FIGARCH model and structural break test (No. 71302). University Library of Munich, Germany.

Lehoczky, J., & Schervish, M. (2018). Overview and History of Statistics for Equity Markets. *Annual Review of Statistics and Its Application*, *5*, 265-288.

Lo, A. W., & MacKinlay, A. C. (1988). Stock market prices do not follow random walks: Evidence from a simple specification test. *The Review of Financial Studies*, *1*(1), 41-66.

Mandelbrot, B. (1972). Statistical methodology for nonperiodic cycles: from the covariance to R/S analysis. In *Annals of Economic and Social Measurement, Volume 1, Number 3* (pp. 259-290). NBER.

Magnusson, M. A. & Wydick, B. (2002). How efficient are Africa's emerging markets? *The Journal of Development Studies*, Vol.38 No.4, 141−156.

Mbua, S. N. (2017). Effect of interest rates capping by the Central Bank of Kenya on the banks listed on the Nairobi Securities Exchange (Doctoral dissertation, United States International University-Africa).

Mlambo, C. and Biekpe, N. (2005). The Efficient Market Hypothesis: Evidence from Ten African Securities Markets. *Investment Analyst Journal*, 7-15.

Ndigwa, D. & Muriu, P. W. (2016). Stock returns and volatility in an emerging equity market: Evidence from Kenya. *European Scientific Journal*, 12(4), 79-98.

Njuguna, J. (2016). Testing the efficient market hypothesis on the Nairobi Securities Exchange. *Investment Management and Financial Innovations*, *13*(3), 75-83.

NSE PLC. (2017). Annual Report 2017. Retrieved from http://www.nse.co.ke/annualreport.

Nyamute, W., Oloko, M., & Lishenga, J. (2017). The Relationship between Investor Behavior and Portfolio Performance at the Nairobi Securities Exchange.

Ogega, H. O. (2014). Analysis of asymmetric and persistence in stock return volatility in the Nairobi Securities Exchange market phases (Doctoral dissertation, Strathmore University).

Opong, K.K., Li, Y., and Hamill, P.A. (2010). Do benchmark African equity indices exhibit the stylized facts? *Global Finance Journal*, 21, 71-97.

Oprean, C., & Tanasescu, C. (2013). Applications of Chaos and Fractal Theory on Emerging Capital Markets. *International Journal of Academic Research in Business and Social Sciences*, *3*(11), 633.

Otieno, D. A. (2017). Macroeconomic Determinants of Stock Market Returns in Kenya*: 1993-2015* (Doctoral dissertation, University Of Nairobi).

Peters E. E., (1994). Fractal Market Analysis: Applying Chaos Theory to Investment and Economics, NY. : John Wiley & Sons, 336 p.

Rachael, N., & Moses, W. (2017). The Effect of Interest Rate Control on the Stock Market Performance, a Case of Nairobi Securities Exchange Market. *International Journal of Current Aspects in Finance (IJCAF)*, *4*(1).

Saadi, S., Gandhi, D., & Dutta, S. (2006). Testing for nonlinearity &Modelling volatility in emerging capital markets: The case of Tunisia. *International Journal of Theoretical and Applied Finance*, *9*(07), 1021-1050.

Sadique, S., & Silvapulle, P. (2001). Long-term memory in stock market returns: international evidence. *International Journal of Finance & Economics*, *6*(1), 59-67.

Sinha, N. R. (2016). Underreaction to news in the US stock market. *Quarterly Journal of Finance*, *6*(02), 1650005.

Statman, M. (2014). Behavioral finance: Finance with normal people. *Borsa Istanbul Review*, *14*(2), 65-73.

Sugimoto, K., Matsuki, T., & Yoshida, Y. (2014). The global financial crisis: An analysis of the spillover effects on African stock markets. *Emerging Markets Review*, *21*, 201-233.

Tabak, B. M., Serra, T. R., & Cajueiro, D. O. (2010). Topological properties of stock market networks: The case of Brazil. *Physical A: Statistical Mechanics and its Applications*, *389*(16), 3240-3249.

Thomas, C. M. (2002). Chaos Theory versus the Efficient Market Hypothesis in Financial Markets. (Honors Thesis Projects, University of Tennessee).

Thupayagale, P. (2010). Essays in long memory: evidence from African stock markets (Doctoral dissertation, University of St Andrews).

Vácha, L., & Vosvrda, M. S. (2005). Dynamical agents' strategies and the fractal market hypothesis. *Prague Economic Papers*, *14*(2), 172-179.

Wang F. (2012) Determinants of Chinese Stock Market Returns. Unpublished Msc Thesis. University of Utara Malaysia.

APPENDICES

Appendix I: All listed Companies in NSE per Sector for Year 2017

AGRICULTURAL	**COMMERCIAL AND SERVICES**	**INSURANCE**
Eaagads Ltd	Atlas African Industries Ltd	Britam Holdings Ltd
Kakuzi Ltd	Express Kenya Ltd	CIC Insurance Group Ltd
Kapchorua Tea Co. Ltd	Hutchings Biemer Ltd	Jubilee Holdings Ltd
The Limuru Tea Co. Ltd	Kenya Airways Ltd	Kenya Re Insurance Corporation Ltd
Sasini Ltd	Longhorn Publishers Ltd	Liberty Kenya Holdings Ltd
Williamson Tea Kenya Ltd	Nairobi Business Ventures Ltd	Pan Africa Insurance Holdings Ltd
	Nation Media Group Ltd	
AUTOMOBILES & ACCESSORIES	Standard Group Ltd	**INVESTMENT**
Car & General (K) Ltd	TPS Eastern Africa Ltd	Centum Investment Co Ltd
Marshalls (E.A.) Ltd	Uchumi Supermarket Ltd	Home Afrika Ltd
Sameer Africa Ltd	WPP Scangroup Ltd	Kurwitu Ventures Ltd
		Olympia Capital Holdings Ltd
BANKING	**CONSTRUCTION & ALLIED**	Trans-Century Ltd
Barclays Bank of Kenya Ltd	ARM Cement Ltd	
CFC Stanbic of Kenya Holdings Ltd	Bamburi Cement Ltd	**INVESTMENT SERVICES**
Diamond Trust Bank Kenya Ltd	Crown Paints Kenya Ltd	Nairobi Securities Exchange Ltd
Equity Group Holdings Ltd	E.A.Cables Ltd	
Housing Finance Group Ltd	E.A.Portland Cement Co. Ltd	**MANUFACTURING & ALLIED**
I&M Holdings Ltd		A.Baumann & Co Ltd
KCB Group Ltd Ord	**ENERGY & PETROLEUM**	B.O.C Kenya Ltd
National Bank of Kenya Ltd	KenGen Co. Ltd	British American Tobacco Kenya Ltd
NIC Group PLC	KenolKobil Ltd	Carbacid Investments Ltd
Standard Chartered Bank Kenya Ltd	Kenya Power & Lighting Co Ltd	East African Breweries Ltd
The Co-operative Bank of Kenya Ltd	Total Kenya Ltd	Eveready East Africa Ltd
	Umeme Ltd	Flame Tree Group Holdings Ltd
		Kenya Orchards Ltd
		Mumias Sugar Co. Ltd
		Unga Group Ltd
		TELECOMMUNICATION & TECHNOLOGY
64 listed companies		Safaricom Ltd

Source: NSE (2017)

Appendix: II Companies Constituting the NSE-20 Share index for year 2017

1	ARM Cement
2	Bamburi Cement
3	Barclays Bank Kenya
4	Britam
5	British American Tobacco Kenya
6	Centum Invest
7	CfC Stanbic
8	Co-operative Bank
9	East African Breweries
10	Equity Group
11	KCB Group
12	KenolKobil
13	Kenya Airways
14	Kenya Electricity Generating
15	Kenya Power Lighting
16	Nation Media
17	Safaricom
18	Sasini
19	Standard Chartered Bank
20	WPP-Scangroup

Source: NSE (2017)

Appendix III: Sample of Data Collection Sheet Period 2010-2017

		NSE -20 share Index	**Natural log of index**	**Daily Return on Index**
Year	Day& Month	P_t	Ln P_t	Ln P_t-Ln P_{t-1}
2010	29/Jan/10	3,565.28	8.178997871	-0.20%
	28/Jan/10	3,572.36	8.180981721	-0.74%
	27/Jan/10	3,598.81	8.188358514	-0.23%
	26/Jan/10	3,607.14	8.190670494	-0.01%
	25/Jan/10	3,607.45	8.190756431	-0.59%
	22/Jan/10	3,628.68	8.196624225	0.00%
	21/Jan/10	3,628.53	8.196582887	-0.32%
	20/Jan/10	3,639.99	8.199736213	0.81%
	19/Jan/10	3,610.60	8.191629243	1.81%
	18/Jan/10	3,545.82	8.173524724	1.55%
	15/Jan/10	3,491.18	8.157995067	1.87%
	14/Jan/10	3,426.41	8.139268345	1.65%
	13/Jan/10	3,370.37	8.122777810	0.77%
	12/Jan/10	3,344.54	8.115084444	-0.15%
	11/Jan/10	3,349.59	8.116593229	1.38%
	8/Jan/10	3,303.56	8.102755954	0.64%
	7/Jan/10	3,282.58	8.096384978	0.49%
	6/Jan/10	3,266.53	8.091483538	0.38%
	5/Jan/10	3,254.26	8.087720186	-0.21%
	4/Jan/10	3,261.17	8.089841306	0.00%

Source: Researcher (2018)