An Assessment of select market timing strategies' performance in Nairobi Securities Exchange

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DECLARATION

I declare that this thesis is my original work and has not been presented to any other to university for the award of a degree. Any work done by other people has been properly acknowledged. To the best of my knowledge and belief, this thesis contains no material previously published or written by another person.

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Sign……. ………Date….3rd June 2019.

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DEDICATION

Dedicated to;

Aurora-Deschanel W.W.

ABSTRACT

Herding behavior among Kenyan traders in the capital markets has been majorly attributed to low levels of income and lack of trading expertise. This focus of this study was on the latter challenge. The study is meant to benefit equity traders in determining optimal entry and exit points in equity markets. The study evaluated the performance of three market timing strategies namely the relative strength index (RSI), simple moving averages (SMA) and hidden Markov model (HMM). This study was based on primary data as well as secondary data. The Secondary data considered in this study included the share price of the NSE-20 index over the period 2004-2018 and share prices of select companies over the years 2011-2018. The primary data was collected from equity dealers working in Kenya fund manager firms, triangulated to the perceptions and opinions of trading experts in Kenyan fund manager firms. Descriptive statistics were used to analyze primary date and the findings compared secondary data findings before making recommendations. The performance of market-timing strategies in this study was determined by a strategy's average annual returns, Sharpe ratio as well as a market timing ability. Using Henrikson and Merton market timing model, this study shows that all the market timing strategies have positive market timing strategies, with HMM having the best market timing ability. By accommodating the autoregressive nature of financial prices this study examined the ability of the strategies to time the market using an autoregressive distributed lag (ARDL) model. The model shows that all the strategies lack the ability to time the market but just like in Henrikson and Merton model, HMM performances ranks best among the three strategies. Over the period 2004-2018 the Sharpe ratio of all the market timing strategies exceed that of SBH. The same is observed when simulated data is used instead of the observed data, on individual stocks as well as in a portfolio setting. When all the tests are considered the performance of HMM strategy ranks first followed by SMA, RSI while SBH was determined to be the least profitable trading strategy. In Kenya, this study found that investors are averse to market timing strategies and tend to herd towards buy and hold strategy. Given the low profitability of the SBH strategy in NSE, this study recommends the use of HMM as a trading strategy to determine entry and exit points.

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LIST OF ABBREVIATIONS AND ACRONYMS

ARLD-M	Autoregressive Distributed Lag Model
CMA	Capital Market Authority
EMH	Efficient Market Hypothesis
FMH	Fractal Market Hypothesis
GBM	Geometric Brownian Motion
HM	Henrikson and Merton
HMM	Hidden Markov Model
HSD	Honestly Significant Difference
MS	Markov Switching
NSE	Nairobi Securities Exchange
RSI	Relative Strength Index
SDE	Stochastic Differential Equation
SMA	Simple Moving Averages
SBH	Simple Buy and Hold

DEFINITION OF TERMS

In the context of this study the following terms will be used to mean;

Hidden Markov Model- A hidden Markov model refers to a variant of Markov models used to fit data that transits between finite states over time. The states themselves are not directly observable and the model is used to deduce the probability of being in a given state at a particular point in time (Awad & Khanna, 2015).

Market Timing- This refers to the determination of optimal buying and selling points in financial markets based on the future outlook of the market states. This is can be done using either technical analysis and or fundamental analysis (Metcalfe, 2018).

Market Regimes/Phases- From Dapena, Serur, & Siri (2018) market regimes refers to states of constant mean and variance through which a process passes. In financial markets, these are taken to represent the bull and bears states of the market.

Performance- This term was used to represent the ability of the market-timing strategy to earn above market returns. It is also synonymous with profitability and viability, this is in line with De Souza, Ramos, Pena, Sobreiro, & Kimura (2018) and Zakamulin (2018) where profitability has been used in this sense.

Relative Strength Index- This is a market timing technique that is based on share price momentum. The strategy determines trading points based on a graphical oscillator which ranks from zero to a hundred percent, Chiang, Ke, Liao, & Wang (2012). This technique is a modification of the relative strength method.

Simple Moving Averages- This is a market timing technique, where buy or sell points are indicated by cross-over of different moving averages (Reilly & Brown, 2011). The method is widely used in technical analysis due to its simplicity (Ilomaki, Laurila, & McAleer, 2018).

Simple Buy and Hold – This is the trading strategy which is opposed to market-timing. It is applied where the market is deemed to be efficient. According to strategy gains in the market can only be realized by trading financial assets after holding them in the long-run (Sanderson & Lumpkin-Sowers, 2018).

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

According to a 2016 survey on the Kenyan capital market only 4% of the Kenyans invest in Nairobi Securities Exchange (NSE) (Oxford Business Group, 2016). In 2018 the Capital Markets Authority (CMA) sought to understand the root cause of the low participation by the local investors. The study majorly attributed the low uptake to low income among Kenyans and lack of trading know-how, (CMA, 2018). As Fransiska, Sumani, & Pangestu (2018) found out, lack of knowledge in trading principles contributes to herding behavior among investors. Szyszka (2013) defines herding behavior as a scenario where investors tend to follow others without any proper analysis of their own. It is therefore conceivable that Kenyans shy away from financial markets due to the perils of herding which include mispricing of securities.

In the bid to maximize returns, an investor aims at buying when the market prices are low and disposing of the holdings when the prices are at the peak (Guidolin & Timmermann, 2005; Kanojia & Arora, 2018). Whereas this assertion may appear theoretically simplistic, practically the determination of the buying or selling point is not straight-forward. To arrive at the 'optimal' trading points, technical analysts attempt to forecast the behavior securities are likely to follow in future, using a varied array of market-timing techniques (Kanojia & Arora, 2018). As many as they are, no one predictive technique has a hundred percent forecasting accuracy (Macchiarulo, 2018). The foregoing has managed to keep researchers interested in continued modeling of financial market dynamics in a bid to develop more precise modeling approaches.

Peters (1994) proposed the Fractal Market Hypothesis (FMH) as a theory that can be used to explain the behavior of security prices. The theory posits that the prices in the exchange market are fractal in nature. Singh, Dimri, & Rawat (2013) found that prices in India followed fractal geometry their study's conclusion was in concurrence with Peters (1994). Technical analysis focuses on future forecast based on past observation in the markets. In line with FMH, technical analysts believe that the market is made up of self-replicating realizations (Kristoufek, 2012; Singh et al., 2013). As such proponents of technical analysis believe that the prices in the market follow a repetitive pattern. These patterns can then be used to deduce profitable trading points. This is called market-timing. On the contrary, individuals opposed to technical analysis tend to follow Fama's (1970) Efficient Market Hypothesis(EMH). According to EMH, for markets which are at least weak-form efficient, the past prices' information is deemed incorporated in the current prices. The theory, therefore, argues that trading strategies based on historical prices will always be futile.

The findings of the study by Ndegwa & Mboya (2015) were that NSE was weak-form efficient. Their findings were similar to those of Bulla (2015), who also concluded that NSE was efficient in the weak-form. According to EMH, this would imply that use any market timing strategy would not earn investors above-market returns. Contrary to the findings by Ndegwa & Mboya (2015) and Bulla (2015) performing weak form efficient tests on the same market Njuguna (2017) concluded that NSE was not efficient in the weak form her findings mirrored those of Owido & Bichanga (2014) who also found weak form inefficiency in NSE. The findings by Njuguna (2017) and Owido & Bichanga (2014) are similar to findings in other exchanges across the world; Taiwan (Nguyen, Chang, & Nguyen, 2012), South East Asia (Nisar & Hanif, 2011), Europe(Dutta, 2015) and in South Africa(Grater & Struweg, 2015). Given the differences in these findings, it is not possible to infer if market timing strategies would work in NSE or otherwise.

The financial markets are complex systems (Tsviliuk, Zhang, & Melnik, 2010). The underlying system of equations that govern them is sophisticated and hard to model, owing to many factors and actors that influence them (Brooks, 2014). Inherent in financial markets are two predominant regimes observed over time. One, a period of decreasing value of financial assets, (bear market), followed by a period of increasing financial prices, (bull market). A study based on National Stock Exchange of India concluded that it is possible to model investors perceptions in bear and bull regimes and be in a position to develop viable trading strategies based on market-timing (Rout, Mohanty, & Kacharia, 2017). This study sought to add on to the findings of these studies by evaluating the viability of market-timing strategies in NSE.

Market trading strategies can globally be viewed as functions of time. The trading strategies can then be viewed in two broad categories; active and passive trading strategies. In active trading, traders continuously look for profitable opportunities to exploit either using fundamental analysis or technical analysis. On the other hand, the passive trading strategy is followed by proponents of EMH theory who believe that there are no instances of mispricing. The passive strategy, therefore, entails buying and holding an investment for a given time horizon. It is therefore evident that in either case investors are concerned with the determination of the optimal entry and exit points. "An investor enters or exits a market based on the future expectation about the market, likewise, the asset allocation decisions are also based on the perceived future states"(Guidolin & Timmermann, 2005).

There is no consensus on superiority between active and passive trading strategies. In Sweden, Svanberg & Karlsson (2018) compared the returns of both actively and passively managed funds. The study found out that even though actively managed funds charged higher fees, the fees had no relationship with risk-adjusted returns. The study recommended a passive management strategy for investors without trading knowledge. Dyck, Lins, & Pomorski (2013) investigated the returns gained by institutional investors both in the United States (US) and in other emerging markets. Their finds were that in the US passively managed investments outperformed those under active management, however, for the emerging markets, the opposite was found to be the case. Naidoo (2017) comparing the performance passively and actively managed funds concluded that neither strategy could outperform the market. The study, however, noted that by inter-comparison analysis, actively managed funds performed better than the passively managed. Contrary to the findings of Naidoo (2017), in Kenya, Nyamute, Lishenga, & Oloko (2015) found that active management strategies could not outperform the passive management strategy. This study sheds light on the controversy between active and passive by analyzing the equity returns in NSE using market-timing strategies vis a viz simple buy and hold (SBH) as variants of active and passive trading strategies, respectively.

From studies conducted in various stock exchanges across the world, two strategies have been shown to have the best market timing abilities. The two strategies are the relative strength strategies which are based on price momentum and moving average strategies(Abbad, Fardousi, & Abbad, 2014; Gurrib, 2014; Masry, 2017). The two techniques are used as indicators of impending bull or bear markets, in so doing analysts are able to identify potentially profitable trading opportunities. Hidden Markov Model (HMM) has emerged as a promising modeling technique in many fields of, especially where systems follow cyclic behavior (Chis & Harrison, 2015). Given that financial markets oscillate between bear and bull markets the model is deemed applicable as a market timing strategy. This study sought to evaluate the performance of relative strength index and simple moving average strategies which are widely used and in addition HMM which is relatively less popular but has application in quantitative finance.

Moving averages form the basics of technical analysis and as reported by Glabadanidis (2015) it is the oldest and most popular strategy followed by investors who apply technical trading rules. The averages are able to bring out patterns based on the historical prices of instruments traded in financial markets. With discernible market patterns, the future direction of the prices can then be predicted (De Souza, Ramos, Pena, Sobreiro, & Kimura, 2018). Zakamulin (2016) demonstrates that all market-timing trading rules have their foundations in moving averages. This shows the significance of the strategy in market timing. There are many trading strategies based on moving averages which include; simple moving average (SMA), exponential moving average (EMA), linear moving averages among others. In this study moving average analysis was based on SMA. This is due to the following reasons. First, this' study concern is the profitability of trading based on bull and bear cycles in the market, as such, all the cycles are considered equally important and therefore equal weighting is more appropriate. Second, instances where the performance of SMA is outdone by EMA as is the case in Raissi & Zakkizade (2011) and Zakamulin (2016), it can be noted that the decay factor is always close to one. A decay factor of one in EMA converges to the SMA.

The SMA strategy is derived from the use of the arithmetic mean of the closing share price over a period of time. The most commonly used SMA strategy is the double crossover moving (DCM) averages. In this method, trading points are generated based on the nature of cross-over points of two moving averages whose averaging window is different. Many studies across the world have shown the superiority of SMA to SBH; Todea, Zoicaş-Ienciu, & Filip (2009) in selected European countries, Nguyen & Zhaojun (2013) in Asian markets and El-Hokayem, & Hejase (2016) in Lebanese Stock Exchange. Similarly, De Souza et al. (2018) found that investors in South Africa could trade profitably using SMA. In analyzing the profitability of technical trading rules in the Kenyan currency exchange market, Wanjiku (2016) applied simple moving averages trading rule. The study concluded that in concurrence with other studies like Nguyen & Zhaojun (2013) and Todea et al. (2009) the strategy was indeed profitable and that profitability only declined when there was government intervention.

The relative strength trading strategies are market-timing methods that are based on price momentum. The Relative Strength Index (RSI) from the work of Wilder (1978) is the most commonly used relative strength strategy. RSI strategy involves graphical representation of an oscillator that over time vacillates stochastically between zero and one hundred. Trading signals are generated when the oscillator reaches certain thresholds. Zero indicates a pure oversold market implying that bull-market is imminent and hence a signal to buy while conversely, a reading of a hundred indicates that the market is purely overbought and hence a signal to sell, (Wong, Manzur, & Chew, 2003). In practice, traders do not wait for the oscillator to reach the two extrema instead the readings of thirty and seventy are used as signals of oversold and overbought conditions, respectively.

The success of RSI as a market-timing strategy is widely documented. Cohen & Cabiri (2015) tested the performance RSI against five global indices. The study found out that RSI outperformed the indices in four out of the five cases. In Taiwan it was found that the RSI strategy outperformed eight other technical trading strategies including SMA and SBH as well, (Chiang et al., 2012). In modeling, the exchange rate between the US dollar and Deutschmark Shik & Chong (2007) found that RSI was more profitable compared to SMA strategy.

The HMM represents a variant of machine learning methods. This method relies on conditional probabilities to determine the chance of the most likely outcome based on training data. HMM is widely used in multiple fields notably in speech and handwriting recognition. A Markov model refers to any system that makes transitions from a given state to another. The term hidden in HMM implies that the states into which the system transits to are not observable. In finance, the market prices are deemed to be generated from either the bull or bear market states. The two states are however not observable. Given so HMM model can be fitted to deduce probabilistically the most likely state that generated a given observed share price. As such the HMM model is able to indicate the points at which markets shift from bull to bear regimes. These points can then be used by technical analysts as buying or selling points.

The HMM model has been studied by various researchers in quantitative finance. Kavitha, Udhayakumar, & Nagarajan (2013) found that in line with FMH market-patterns are repetitive in addition the study showed how the HMM model can be trained to learn these patterns. By analyzing large-cap stocks in the USA between 2000 and 2011 Ahuja & Eksombatchai (2012) determined that investors could apply HMM to trade profitably. In their study, HMM was found to outperform SBH for most stocks. Fu & Wu (2017) performed a comparative analysis of HMM against DCM and SBH in China and in the USA. The study concluded that HMM risk-adjusted returns generated by HMM in the two markets surpassed those of SBH strategy. Sun (2018) by analyzing three Chinese Stocks in Telecom industry also concluded that market-timing using HMM was indeed more profitable compared to SBH. The study further showed that by extending the market states to three states, HMM was able to identify not just the buy/sell points but also points in which buy and hold strategy was more appropriate. On a single stock price modeling, Otieno, Otumbo, & Nyabwanga (2015) sought to understand the trend of the share price of Safaricom and derive the probabilities of the future states the share price will be in, based on Markov modeling. The study showed that investor could rely on this strategy to decide if it was worthwhile holding onto a given share.

The studies reviewed so far in this study shows that SMA, RSI and or HMM as market-timing strategies outperform the SBH strategy. However, it is to be noted that this performance is not universal. There are studies which on the contrary have shown SBH strategy to be the most profitable trading strategy. In Italian Market Borri & Cagnazzo (2018) concluded that for the equity mutual funds in the country the SBH trading strategy outperformed market-timing strategies. These findings closely match those of Zakamulin (2018), who found out that the superiority of moving averages reported by Glabadanidis (2015) was mainly due to look-ahead bias. His study showed by eliminating the bias the returns of SMA were not statistically different from those of SBH.

RSI and SMA are widely used and relatively quite successful trading strategies as shown in (Chiang et al., 2012; Cohen & Cabiri, 2015; Glabadanidis, 2015; Hejase, El-Hokayem, & Hejase, 2016). However, the two strategies suffer a major shortcoming in that they can only act as graphical indicators, (Reilly & Brown, 2011). As such the two technical indicators cannot be used as statistical models of future trends, they can only be used to infer when a regime change is likely to occur. Even though the HMM strategy is not widely used as RSI and SMA, the strategy can be used as a trend indicator as well as a statistical forecast tool. This technique is backed by the solid statistical foundation, like sell or buy points are determined by the switching of returns and variance from one regime to another (Hassan & Nath, 2005). Though there are studies which have compared the performance of the HMM model to SMA and in other cases RSI, the performance has been in terms of absolute profit. This study is the first to analyze the performance using Henriksson & Merton (1981) model. The model is able to deduce if a strategy has the market-timing ability and in addition provide a ranking of the strategies analyzed.

From the HMM models implemented in Sun (2018), Ahuja & Eksombatchai (2012) and Fu & Wu (2017) it can be noted that the models were either modeled using either daily or weekly differenced share prices. On the positive side of such analysis is that the data studied is stationary on the negative side stationarity infers that share-prices contain no past information. This negates the principles of technical analysis and furthermore negates a stylized fact of financial data, that is, financial prices possess serial correlation, (Brooks, 2014). This study is the first to evaluate the profitability of an extended HMM which allows for auto-regression. By allowing for auto-regression this study used the assertion that 'market-timing strategies are a function of moving averages' by Zakamulin (2016) and model, HMM using returns ten-month smoothed share prices instead of daily prices. This helped in the identification of trading points based on true bull-bear regime switches.

1.2 Problem Statement

In the CMA (2018) low participation in capital markets was attributed majorly to lack of trading awareness and low levels of income. Lack of trading knowledge is a contributing factor to the herding effect (Fransiska et al., 2018). Herding effect causes mispricing in security prices. It is therefore conceivable that Kenyans do shy away from capital markets since they trade at the wrong price and therefore end up losing on their investments. The objective of this study was to analyze the performance of market-timing strategies in NSE and provide recommendations to current investors and potential investors on the strategies they can apply to trade profitably in NSE.

Studies have shown that market-timing strategies work in developed markets, (Fu & Wu, 2017; Shik & Chong, 2007; Sun, 2018), in emerging markets (Masry, 2017; Metghalchi, Hayes, & Niroomand, 2018; Singh et al., 2013) and in frontier markets as well (Nyamute et al., 2015; Wanjiku, 2016). Ability to profit from market timing implies that EMH in its basic form (weak form) fails to define the behavior of security prices in the market. Given that the theory is widely taught would imply that financial students are being taught a fantasy rather than what is there in a practical sense. This study looked at the possibility of trading profitably based on market patterns (which would infer fractal behavior in NSE) or otherwise (which would imply that NSE follows EMH hypothesis).

Lastly, this study addresses the problem in the estimation and evaluation of HMM profitability in previous studies. In estimation, Sun (2018), Ahuja & Eksombatchai (2012) and Fu & Wu (2017) all estimated the model without allowing auto-regression which is inherent in share-returns. Failure to account for auto-regression leads to the realization of wrong model parameters and hence wrong conclusions (Mills & Markellos, 2008). Furthermore, the studies on HMM have not focused on the determination of entry and exit points in equity markets of frontier markets. This study addressed this challenge by choosing an estimation method that allowed for auto-regression and applying the model to determine the entry and exit points in NSE.

1.3 Research Objectives

1.3.1 General Objective

The general objective of this study was to evaluate the performance of select market-timing strategies in the Nairobi Securities Exchange.

1.3.2 Specific Objectives

1. To analyze the performance of RSI, SMA and HMM market-timing strategies in Nairobi Securities Exchange.
2. To determine the most profitable market-timing strategy among RSI, SMA, and HMM in Nairobi Securities Exchange
3. To establish the significance of market timing strategies to fund managers in Kenya.

1.4 Research questions

1. How do RSI, SMA and HMM market-timing strategies perform in Nairobi Securities Exchange?
2. Which is the most profitable trading strategy among SMA, RSI, and HMM in Nairobi Securities Exchange?
3. What significance do Kenyan fund manager firms attach to market timing strategies?

1.5 Scope of the Study

This study sought to provide an evaluation of the profitability of various market-timing strategies. The study focused on the profitability of commonly used trading strategies; SBH, SMA and RSI and in addition also analyzed the profitability of the HMM when applied as a market-timing strategy. The analysis was limited to NSE and only applied the equity market index as the indicator of the general movements in financial markets in Kenya. The period of analysis was from 2004 to 2018 based on evident structural break in the economy. The primary source of primary data was sourced from the registered fund managers in Kenya. The primary role of fund managers is to optimize returns and as such the individual equity traders in such firms were deemed best respondents for this study.

1.6 The significance of this study

1.6.1 Fund managers and individual investors

This study seeks to provide financial literacy to Kenyans invested or who would like to invest in NSE. The findings of this study provide in detail how an individual can assess the market and trade profitably. The role of fund managers is to earn a gain on the portfolios they are responsible for, this may necessitate alteration of portfolio occasionally. By comparing the performance of market-timing strategies with the performance of the buy and hold strategy, this study was able to provide evidence for active management of equity investments in NSE.

Investors who follow active trading based on market-timing usually employ the services of financial analysts. This, therefore, raises their transactional costs. This study proves that the market-timing strategies considered here are profitable, this can be considered as a rationale for fees paid to such analysts. This study shows that an investor who buys and holds a given equity instrument is more likely to lose than an investor who trades based on considering market timing strategies.

1.6.2 Capital market policy makers and players

The role of investor education is legally bestowed upon CMA. As such investor education is a strategic objective as noted in their strategic plans. In the 2018-2023 strategic plan, the authority notes that’s in the 2013-2017 strategic plan all activities towards investor education and awareness were fully implemented but the objective was not achieved. In the 2018-2023 plan, the authority hopes to partner with the ministry of education and intermediaries to boost investor education.

Given that investors' objective is to achieve financial gain it was the objective of this study to provide those who will be conducting investor education with information regarding the performance of selected trading strategies. This would ensure that the target subjects are exposed to practical knowledge about trading rules and not just theoretical knowledge.

1.6.3 Researchers and Academics

The debate among researchers on the strength of market-timing strategies is one that has remained unsettled over a long period of time. The debate is on two facets, one if the market-timing strategies can out-perform the market and two if affirmative which strategy performs best. To answer the first question this study evaluated how three market-timing strategies (RSI, SMA)) and HMM perform and compared the respective models' performance to the performance of the market. The second question was addressed by inter-comparison of the models' performance.

This study also extended the HMM model to develop a model that can accommodate time-series that are auto-regressive in nature. The proposed modification provides a new way to analyze auto-regressive data, for example, the currency exchange rate of different countries.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter begins with the theories upon which this study was based on. An empirical review follows, which evaluates the relevant studies covering regime switches and market timing based on various market timing strategies. After empirical review based on the literature surveyed, a section on the justification of the research gap follows, the chapter is then concluded by the conceptual framework that the study followed.

2.2 Theoretical Framework.

The section presents a set of theories that are relevant in explaining and modeling the behavior of prices in the stock markets. This study relied on three theories; Charles Dow's Theory, Fractal Market Hypothesis, and the Efficient Market Hypothesis. The theories are discussed in detail below.

2.2.1 Dows Theory

Charles Dow's works of 1896 in financial market analysis presents one of the earliest techniques developed to forecast the future states of the market, in what later came to be known as the Dow's Theory after the compilation of the principles from his work by Hamilton in 1902, (Ghobadi, 2014). Dow's Theory compares the movement of stock markets to the movement of sea waters. In particular, the theory says that the market will exhibit three distinct patterns, primary, secondary or tertiary which can be likened to the tides, waves or ripples, respectively. The tertiary phase just like the ripples represents small changes in the stock prices, usually the daily fluctuations. The waves represent bigger stock price changes over a relatively long period compared to the ripples. The final phase is the tidal action, this phase is characterized by long and significant changes in the averages of the stock prices (Hammond, 2018).

The theory explains that rational investors are neither too concerned by ripples nor the waves but the tidal action of the primary phase (Ghouse & Ahmad, 2014; Reilly & Brown, 2011). The primary phase shows two distinct and persistent regimes. The bull and bear regimes characterized by persistent increase and decline of prices respectively. Each of the regime according to the theory will have three phases. The three phases in the bull regime are; one, the revival of confidence in the markets, followed by a good response by stock prices owing to the improved economic system, the final state is marked by widespread speculation and evident inflation. This phase paves the way to the first of the three phases of the bear regime. The phase realization that the stocks were at an inflated price and subsequent abandonment of hopes in stock markets, (Yadav, 2017). A key feature that hinges Dow's Theory is reliance on average. According to the theory, the averages speak volumes. Its proposition is that at any particular point in time, the averages represent all that is known and that which can be foreseen by ordinary people and financial analysts. As such the averages are known to incorporate all the information that has any relevance to the market. The only exception is 'acts of God', and even in that case, the theory postulates they after effect are quickly incorporated (Lowenstein, 1996).

The theory has been criticized for the late identification of changes in market phases and lack of statistical tests, (Ghobadi, 2014). Notwithstanding, the theory has been widely applied for over a century and still has relevance to date. The theory has been advanced to develop trading rules which are guidelines for investment strategies, (Reilly & Brown, 2011). The significance of this theory was that the evaluation of all the strategies was based on the moving averages of daily actual or differenced share prices

2.2.2 The Fractal Market Hypothesis

The process followed by financial markets is assumed to be governed by Geometric Brownian Motion, (GBM). Brownian motion is used to model processes which are subject to randomness, elsewise known as "noise". GBM refers to a lognormal stochastic process in continuous time which is defined by a combination of a deterministic part (drift) and a stochastic part (volatility), (Hull, 2014). Of relevance to this study are two properties of Brownian motion, independent increments and that Brownian motion processes have continuous sample paths. The latter two properties yield Fractal Brownian Motion which is a generalization of Standard Brownian Motion, (SBM), (Leonenko, Petherick, & Sikorskii, 2012). A Fractal Brownian motion with independent increments through time is characterized by a self-similarity a feature which is quite profound in financial time series. The financial markets will exhibit a pattern of up and down irrespective of the time span selected.

The Fractal Market Hypothesis, (FMH) was coined and formalized by Peters (1991) by applying fractal geometry, proposed by Mandelbrot (1982) and later revised it in Peters (1996). Due to the shortcomings of the Efficient Market Hypothesis, FMH has been recommended as an alternative to EMH. Unlike the Efficient Market Hypothesis, which assumes a single investment horizon for all investment FMH is premised on the position that the stability of the market is defined by the variant time horizons for all market participants. FMH is able to provide an explanation of the behavior through the cycles inherent in financial markets. The theory has also been used to explain extreme events occasionally witnessed in financial markets (Kristoufek, 2012). FMH is based on a central premise that history repeats itself and, the stock market follows a cyclic and repetitive pattern. The theory is central to financial technical analysts. In this study, the feasibility of market-timing strategies assumes that history repeats itself and as such the historical prices can be used to estimate the most likely future market conditions.

2.2.3 Efficient Market Hypothesis

The EMH theory was developed by Eugene Fama in 1970. The theory classifies the states of the market based on their ability to incorporate the past, present and future information in the trading prices of the securities. A weak form of efficient markets refers to a market which is only able to incorporate past information, semi-strong markets incorporate the present and past information, whereas the strong form efficient markets are able to incorporate the past, current and future information in the trading prices (Fama, 1970).In his work, Fama Posited that markets in the weak form of efficiency took time to reflect the information in the market, as such markets could form patterns which could be predicted and potentially earn above market returns. On the other hand, the semi-strong form of efficiency inferred that no matter what technique applied to forecast future prices could not work (Fama, 1970). In concussion Buguk & Brorsen (2003) supported the work of Fama and in addition showed that markets in the developing stage were likely to fall under a weak form of market efficiency, this latter finding has also been supported by Tharavanij et al. (2015).

Fama (1970) model of classifying the markets has received a fair share of criticism. First, the theory assumes at the very worst, the market prices will incorporate all past information at any given time. However, Dong, Bowers, & Latham (2013), by analyzing equity indices in the United States, showed that at times certain markets portray information digestion effect thus fail to meet the basic weak form of market efficiency. Central to the EMH theory is the assumption that the market is made up of homogenous and rational players operating in a perfect market. The practicality of this in the markets has been criticized, markets are actually imperfect with heterogeneous rational and irrational players. As such future predictions in developing and developed markets are possible, (Malkiel, 2003). Kristoufek (2012) argues that market predictability does not necessarily infer market inefficiency given that the future expectation will be interpreted differently by the different users of the predictions.

This study relied on the precept of this theory that developing markets are likely to be EMH-inefficient, portraying patterns which can be modeled to derive future forecasts. This study sought to evaluate if there exist such patterns in NSE and if so if investors can rely on such patterns to trade profitably.

2.3 Empirical Review

This section presents the findings of the studies that have been carried out in relation to three thematic areas of interest to this study; market regimes, commonly used market timing strategies (moving averages and relative strength) and then an empirical review of the HMM model and its applications in finance. The review follows the categorical approach than a systematic review based on how the findings inform this study.

2.3.1 Bull and Bear Market Regimes Turning Points' Timing

Deb, Banerjee, & Chakrabarti (2007) defined market timing as the skills necessary to correctly assess the direction of the markets, bull or bear and position portfolio(s) accordingly. Prevailing market phases play an important role in investors' decision of buying or disposing of securities (Kole & van Dijk, 2013). As such investors are interested in the identification of which regime the market is in at any given point in time. Market phases are mainly determined on ex-post (based on observed data) basis, informed by distinct returns characteristics and persistence duration, (Gonzalez, Hoang, Powell, & Shi, 2006). The investors can then use the identifications to make ex-ante (forecast based) trading strategies.

Ex-post identification follows two approaches, parametric and non-parametric. An example of Non-parametric market-regime identification methods includes algorithms by Bry & Boschan (1971)-(BB-algorithm), Pagan & Sossounov (2003) as well as Lunde & Timmermann (2004) while Markov-Switching model is the commonly used parametric approach. Non-parametric identification methods determine local minima and maxima in cycles, then establish rules to extract the turning points. In Pagan & Sossounov (2003) the study imposed a restriction on the duration a market must remain in a given state before a shift is considered on the other hand Lunde & Timmermann (2004) imposed restrictions in terms of price change between one trough and the next peak and vice-versa.

Comparing how parametric and non-parametric methods perform in the identification of cycles in equity markets based on S&P 500, Pagan & Sossounov (2003), in their study concluded that non-parametric BB algorithm dating performed better than Markov-switching (MS) model. A similar conclusion was drawn by the Kole & van Dijk (2013), who found out that in terms of in-sample identification of market states non-parametric methods out-performed the MS model. In terms of out-sample predictions, MS-model was found to have higher statistical accuracy. This was attributed to the model's ability to take into account both the signs and the volatility of returns and in addition ability to accommodate booms and crashes (Kole & Dijk, 2017).

2.3.2 Trading Strategies Based on Market Phases

There are many technical trading strategies that are used in the financial markets, including; moving averages indicators, candle-stick charts, relative strength indicators, machine learning among others. Glabadanidis (2015) found that trading strategies based on moving averages are the most popular. In concurrence Rousis & Papathanasiou (2018) and Wong et al. (2003) determined that moving average strategies to be popular in addition they also noted that relative strength index strategy was quite popular as well. In light of these studies, this subsection reviews empirical works that have been conducted in relation to the performance of the two strategies in financial markets.

2.3.2 .1 Moving Averages Strategies

Moving averages form the basis of technical analysis. The averages are able to bring out patterns based on the prices of instruments traded in financial markets. With these patterns, the future direction of the prices can then be predicted (De Souza, Ramos, Pena, Sobreiro, & Kimura, 2018). There are many variants of moving average trading strategies; simple moving averages, exponential moving averages, linear weighted moving averages, reverse exponential moving averages (Pal, 2009; Reilly & Brown, 2011; Zakamulin, 2018). The commonly used moving averages strategies used in financial market timing are simple moving averages and exponential weighted moving averages (Glabadanidis, 2015). While simple moving averages assign equal weights to the past observations included in getting the average values. The exponential smoothing, on the other hand, assigns more weight to the more recent observations. Praekhaow

(2010) analyzed the profitability of using trading points determined by simple moving averages, weighted moving averages, and exponential moving averages. The study was limited to fifty stocks in Thailand stock market. The study found out that all methods were profitable, however, the SMA strategy was the most profitable.

As opposed to the findings Praekhaow (2010) tests done moving average trading rules, Pavlov & Hurn (2009) found that trading on exponential moving average had the best returns, though contrarian. The study was based on securities listed in the Australian Stock Exchange (ASX) over the period 1973-2008. The study considered monthly returns as the aggregate of the capital gains plus dividend yield. In conclusion, the study pointed out that the simple moving averages could not adequately describe the behavior of financial prices and recommended that further investigation into the force that drives the behavior in financial markets, (Pavlov & Hurn, 2009).

For the period 2005-2012 Greece conducted four general elections and the country was also affected by the financial crisis in 2011. Rousis & Papathanasiou (2018) showed that using SMA trading rules an investor could be able to earn significant profit in the stock market, regardless of the prevailing economic conditions in the said period is in line with Dows This is in line with Dow's theory which asserts that in the long run there exist patterns in financial markets. The patterns remain unchanged due to one of the basic tenets of Dow's Theory; the averages discount everything (Lowenstein, 1996).

The Study by Todea et al. (2009) sought to establish the profitability of SMA trading rules and dynamics of such rules. In the study, five market indices from five European countries were analyzed over a period of 10 years from 1997-2008. The study found out that there exist profitable opportunities in financial markets which occur from time to time. These opportunities were attributed to linear and non-linear dependencies in stock markets. The study applied Portmanteau tests to test linear correlations and bi correlation for nonlinear cases based on a rolling sample. The study asserted that financial time's series contains trends and furthermore the cross-over between short-term moving averages could be used to detect a shift in trends (Todea et al., 2009). On profitability, a study based on selected Asian markets arrived at the same conclusion that moving averages are profitable (Nguyen & Zhaojun, 2013). This study further provided evidence that short-term moving averages were more profitable to the longer-term moving average. Even though profitable, it was found that the strategy could not return positive excesses when transaction costs were considered.

In their analysis of the profitability of trading using technical analysis, De Souza et al. (2018) used SMA cross-over rules in an automated environment to establish viable entry and exit points in BRICS Block stock markets. Compared to SBH, their study found that the trading informed by moving averages gave far superior returns just like in (Nguyen & Zhaojun, 2013; Praekhaow, 2010; Todea et al., 2009). In their study, they further found that though taken as a block, the profitability of SMA exceeded that of SBH strategy, the results are taken as country-specific were not homogeneous. While in some countries SMA exceeds the SBH strategy in others this was not the case. In Lebanese Stock Market Hejase, El-Hokayem, & Hejase (2016) analyzed how SMA compare to the SBH. The study found that SMA had a strong predictive ability and outperformed the SBH strategy.

Ansary & Atuea (2017) analyzed the bull and bear markets in the Egyptian stock market for the period 1998 to 2016 using moving averages. They concluded that trading based on the timing of the bull and the bear markets was profitable in addition similar to the finding in Nguyen & Zhaojun (2013) they too concluded that trading on short-term simple moving averages was not profitable at all. Davies (2013) by analyzing the All Share Stock Index (ALSI) in South Africa provided statistical evidence of how the bull and bear markets can be modeled and in addition be predicted. He argued that timely detection of a turning point and active portfolio management would help investor earn superior returns to passive SBH. This assertion is validated by the findings of De Souza et al. (2018) who found that market timing using SMA in South Africa was indeed profitable when applied to the South African equity market. However, contrary to the findings of Ansary & Atuea (2017) and Nguyen & Zhaojun (2013) that short-term trading was not profitable, they found that within given ranges short-term moving averages as a strategy was profitable in South African.

2.3.2 .2 Relative Strength Index

Relative strength index, developed by J. Welles Wilder in 1978, is a momentum oscillator that measures the speed at which price movements' change, (Wilder, 1978). According to Wilder's formulation, the oscillator oscillates between zero and a hundred percent The RSI can be used to signal the end of a given regime if the index goes above seventy this is taken to mark the coming to an end of a bullish regime, while if below thirty this marks the end of a bear regime, (Ramlall, 2016).

This tool has been widely researched on with mixed results on its ability to earn above market returns. Cohen & Cabiri (2015) by testing the performance RSI against five global indices, found out that RSI outperformed the indices in four out of the five cases. In Taiwan, it was found that the RSI strategy outperformed eight other technical trading strategies including SMA and SBH as well (Chiang, Ke, Liao, & Wang, 2012). In modeling, the exchange rate between the US dollar and Deutschmark Shik & Chong (2007) found that RSI was more profitable compared to SMA strategy. In a comparative analysis, Ghobadi (2014)found that applied in selected commodities and Dollar exchange rate in the London Securities market, returns based on RSI trading were far superior to those of SMA and other strategies like money flow index and commodity channel index, (Ghobadi, 2014). In Lebanese equity markets, RSI was found to have no predictive power and could not out-perform the market returns (Hejase et al., 2016). Focusing on RSI as the sole basis of making investment decisions, Halilbegovic, Celebic, & Kulovic (2018) found that RSI trading strategy was profitable but not consistent. Their study was based on three stocks, Amazon, Apple, and IBM. Regression and paired t-test were used to analyze the results.

2.3.2.3 Limitations of SMA and RSI Market-timing Strategies

A major drawback to RSI and moving averages is that they only work best where the market is operating in oscillations (Gerson, 2010). This is because as reported by Ghobadi (2014), these strategies are basically graphical. This implies that when markets are following persistent and strong trends these indicators tend to lose their predictive ability of market turning points. This can be used to explain why Tharavanij et al. (2015) and Halilbegovic et al. (2018) that technical market timing strategies(moving averages and relative strength index) lacked consistency in their predictions. Another short-coming of graphical market-timing strategies is that they cannot be tested for precision (Ghobadi, 2014).

2.3.2.4 Hidden Markov Model

The Hidden Markov Model is a statistical tool that has been applied in many fields to depict systems that transit through a finite number of states. The model is derived from the intuition that the observed states at any given point in time are driven by ‘unobserved’, states that follow a Markovian behavior. Forecasting using Markov modeling is an area that has continued to draw much attention. This can be explained by the fact that Markov models have a high degree of accuracy in fitting data, especially where the data are nonlinear (Hamilton, 1989). Due to the inability of Hamilton's model to capture state duration dependence, Durland & McCurdy (1994) developed a more parsimonious extension of the Hamilton model to incorporate higher order Markov chains, allowing the transition probabilities to be duration dependent. This work was later extended to have the estimation within Durland & McCurdy (1994) parameterization but with conditioned mean and variance in Maheu & McCurdy (2000).

Finance data are inherently non-linear, which implies that the data-generating process in the field would best be captured by a non-linear model. The HMM model has been proposed as a model that can be used to remedy the linearity shortcomings identified in Towler (2016) and Wyman et al (2013) when it comes to financial applications. The model is premised on a principle that finance variables like prices, interest rates, volatility, etc., are governed by discrete-time, finite-state, hidden Markov chain whose states represent the hidden states of the economy (Chuin & Kuen, 2010). If a system has finite internal states that generate a set of external observations, the internal states are outside the system and the current state is dependent on the previous state, then a state-predictive model can be developed. HMM, models have been developed to model a wide array of financial aspects. In asset prices, the following studies applied the framework to predict the future direction the prices are likely to follow, (Maheu, McCurdy, & Song, 2012; Otieno et al., 2015).

In economic time series modeling these states have mostly been limited to two states (Liu, Margaritis & Wang 2012). By modeling currency returns of four currencies, Naira, British Pound, Japanese Yen, and Euro, Ayodeji (2016) did a comparative analysis of two-state and three-state Markov models. Using information Criteria (Archaic & Bayesian), the study found that the two-state model was more preferred. Maheu, McCurdy & Song (2012) argued that though the two-state model had been applied in various studies in financial modeling, the models were ineffective in financial prediction. Their arguments were premised on the fact that the models formulated before were based on an ex-post assessment of peaks and troughs. They argued that this assessment does not provide enough information to the investors in the market. In response to this problem, the trio proposed a four-state Markov Switching Model that was consistent with the two-state models. In addition to the commonly used bear and bull patterns, they proposed two additional states that precede each state, bear rally and bull correction for the onset of bear and bull markets respectively.

Unlike the rule-based method, which only reflects the direction of the markets in the characterization of bull and bear markets the Markov regime-switching models are favored due to their ability to incorporate the sign and volatility of returns. Due to this ability, Markov regime switching models are known to have a high degree of statistical accuracy of in out of sample prediction and are able to outperform buy and hold strategy earning beyond ten percent in excess returns (Kole & Dijk, 2017). On a single stock price forecasting, Otieno et al. (2015) sought to understand the trend of the share price of Safaricom and derive the probabilities of the future states the share price will be in. The study found that after some time the model went into a stability phase where the future probabilities of being in a given state were constant. The study showed that investor could rely on this strategy to decide if it was worthwhile holding onto a given share. The study was based on a first-order Markov process and recommended further studies in share price modeling by applying for higher order Markov, a similar recommendation was made by Mulinge (2013) who modeled NSE-20 share index using a Markov-Switching model. The study by (Otieno et al., 2015) was however not based on the HMM model but rather the general Markov model.

The study by Zhiyuan & Likai (2010) focused on three models used in financial markets and their ability to predict the S&P 500 index. The three were Markov Model, HMM and Radial Basis Function (RBF). One of the study's finding is that though the Markov model was easy to use and understand, the model had no predictive ability. This finding, therefore, discredits the predictions done by Otieno et al. (2015) who applied a Markov Model to forecast Safaricom PLC shares in Kenya. The second finding of the study was that HMM and RBF had good predictive abilities. It was noted that the two models were affected by volatility and returned significant forecast errors. The errors generated by RBF were noted to be higher than those of HMM in instances of high volatility (Zhiyuan & Likai, 2010).

2.3.2.5 Simple Buy and Hold Strategy

Investors and researchers who are opposed to market-timing believe that the markets are in themselves efficient in the long-run. This implies that such individuals advocate for buying a stock and holding for at least a year without being bothered by the nature of market conditions (Cohen & Cabiri, 2015). Metcalfe (2018) argues that from a mathematical perspective market-timers will always stand to lose.

Technical analysts opposed to the buy and hold strategy argue that information in the market is not as quickly assimilated in the market as postulated in EMH. With this, the technicians' success in technical trading is not governed by the supply-and-demand phenomenon but rather by the sluggishness in the response of stock prices (Wong et al., 2003). As such, they concluded that with market-timing, investors stand a chance to gain above-market returns. However, there are studies which on the contrary have shown SBH strategy to be the most profitable trading strategy. In Italian Market Borri & Cagnazzo (2018) concluded that for the equity mutual funds in the country the SBH trading strategy outperformed market-timing strategies. These findings closely match those of Zakamulin (2018), who found out that the superiority of moving averages reported by Glabadanidis (2015) was mainly due to look-ahead bias. His study showed by eliminating the bias the returns of market-timing were not statistically different from those of SBH.

2.4 Research Gap

There exists a set of studies which show that with appropriate strategies market timing works, (Ghobadi, 2014; Glabadanidis, 2015; Rousis & Papathanasiou, 2018; Shen, 2003). However, there are studies which argue that it is impossible to formulate a profitable trading strategy based on market timing (Borri & Cagnazzo, 2018; Metcalfe, 2018; Zakamulin, 2018). This study, therefore, seeks to shed light on this controversy regarding the performance of market-timing strategies. This study differs from the other studies in that it is the first one to look at the market-timing ability generated by HMM strategy when the model is used as technical indicator alongside common market–timing strategies; RSI and SMA.

Hidden Markov has been shown to have high ability to model economic financial market data with a high degree of accuracy, (Hamilton, 1989; Maheu & Yang, 2016; Maheu & McCurdy, 2000; Pagan & Sossounov, 2003). The HMM model can specifically be applied to model bull and bear regimes where the model is allowed to learn and classify the two variant regimes based on the shifting, but relatively constant mean returns and volatility when considered regime specific. It is, however, to be noted the many of the studies which have focused on modeling of market regimes, (Maheu & McCurdy, 2000; Maheu et al., 2012; Pagan & Sossounov, 2003), interest has been on the goodness of fit of the model. Given that the model is probabilistic, probabilities alone are not sufficient, first, there is a need to translate the probabilities into trading strategies as applied in Sun (2018). But this is not enough, to evaluate the superiority of the Markov model there's a need to compare the model with other market timing models as conducted in Gupta & Dhingra (2012). In their study, however, their comparison was in terms of prediction accuracy and not returns. This study will seek to address the question of how profitable HMM is relative to other known and widely used market timing strategies. The performance of the three market timing strategies was evaluated using Henriksson & Merton (1981) model. There is no study which has been carried out to test market-timing ability based on the said model and thus constitutes a research gap.

This study has also considered the research gaps relating to the estimation and application of HMM as a market-timing strategy. Mulinge (2013) study on NSE using HMM was concluded by establishing the probabilities of a given state, the study does not show how a trader can benefit from these probabilities. In Sun (2018), Ahuja & Eksombatchai (2012) and Fu & Wu (2017) the authors estimated the HMM model without allowing for auto-regression. Auto-regression is a stylized fact of financial time-series and should not be ignored. This study sought to address these gaps which have been identified.

2.5 Conceptual Framework of Evaluating Performance of Market-Timing Strategies

The focus of this study lies on how market traders can improve investment performance by making investment decisions based on market regimes shifts. The study, therefore, evaluated the performance of RSI, SMA, and HMM as a market-timing strategy and determined the strategy that has the best market-timing ability.

The Evaluation in this study was based on three criteria. First, was on the average log by each trading strategy. The second criterion considered the ranking of the strategies after accounting for risk using both the Sharpe ratio and Sortino ratio as well. The last criterion determine superiority in this study was the strength and direction of and the strength of a market timing ability as determined by the Henriksson and Merton (1981) model. The diagrammatic representation of how superiority was determined is portrayed in

Figure 2. 1.

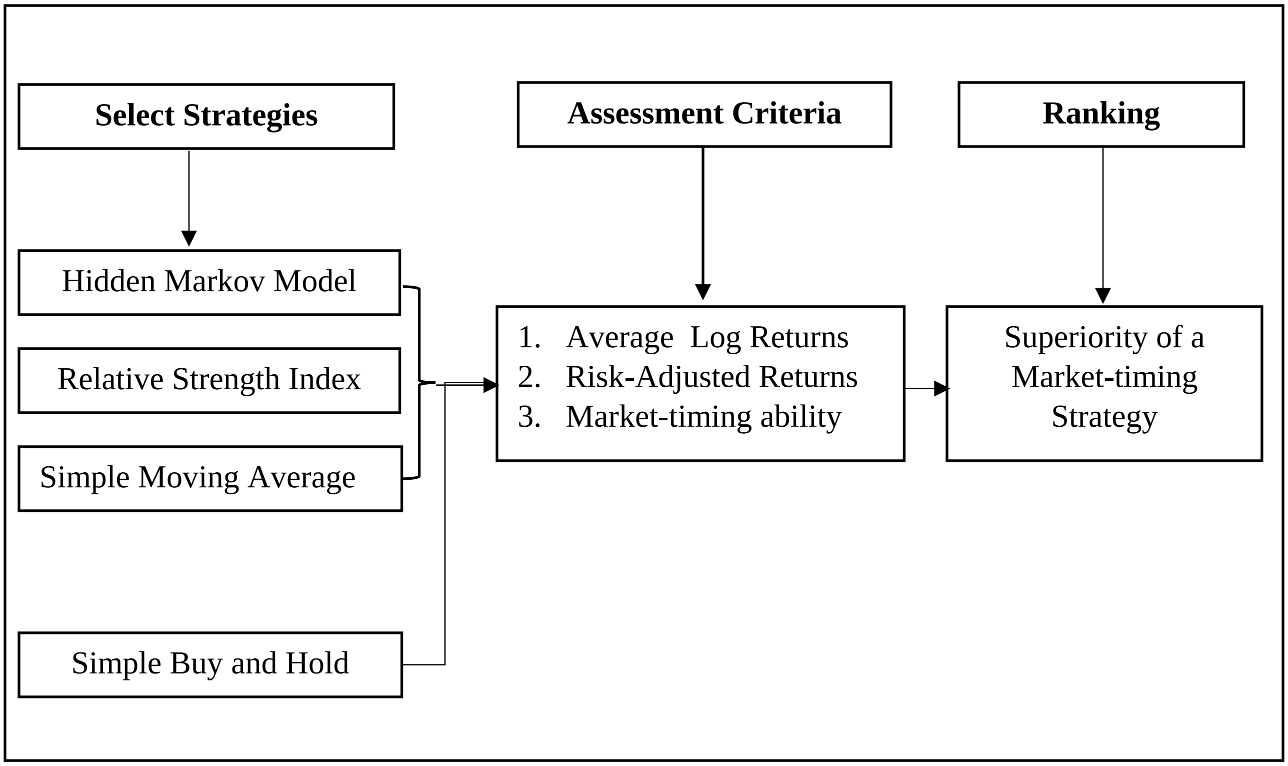

Figure 2. 1: Conceptual Framework

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the research Philosophy and the research design to be followed in this study. This is then followed by the description of the population to be considered and how sample selection was done succeeded by how data was collected. The methodology of how data was analyzed follows and the chapter is then concluded with ethical considerations observed in this research.

3.2 Research Philosophy

Research philosophy relates to the nature of the approach adopted in the development of Knowledge. There are many approaches that can be taken; Positivism, realism, pragmatism among others, (Saunders, Lewis, Thornhill, & Bristow, 2015). This study followed a positivism paradigm. This approach entails the study of data that are observable, quantifiable and from which statistical analysis can be made. Given that this study was majorly based on historical market prices which have been observed, this approach was deemed most appropriate for this study.

3.3 Research Design

This study follows a descriptive research design. This research design entails observing and describing the behavior of a subject without influencing it in any way(Boudah, 2010). This type of design allows for the employment of mathematical models, theories and hypotheses to explain an observed phenomenon. The data utilized can be both quantitative as well as qualitative, (Babbie, 2012). Furthermore, this research design allows for comparative analysis. This study aimed at establishing the most profitable trading strategies through comparison of the performance of all the strategies considered and also corroborate the finding with some qualitative data sourced from fund managers. As such the descriptive research design was considered most appropriate for this study.

3.4 Population and Sampling

For primary data, this study focused on registered fund managers in Kenya. In these institutions, the target respondents were individual analysts that deal with equity investment decisions. In each institution at least one individual was considered to provide the information. As of 2018, the

Retirement Benefits Authority had twenty two registered fund managers, (RBA, 2018) as evidenced in Appendix 4. The population considered in this study was, therefore, the twenty-two fund manager firms in Kenya, due to the small number a census approach will be applied. The study received responses from 15 fund managers, a response rate of 68.2%.

The secondary data consisted of all the trading days between 2004 and 2018. This was determined by the structure of NSE-20 series which shows evidence of a structural break around 2003-2004. This is later confirmed after conducting Chow's break-point test which portrays the first trading day of 2004 as a structural breakpoint.

3.5 Data Collection

This study utilized both primary as well as secondary data. The secondary data regarding the daily prices of the NSE-20 share index over a period of fifteen years from 2004-2018 and Treasury bill rate in the same period. Data relating to index prices were purchased from Synergy Systems Limited, a vendor licensed by Nairobi Securities Exchange to sell market data. The Treasury bill rate statistics were collected from the website of Central Bank of Kenya, (CBK).

In this study, the NSE-20 share index was preferred over the All-Share Index (NASI) given that NASI was introduced in 2008 and therefore would not cover the entirety of period under consideration. This timeframe was chosen as there appears to be no structural break in the time series under this period of considerations making it easier to analyze the data from this span. Under the same period more than two troughs can be observed, which is in line with the recommendation by Pennathur et al. (2010). This period was also considered ideal for the study because it accommodates the 2007-2008 financial crises. As noted by Cohen & Cabiri (2015), it is important to consider market crashes when evaluating the performance of market-timing strategies.

The target sources of primary data were licensed fund managers in Kenya. The information collected from the fund managers pertained to the relevance and extent of use of market timing strategies. This information was collected using a questionnaire. This method of data collection was preferred for this study as it is easy to be administered and offered the researcher varied options of administering it; online, in hard copy or in self-administered whichever mode was deemed best applicable to the varied respondents.

3.6 Data Analysis

This subsections details how the data collected was analyzed. To start with, this study discussed the salient features of the NSE-20 over the period of study. In so doing the study followed Lunde & Timmermann (2004) approach of categorizing bull and bear regimes and proceeded to give the descriptive feature for each given regime. Next, the study determined the returns of each given by the three market-timing strategies and the SBH as well. The subsection is concluded by looking at how market performance was evaluated for each market-timing strategy and how the performance of a given strategy compared to the performance of the other strategies.

3.6.1 Descriptive Statistics

Data analysis in this study commenced by deriving the descriptive features of the two predominant market regimes. The necessity of this step is since market-timing strategies are based on market cycles as such there is a need to understand the features of these cycles. The study sought to address three key features regarding market regimes; average returns in each regime, variance and the average duration for each respective regime.

To classify the market regimes this study utilized local minima-maxima analysis based on the smoothed index prices. The smoothed index share prices were used instead of actual prices to filter out the noise and shocks. A bull regime in this context was defined as a time-span between a local minima and the subsequent local maxima, conversely a bear regime is then defined as the period between local maxima and the next local minima, this is in line with Lunde & Timmermann (2004) who defined the market regimes with the respect to change from one minimum point to the next maximum point and vice-versa.

The stock prices series possess a unit root and therefore cannot be used in their raw form. The first step in the data analysis will be to obtain the order of integration. If the share prices contain a unit root, the analysis will be based on the stock prices differenced with respect to the order of integration or in other words the share returns. The returns were measured in the logarithmic form to minimize the effect of heteroscedasticity following the recommendation of Brooks (2014).

$$R_t = Ln\left(\frac{P_1}{P_0}\right)$$

Where R_t represents returns, P_1 represents the current share price while P_0 represents previous share price as informed by the order of integration.

This study seeks to fit a Hidden Markov model and apply its ability to identify regimes to develop a trading strategy. HMM is suitable for non-linear processes. As such the second step in this process will be to confirm the nonlinearity of the NSE-20 index returns. This will be done by use of BDS Test, as carried out in Akintunde, Oyekunle, & Olalude (2015) and likewise in Vlad & Pentiu (2010).

3.6.2 Performance of the Select Market-timing Strategies.

The first objective of this study was to determine the returns generated from the HMM, RSI and SMA market timing strategies. This subsection provides details of the models used to estimate the returns from the strategies.

3.6.2.1 Simple Moving Averages

This study used a double cross-over strategy for the identification of trading points. This is to avoid false signals (whipsaws) encountered when trading points are determined based on the prevailing price and a given moving average, (Zakamulin, 2016). This research was based on 50SMA- 200SMA cross-over points to signal a shift in market regimes. A bull regime was signaled by 50-SMA crossing the 200-SMA from below, was used to indicate the buying points. The bear regime was determined when the 50-SMA cross the 200-SMA from above, this was taken to indicate the selling points. This can be represented as follows;

Let the simple moving average be described as follows;

$$SMA(n)_t = \frac{1}{n}\sum_{i=0}^{n-1} P_t$$

Where n is the length of the moving average in days, P_t is the index price. The buy or sell signals can then be given as follows;

If,

$$x = SMA_{200} - SMA_{50}$$

Then,

$$f(x) = \begin{cases} Sell, & x < 0 \\ Buy, & x \geq 0 \end{cases}$$

3.6.2.2 Relative Strength Index

This is a price momentum indicator, which can show opportune trading times by tracing the RSI oscillator. The oscillator dithers between 0-100 percent. This technique compares the magnitude of the recent gains to recent losses, (Knowles, 2015). The RSI model can be depicted as below;

$$RSI = 100 - \left(\frac{100}{1 + RS}\right)$$

Where;

$$RS = \frac{Average\ of\ 14\ months'closes\ UP}{Average\ of\ 14\ months'closes\ DOWN}$$

At 30% and below the market is deemed oversold and subject to a correction which will be bullish in nature whereas if the RSI is above 70% the market is considered the overbought subject to a bearish correction (Lachhwani & Khodiyar, 2013). The instances of oversold are considered as buying points whereas the instances of overbought are considered selling points.

This study considered this framework in the detection of the market regimes and subsequent consideration of trading actions inferred. The study further analyzed the returns based on the trading points so determined.

3.6.2.3 Hidden Markov Model

3.6.2.3.1 The Model

The HMM model is based on the Markovian Principle that the next state is entirely dependent upon the current state and is in no way affected by the previous state. As such the transition probabilities are then given as below;

$$P = \begin{bmatrix} \mathbb{p}\langle s_t = A | s_{t-1} = A\rangle & \mathbb{p}\langle s_t = B | s_{t-1} = A\rangle \\ \mathbb{p}\langle s_t = A | s_{t-1} = B\rangle & \mathbb{p}\langle s_t = B | s_{t-1} = B\rangle \end{bmatrix}$$

$$= \begin{bmatrix} \mathbb{p}_{AA} & \mathbb{p}_{BA} \\ \mathbb{p}_{AB} & \mathbb{p}_{BB} \end{bmatrix}$$

This is by considering a Markov process that transits between two states, A and B. The process can either remain in the same state or move to the next state, (Kole & Dijk, 2017).

3.6.2.3.2 Selection of the Ideal Number of States

For any given time-series where HMM can be fitted there exists the optimum number of states over which it switches. This study employed the Bayesian Information Criteria (BIC) to determine the optimum number of states to model. The number of states was tested randomly and the study proceeded with the state that results in the minimal BIC statistic in accordance with Brooks (2014). After iteratively testing for the number of states, this study then proceeded to perform a confirmatory test on the regimes identified. This was determined by checking for regime persistence by evaluating the persistence of regime transition probabilities as proposed in Kuan (2002).

3.6.2.3.3 Model Set-Up

This study assumed that the NSE-20 share index returns, Y_t, depends on a latent process S_t. Further the study assumes that at any given point in time the process S_t is in one specific state represented by either 0 or 1. If regime one is represented by S_t=0 and regime two by S_t=1 it follows that the returns Y_t are expected to follow a normal distribution as below;

$$Yt = \begin{cases} N(\mu_0, \sigma_0^2) & if\ S_t = 0 \\ N(\mu_1, \sigma_1^2) & if\ S_t = 1 \end{cases}$$

In this study $S_t = 1$ was taken to represent the bull state while $S_t = 0$ was be assumed to represent the bear market state. In a regime switching model the mean and variance are expected to be constant in each regime but of different values in each given regime (Kole & Dijk, 2017).

3.6.2.3.4 Inference on the Underlying Latent Process S_t

Given that the process St is unobserved it is not possible to tell with certainty in which state the process is at a given point in time. It is however assumed that process follows first-order Markov chain, in that the current state depends solely on the previous state, such that the probability of being in regime 0 at a time is only dependent on the previous regime at time t_{-1}. This can be denoted as;

$$P_{ij} = \Pr[S_t = i | S_{t-1} = j\}$$

Bayesian probability rules can be applied to infer the state in which the process is most likely. To do so, current and past observations are used together with transition probabilities to infer $P_r[S_t=0|y_t,y_{t-1}\dots,y_1]$.

To infer the regime at time t =1 we apply Bayes' Theorem as follows;

$$\Pr[S_1 = 0|Y_1] = \frac{\Pr[Y_1|S_1 = 0\,].\Pr[S_1 = 0]}{\Pr[Y_1]}$$

$$= \frac{\Pr[Y_1|S_1 = 0\,].\Pr[S_1 = 0]}{\Pr[Y_1|S_1 = 0\,].\Pr[S_1 = 0] + \Pr[Y_1|S_1 = 1\,].\Pr[S_1 = 1]}$$

If regime at time t=1 can be inferred, the inferences can then be used to make a forecast for the most likely regime at time t=2 as follows;

$$\Pr[S_2 = 0|Y_1] = \Pr[S_2 = 0|S_1 = 0].\Pr[S_1 = 0|Y_1] + \Pr[S_2 = 0|S_1 = 1].\Pr[S_1 = 1|Y_1]$$

$$= P_{00}\Pr[S_1 = 0|Y_1] + \ P_{01}\Pr[S_1 = 1|Y_1]$$

As can be derived from the above set of equations calculation of inferred and forecasted regime probabilities is a recursive process. Therefore, by considering the forecast probabilities for time t=2 and the observation Y_2, it is possible to calculate the inference probabilities for the regime at t=2. In turn, these inferences can then be used to forecast the probable regime at time t=3, (Kole & van Dijk, 2013).

3.6.2.3.5 Buy or Sell Signals

In the HMM strategy buy or sell signals were generated as follows;

If the prior probabilities shifts to a P_0 value when P_0 is greater than 0.95, to another value P_1 which is less than, 0.95 this was taken to indicate the shift from the bull regime to a bear regime and hence a sell signal the reverse was assumed to indicate a shift to a bull market state and hence a buy signal.

Buy if $\quad P_r[S_1 = 1|Y_1] > 0.95$

Sell if $\quad P_r[S_1 = 0|Y_1] > 0.95$

Where P=0 represents the probability of being in a bear market while P=1 represents the probability of being in a bull market.

3.6.3 Comparative Analysis of Market-timing Strategies' Superiority

As noted by Kim & Sohn (2013), there is no consensus on how to evaluate the performance of market-timing strategies. Given so this study applied both non-parametric and parametric tests. In non-parametric tests, this study considered the difference in annual percentage returns as measured by the Tukey HSD test and risk-adjusted returns which were measured using the Sharpe ratio. Regression analysis of returns generated by each market-timing strategy constituted, parametric test. By conducting these tests, this study aimed to achieve robustness-checks in determining the superiority of the market timing strategies.

3.6.3.1 Evaluation of Average Annual Returns

For statistical comparison of the returns for the three strategies, this study compared the statistical difference between the mean returns in each approach. To achieve this, this study conducted One Way-Analysis of variance as applied in Ghobadi (2014) and in Praekhaow (2010). The test used the buy and hold strategy mean returns as the control group and proceeded to test the other three means against it.

3.6.3.2 Evaluation Risk-Adjusted Profitability of Market-timing Strategies

There are three main measures of the viability of financial returns; Treynor Measure, Sharpe ratio, and Jensen measure, (Reilly & Brown, 2011). The Treynor measure is derived by dividing the excess returns of a strategy with the beta which represents the systematic risk. On the other hand, the Sharpe ratio is derived the same way, but the beta is replaced with the standard deviation. The Sharpe Ratio is preferred where the data analyzed represent actual observation. Since the data analyzed in this study has already been observed the performance of market-timing strategies was based on the Sharpe ratio. The ratio was determined as follows;

$$SR = \frac{R_{mts} - R_f}{\sigma_{mts}}$$

Where;

SR is the Sharpe ratio**,**

$\boldsymbol{R_{mts}}$ represents returns of a market-timing strategy,

$\boldsymbol{R_f}$ is the risk-free rate and

$\boldsymbol{\sigma_{mts}}$ represent the standard deviation of a given market timing strategy.

3.6.3.3 Performance Evaluation of Market-timing Strategies based on Regression

To evaluate the performance of market-timing strategies this study followed the Henriksson & Merton (1981), model. This model is a modification of Jensen measure which according to Reilly & Brown (2011) is the most rigorous test for risk-adjusted returns. The model can be represented by the equation given below.

$$(R_{mts} - R_f) = \alpha + \beta(R_{sbh} - R_f) + \gamma(R_{sbh} - R_f)D + \varepsilon_t$$

Where;

$\mathbf{R_f}$ is the risk-free rate.

$\mathbf{R_{mts}}$ is the return of a given market-timing strategy

$\mathbf{R_{sbh}}$ represents the return on the market

$\boldsymbol{\alpha}$ represents regression intercept

$\boldsymbol{\beta}$ and γ is the represent regression coefficient while

D represents a dummy variable taking a value of one if the value of *(Rmts - Rf)* is positive and zero if otherwise

$\boldsymbol{\varepsilon_t}$ represents white noise.

In this model, the value of market timing for any given strategy is based on the signage and the significance level of the gamma. If the coefficient is positive and statistically significant it implies that a market-timing strategy is more profitable to the buy and hold strategy. This study used this model for each specific strategy and conclude on their strength after comparison.

The model diagnostics included the LaGrange Multiplier, Whiteness test, Durbin-Watson test for serial correlation and Bera-Jarque test for normality.

3.6.4 Evaluating the Significance of Market Timing Strategies by the Fund Managers in Kenya

This study sought to understand how fund managers are influenced by market timing when making investment decisions.   This study applied a measure of central tendency to evaluate the frequency of usage of the selected market-timing strategy. The study further sought to explain if there exists congruence between strategy frequently used and strategy's profitability.

To achieve the set goals the study sought to determine how efficient the fund managers deem NSE to be. From this perception, the study went ahead to evaluate if their perceptions are on concurrence with their application of either technical or fundamental analysis. For the participants who use technical analysis, the study sought to understand the significance that the attached to market ting and consequently the frequency at which the applied the market timing under consideration.

3.7 Research Quality

Validity and reliability were used as the determinants of quality in this research. Reliability refers to the consistency of a measure, (Heale & Twycross, 2015). Reliability in this study was achieved by ensuring that all the returns are measured as a percentage difference of prices between any two consecutive trading days. The validity in this study was observed in terms of content validity where the focus was on how well the questionnaire to be administered is structured to ensure that market participant's perceptions on market-timing strategies are accurately and adequately captured.

3.8 Ethical Considerations

The objective of this study was to provide a truthful evaluation of market timing strategies with the aim of promoting knowledge in this area of quantitative finance. As such this study was conducted in strict conformity to the norms of ethics in research. The primary data collected was treated with the utmost confidentiality and the use of the same was restricted to the writing of this thesis. Information was only sought from those who were willing to freely provide it. At no point in time was data obtained through coercion. This is in line with the ethical principles of conducting research as outlined by Bryman & Bell (2007).

CHAPTER FOUR

RESEARCH ANALYSIS AND FINDINGS

4.1 Introduction

This chapter presents the analysis conducted to evaluate the performance of market-timing strategies in the NSE. The analysis commences by providing the descriptive statistics relating to the NSE-20 share index over the period 2004-2018. This is followed by an explanation of how the final samples were derived. The estimation of ex-post returns realized by the market timing strategies under consideration then follows. These returns are then subjected to both parametric and non-parametric tests to determine the superiority of the market timing strategies. The study then evaluates the significance of market timing strategies to fund managers in Kenya and concludes by triangulation of secondary data findings to those of primary data.

4.2 Data and Final Sample

This study was based on both primary and secondary data. The secondary data utilized was univariate in nature, the study utilized the NSE-20 share index as the indicator of price markets in NSE over the period 2004-2018. The data was subjected to data cleaning procedures. A cross-check was conducted to ensure that there were no missing values. Where missing values were noted, the average between the preceding and succeeding days was used to fill the gaps.

The final sample (secondary data) was determined after checking for existence any structural break. This study tested for the existence of a structural break on the first trading day in 2004 using Chow Break-point Test. According to the results in Table 4. 1with a P-value of 0.0101, the null hypothesis of no breakpoint is rejected. This implies that the returns before 2004 and after 2004 are best analyzed separately. Consequently, this study focused on the returns from 2004-2018 as the final sample.

Table 4. 1 Chow Break-Point Test

Chow Breakpoint Test: 1/02/2004
Null Hypothesis: No breaks at specified breakpoints

Equation Sample: 1/04/2001 12/31/2018

F-statistic	2.321085	Prob. F(10,4454)	0.0101
Log likelihood ratio	23.47051	Prob. Chi-Square(10)	0.0091
Wald Statistic	83.30057	Prob. Chi-Square(10)	0.0000

The primary data mainly sought to understand the relevance of market-timing strategies among fund managers in Kenya. A census approach was followed, and responses were sought from all the twenty-two fund managers. The study collected responses from individuals who deal with equity investment decisions in each fund manager firm. Out of all the 22 firms to whom questionnaires were issued to, this study received responses from 15 of them which translates to a response rate of 68.2%. For a survey which is conducted online, a response rate of sixty response rate above 60% is considered sufficient (Boudah, 2010).

4.2.1 Descriptive Statistics

This study examined market-timing from a primary trend perspective in that study's focus was on long-term market-timing. The descriptive statistics provided are based on the daily prices from the first trading day in the year 2004 to the last trading day in 2018. This period generated 3728 trading days averaging to approximately 250 trading days per year. The troughs and peaks were then used to determine the bull and bear cycles from which mean returns, standard deviation, and average duration were derived. The graph in Appendix 6 represents the daily price movement of the NSE 20 share index over a period of fifteen years. In this subsection, the bear market is defined as the period between a peak and a trough while the period between a trough and a peak is considered as a bull market.

Table 4. 2: NSE Descriptive Statistics 2004-2018

	Bull Market	**Bear Market**
Mean Duration	567.75 days	377.67 days
Average Annual Returns	23.0592%	-23.8591%
Volatility	0.0042	0.0053

Source: Researcher

From the table above it can be noted that first, in NSE the bull phases are more persistent than the bear phases, second, the magnitude of returns in the bear phases is slightly higher than that of the bull phases, this consistent with other studies in other exchange markets (Pagan & Sossounov, 2003). Lastly, on average, the standard deviation during the bull regimes is lower compared to the standard deviation during the bear regimes.

A country's Gross Domestic Product (GDP) growth is intuitively expected to be correlated with the behavior of financial asset prices (Ogutu, 2012). From Figure 4. 1it is evident that the behavior of the NSE-20 index and Kenya's GDP growth are related. The cyclic behavior of the NSE-20 appears to reflect the GDP growth in Kenya. Though this study did not explicitly test for co-movement between the two series, from the graphical the two do co-move contrary to the findings of (Forson & Janrattanagul, 2014).

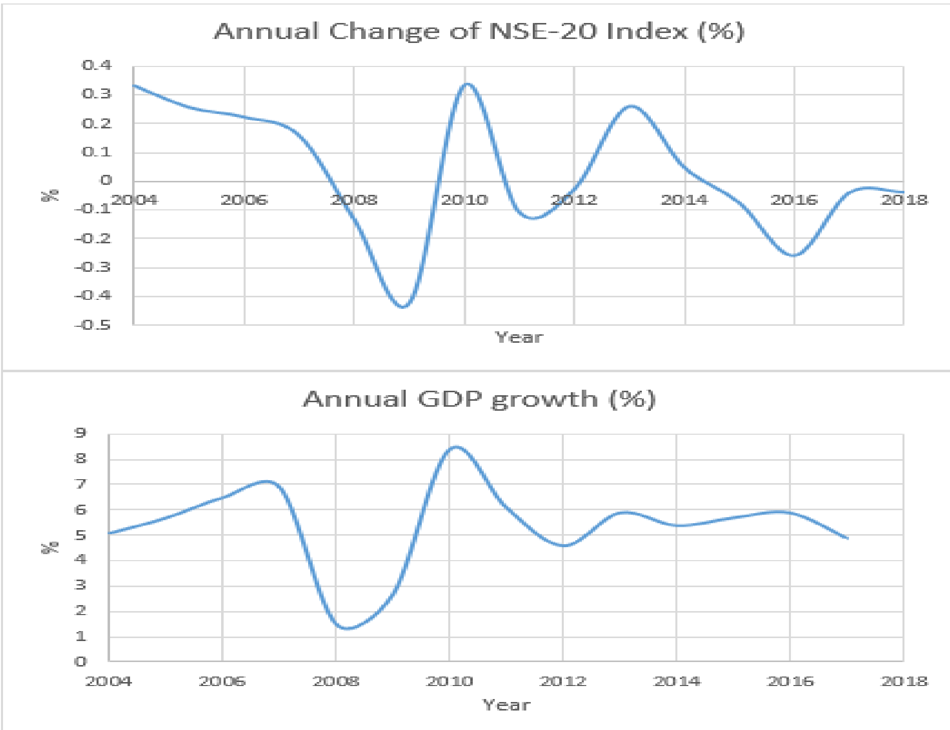

Figure 4. 1: Graphs of NSE-20 Index and GDP 2004-2018

Over the period 2004-2018, the NSE-20 returns were on average, zero. From this, it is implied that an investor who buys and hold equity instruments should expect approximately zero returns. In the same period, the average return of the 91-days Treasury Bills was 8.36%. With this as the benchmark return and that equity investment are not risk-free a viable investment in NSE can be deemed as an investment that is able to generate returns in excess of 8.36% annually. The Jarque-Bera is statistically significant as shown in Figure 4. 2 which implies that the returns in NSE do not follow a normal distribution. This can be explained by the high kurtosis of 16.1595. This value is in excess of zero which depicts a distribution with heavy tails. According to Brooks (2014), financial time series are characterized by the presence of heavy tails, therefore the returns in NSE follow a distribution similar to returns of other exchange markets.

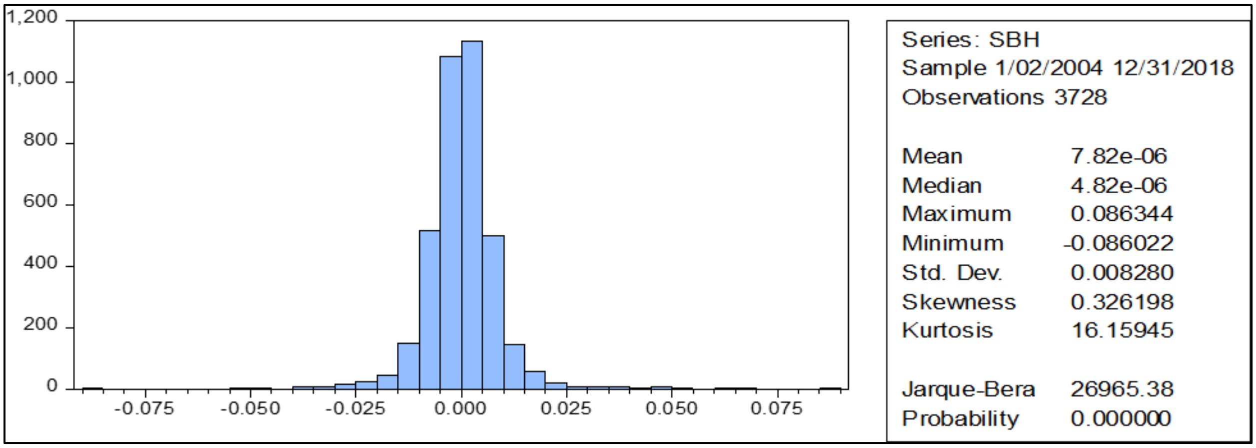

Figure 4. 2: Descriptive Statistics

4.2.2 Diagnostics Checks

The diagnostic checks performed included: stationarity, non-linear dependency, and normality tests. Normality tests show that the share returns are not normally distributed, the share returns follow a leptokurtic distribution with kurtosis of 16.1595. The mean and median though not exactly zero, the two are close to zero which is the expected value according to the Random Walk Hypothesis. As shown in Table 4. 3, the NSE prices are serially correlated with the integration of order one. Given the serial correlation, this study determined the ARMA structure that best fits the share process as shown in Appendix 8. From the correlogram, the NSE share prices follow AR(3) MA(2). Next, this study regressed the returns against the determined ARMA terms using a GARCH (1,1) model with the resultant output as shown in Appendix 11. To test for non-linear dependency, BDS Test was used based on Broock, Scheinkman, Dechert, & LeBaron (1996). Using six correlation dimension the P-value of all the six dimensions are below 0.05. Therefore, the hypothesis of linearity in the share returns is rejected. It can, therefore, be concluded that share prices in NSE follow a non-linear behavior.

Table 4. 3: Diagnostic Tests

Stationarity Test

Lag Length: 1 (Automatic - based on SIC, maxlag=29)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-31.68318	0.0000
Test critical values:	1% level	-3.431919	
	5% level	-2.862119	
	10% level	-2.567122	

Non -Linearity Test

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.024883	0.001443	17.24887	0.0000
3	0.045949	0.002286	20.10203	0.0000
4	0.058009	0.002714	21.37321	0.0000
5	0.063414	0.002821	22.48093	0.0000
6	0.064144	0.002713	23.64706	0.0000

Raw epsilon	0.009081		
Pairs within epsilon	9760482.	V-Statistic	0.702295
Triples within epsilon	2.78E+10	V-Statistic	0.537252

Dimension	C(m,n)	c(m,n)	C(1,n-(m-1))	c(1,n-(m-1))	c(1,n-(m-1))^k
2	3598354.	0.518241	4877008.	0.702395	0.493358
3	2722880.	0.392364	4873840.	0.702315	0.346415
4	2089499.	0.301256	4870998.	0.702283	0.243247
5	1626677.	0.234654	4870731.	0.702621	0.171241
6	1279036.	0.184605	4869084.	0.702761	0.120461

4.3 The Performance of Market-timing Strategies.

The first objective of this study was to determine the performance of the market timing strategies. The performance of the strategies was measured using the average annual log returns. The returns were determined by the percentage change between the buying and the selling point as determined by the select market timing strategies.

4.3.1 Performance of Simple Moving Averages Strategy

Under SMA strategy the trading points are determined by the nature of the cross-over. Buying points are depicted as points where the 50 moving average cross the 200 moving average line from below conversely a selling point is indicated by the cross of the 200 moving average by the 50-moving average from above. In NSE the cross-over points were as shown in Figure 4. 3.

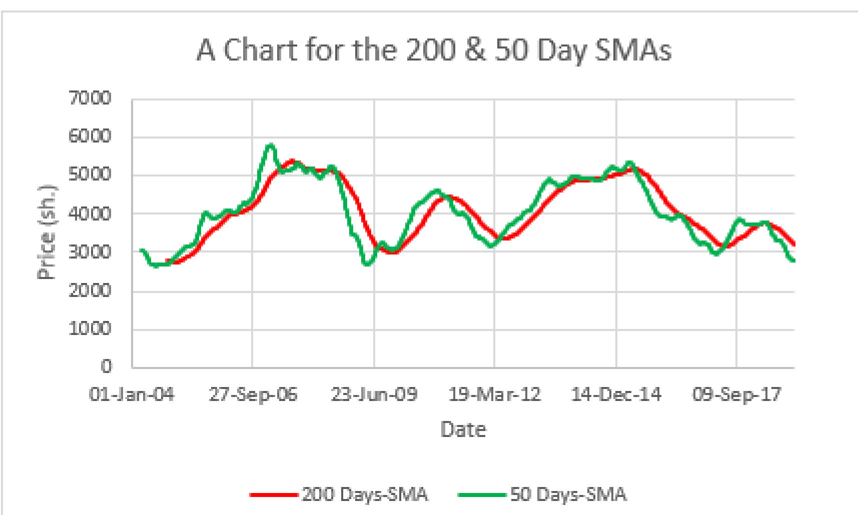

Figure 4. 3: A Graph for 50 & 200 Simple Moving Averages

The Returns of SMA strategy were based on double-cross method of the 200-day and 50-day moving averages realizing the trading points and subsequent returns as tabulated in Table 4. 4. Like in all the other trading strategies in this study, the returns are based on the lognormal returns. The is informed one according to Hull (2014) asset prices follow a lognormal distribution and second, in regression analysis variables taken in their log form minimize the risk violating the homoscedasticity assumption, (Brooks, 2014).

Table 4. 4 SMA Log Returns

Date	Signal	Price	Log returns
02-Jan-04	Invest	2753.33	-
26-Nov-04	Buy	2,921.53	8.32%
07-May-07	Sell	5,091.12	148.66%
06-Jun-08	Buy	5,477.70	20.23%
12-Aug-08	Sell	4,588.27	-42.58%
27-Jul-09	Buy	3,295.47	17.71%
04-Feb-11	Sell	4,390.46	57.25%
27-Apr-12	Buy	3,534.53	47.08%
12-Jun-14	Sell	4,811.00	75.78%
29-Aug-14	Buy	5,139.39	4.71%
15-May-15	Sell	4,980.71	-16.47%
29-May-17	Buy	3,438.20	44.78%
03-May-18	Sell	3,662.98	6.33%
Mean Annual Return			**10.47%**
Standard Deviation			**0.0083**

Source: Researcher

Using the 200 days and 50 days' double crossover strategy, the NSE 20 share index generated twelve trading points over the period 2004-2018. The strategy generated six 'buy' trading points and an equivalent count of 'sell' trading points. The total cumulative returns realized from this strategy over the fifteen-year period amounted to 156.72%, which translated to an average annual return of 10.57%. By considering the trading points of SMA strategy, the standard deviation over the period under consideration stood at 0.0083.

4.3.2 Performance of Relative Strength Index

The RSI strategy is a price momentum-based trading strategy. The graph in Figure 4. 45 shows the RSI oscillator based on fourteen-month periods. As can be noted from the figure the RSI crossover points are not definitely continuous in a permanent trend especially when close to the threshold. It is common for the oscillator to exceed the threshold then retract back to a point below the threshold, such swings according to Wilder (1978) are referred to as failure swings. According to his study, such swings represent a reversal of a trend. This study followed this concept in determining trading points under RSI Strategy.

Figure 4. 4: A Graph of RSI Oscillator

The Figure 4. 4 Shows the RSI oscillator and below it a graph showing the trend of NSE-20 index. The ‘buy’ points are determined when the RSI crosses the 30% threshold while the ‘sell’ points are indicated when the RSI crosses the 70% threshold. The points determined were then used to generate returns as shown in Table 4. 5.

Table 4. 5: RSI Log Returns

Trading Points	Trading Signal	Price	Log returns
02-Jan-04	Invest	2,753.33	-
28-Apr-06	Sell	4,025.21	93.16%
30-Sep-09	Buy	3,005.41	60.27%
28-Jun-13	Sell	4,598.16	112.48%
31-May-17	Buy	3,441.05	117.78%
Mean Annual Returns			**10.32%**
Standard Deviation			**0.0020**

Source: Researcher

The RSI generated the trading points as depicted in Table 4. 5; three 'buy' points and two 'sell' instances. Cumulatively the strategy returned a return of 154.59%, which translates to an annual return of 10.32%. The strategy's standard deviation was 0.0020.

4.3.3 Performance of Hidden Markov Model

This study evaluates how the non-linear approach to market-timing performs relative to other market timing strategies. This was done by determining the trading points generated by Markov Switching regression as estimated in Table 4. 6.

Table 4. 6: HMM Estimation Out-put

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	0.000843	1.47E-05	57.14180	0.0000
		Regime 2		
C	-0.001026	1.81E-05	-56.65992	0.0000
		Common		
LOG(SIGMA)	-7.374168	0.011944	-617.4116	0.0000
		Transition Matrix Parameters		
P11-C	5.745599	0.384041	14.96088	0.0000
P21-C	-5.411959	0.389814	-13.88344	0.0000

Mean dependent var	7.50E-05	S.D. dependent var	0.001113
S.E. of regression	0.000619	Sum squared resid	0.001352
Durbin-Watson stat	0.017093	Log likelihood	20958.37
Akaike info criterion	-11.87496	Schwarz criterion	-11.86622
Hannan-Quinn criter.	-11.87185		

Table 4. 6 shows the summary output for two-state regime switching regression. The regime one coefficient is positive (0.0008) which translates to bull regime while that of regime 2 is negative (-0.0010) translating to bear regime. The P value for each regime is less than 0.05 which implies that at a 95% confidence level both regimes are statistically significant.

4.3.3.1 Regime Transition Probabilities and Duration

Table 4. 77 shows the long run average transitional probabilities. The results show that once a given regime is entered there is a 99% chance of remaining in that regime.

On average the bull regime lasts 314 days, while the bear regime lasts 225 days.

Table 4. 7: HMM Transitional Probabilities and the Expected Duration

Constant transition probabilities:
P(i, k) = P(s(t) = k | s(t-1) = i)
(row = i / column = j)

	1	2
1	0.996813	0.003187
2	0.004443	0.995557

Constant expected durations:

	1	2
	313.8174	225.0591

Figure 4. 5 represents a graphical representation of how the regime switches over the years of 2004-2018. The upper part of the graph P(S(t)=1) represents the time in which the market was in a bull state whereas P(S(t)=2) represented the market being in the bear state.

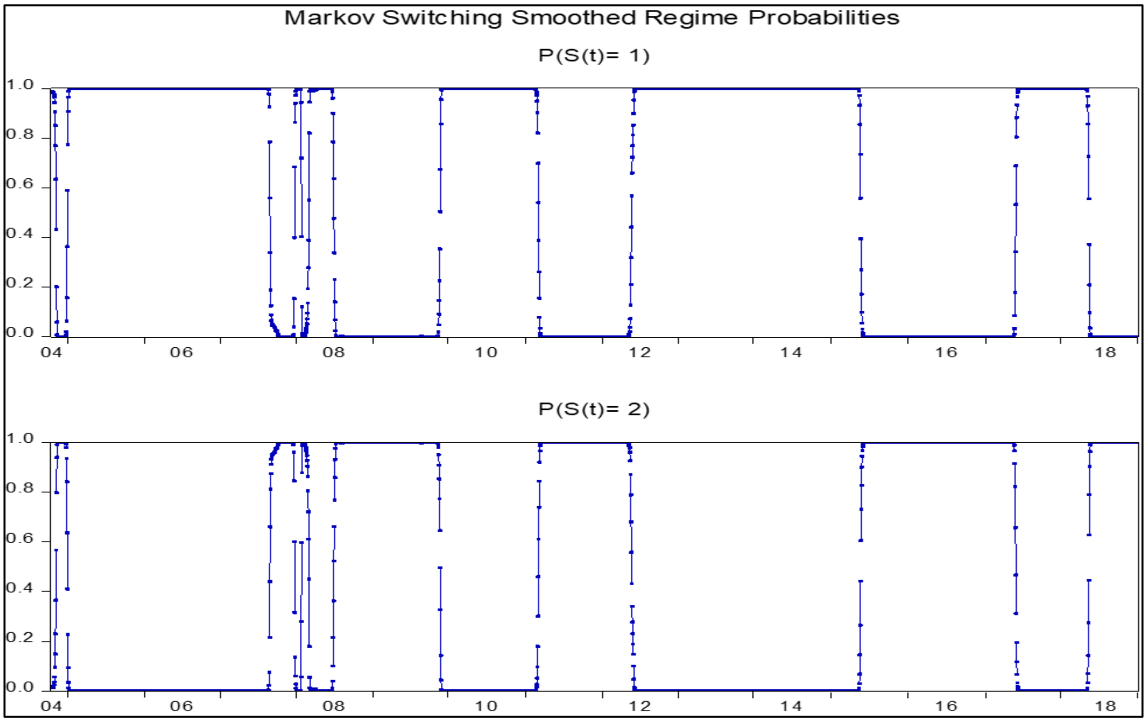

Figure 4. 5: Regime-Switching Probabilities in NSE Between 2004 and 2018

In this study, a regime change was deemed to occur if the probability of being in that regime shifts from a probability less than 0.95 to a probability equal or greater than 0.95. Based on this rule the trading points generated and subsequent returns are as tabulated in Table 4. 8.

Table 4. 8: HMM Log Returns

Date	Signal	Price	Log returns
02-01-04	Invest	2,753.33	-
27-10-04	Sell	2,802.37	4.39%
05-01-05	Buy	2,991.32	3.88%
13-09-07	Sell	5,470.14	150.86%
18-12-07	Buy	5,291.69	4.53%
29-01-08	Sell	4,576.31	-35.92%
03-03-08	Buy	5,142.27	2.05%
03-07-08	Sell	5,158.81	21.81%
26-11-09	Buy	3,191.93	25.40%
08-03-11	Sell	4,090.07	57.23%
29-05-12	Buy	3,627.64	45.54%
02-06-15	Sell	4,816.66	70.46%
02-06-17	Buy	3,473.19	43.96%
17-05-18	Sell	3,519.78	14.78%
Mean Annual Returns			**11.63%**
Standard Deviation			**0.0072**

Source: Researcher

On average the HMM strategy returns amounted to 164.55% cumulatively which translated to an average annual return 11.63%. The returns were associated with a standard deviation of 0.0072 Over the period 2004-2018, the annualized mean returns of the NSE-20 amounted to -0.29% with an annualized standard deviation of 0.0158.

By analyzing the returns generated by the three strategies, all the strategies generated returns much higher than the buy and hold strategy. HMM, returns were the highest, at 11.63% with a standard deviation of 0.0072, followed by SMA with returns of 10.47% and a standard deviation of 0.0083 and the least profitable strategy was RSI with returns of 10.32% and a standard deviation of 0.0020, which was the least deviation.

4.3.4 Correlation of the Market-timing Strategies' Returns

Kendall's tau is a non-parametric rank statistic that measures the strength of the relationship between two variables. Unlike the Pearson coefficient correlation, Kendall's tau does not assume linearity. Since this study proved existence a non-linear structure in NSE, Kendall's tau coefficient is deemed most applicable Correlation measure.

Table 4. 9 shows the output of Kendall's tau Correlation Matrix. The matrix indicates how the returns of the strategies under consideration correlate with each other. The results show that the returns generated by all the strategies correlate with each other positively. Moreover, the correlations between all the strategies are statistically significant at 1% significant level. The highest correlation is between HMM and SMA at 0.593 which, like in all the other cases is statistically significant. For the market timing strategies, the correlation can be explained by the fact that each strategy tries to determine the turning point of bull and bear regimes. As such the trading points generated by the strategies are at times very close to each other for example both RSI and SMA indicated buying points in May 2017 while SMA and HMM indicated selling points in May 2018.

Table 4. 9: Correlation Matrix of the Strategies' Returns

Correlations						
			SBH	RSI	SMA	HMM
Kendall's tau_b	SBH	Correlation Coefficient	1.000			
	RSI	Correlation Coefficient	.227**	1.000		
	SMA	Correlation Coefficient	.217**	.243**	1.000	
	HMM	Correlation Coefficient	.239**	.251**	.593**	1.000
		N	3728	3728	3728	3728
**. Correlation is significant at the 0.01 level (2-tailed).						

Source: Researcher

4.4 Superiority of Market-timing Strategies in NSE

The second objective of this study was to conduct a comparative analysis and evaluate how the performance of the strategies compared.

The comparison of the returns in this study was done using three approaches. The first approach is a comparison of mean raw returns using Planned Contrast test, which tests and ranks the strategies based on the significance of the difference between their mean return. The second comparison analyzed risk-adjusted returns by determining the respective Sharpe-ratios and finally a comparison of market-timing ability as determined Henrikson and Merton, model. The findings of this study are as discussed next.

4.4.1 Planned Contrast Test

This test considered the absolute returns from each given strategy and determined if there was any statistical difference between the returns so realized and returns garnered in the case on no market-timing.

Table 4. 10: Test of Homogeneity of Variances

Test of Homogeneity of Variances			
Returns			
Levene Statistic	df1	df2	Sig.
3005.501	3	14908	0.000

Source: Researcher

The Planned Contrast test assumes homoscedasticity, as such the first step in this analysis was to test for homogeneity of returns from the various strategies. At an alpha of 0.05, the Levene statistic produced (0.000) is significant implying that the strategies' returns are heterogeneous. Though homogeneity is desirable in mean comparison among groups, analysis can still be conducted with heterogeneous groups. In such cases, the problem of heterogeneity is addressed by increasing the sample size and ensure that the number of elements in the sample groups is equal or almost equal. In this study, all the sample sizes are equal each with a count of 3728. This can be considered robust enough to allow for analysis with heterogeneous datasets.

Table 4. 11: Analysis of Variance

ANOVA					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	301944.285	3	100648.1	9.417	0
Within Groups	59,339,817.30	14908	10688.21		
Total	159641761.6	14911			

Source: Researcher

The planned Contrast test checks for statistical differences between the means of various groups. The ANOVA output under Table 4. 11 shows that there exists a statistical difference between the returns generated by the RSI, SMA, HMM and the benchmark strategy, SBH. However, this analysis above cannot show explicitly the strategies whose returns are different. This challenge is solved by the application of Tukey HSD, post hoc test, whose results are illustrated in Table 4. 12.

Table 4. 12: Tukey HSD Test Output

Dependent Variable: Returns						
(I) Strategy	(J) Strategy	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
HMM	RSI	1.3027*	0.3522	0.0012	0.3977	2.2076
	SMA	1.1532*	0.3522	0.0059	0.2482	2.0581
	SBH	11.9133*	0.3522	0.0000	11.0083	12.8182
RSI	HMM	-1.3027**	0.3522	0.0012	-2.2076	-0.3977
	SMA	-.1495	0.3522	0.9743	-1.0544	0.7555
	SBH	10.6106*	0.3522	0.0000	9.7057	11.5156
SMA	HMM	-1.1532*	0.3522	0.0059	-2.0581	-0.2482
	RSI	.14950	0.3522	0.9743	-0.7555	1.0544
	SBH	10.7601*	0.3522	0.0000	9.8552	11.6651
SBH	HMM	-11.9133*	0.3522	0.0000	-12.8182	-11.0083
	RSI	-10.6106*	0.3522	0.0000	-11.5156	-9.7057
	SMA	-10.7601*	0.3522	0.0000	-11.6651	-9.8552
*. The mean difference is significant at the 0.05 level.						

Source: Researcher

Table 4. 12 shows the statistical significance of the differences among all the strategies. The column (I) represent the strategy against which the strategies in (J) are compared to. The difference between the strategies is then Showed under column (I-J). A positive figure under the Column (I-J) indicates that the return of the Strategy under (I) exceed the returns of the strategies under (J). The returns with Asterix (*) indicate that the returns are significantly different at 5% level of Significance. The differences between all the strategies are statistically different except for the

difference between SMA and RSI. The difference between the return of the two strategies is 0.1495 which is the least difference. The highest difference is between HMM and SBH at 11.0133 which is statistically significant.

4.4.2 Sharpe Ratio Analysis

Sharpe ratio is used to evaluate financial performance by adjusting the returns for risk. In other words, the ratio is used to determine the excess returns of a given investment per unit of deviation. In this study, the Sharpe ratio was determined using annualized returns, standard deviation, and the average annual 91-day Treasury Bills' rate.

Table 4. 13: Sharpe Ratio Comparison

	HMM	RSI	SMA	SBH
Average Annual Returns	11.63%	10.32%	10.47%	-0.29%
Standard Deviation	0.0072	0.0020	0.0083	0.0158
Average 91-day Treasury Bills Rate	8.36%	8.36%	8.36%	8.36%
Sharpe Ratio	**4.55**	**9.95**	**2.55**	**-5.48**
Sortino Ratio	**0.3691**	**1.2378**	**0.1790**	**-0.3477**

Source: Researcher

RSI strategy generated the highest positive Sharpe ratio at 9.95 followed by HMM at 4.55 and then by SMA at 2.55. The buy and hold strategy generated a negative return -5.48 per unit of risk. The Sharp Ratio as a gauge of performance in terms of risk-adjusted returns is crippled by one short-coming. The shortcoming that the upward movements like downward movements are incorporated as measures of risk in the computation of standard deviation. Sortino Ratio merits this shortcoming by only incorporating the downward movements in the computation of standard deviation. From the results Table 4. 13, the Sortino ratio ranking follows those of the Sharpe ratio. RSI has the highest Sortino ratio of 1.2378, followed by HMM and SMA at 0.3691 and 0.1790 respectively. The value of the ratio under SBH remains negative.

4.4.3 Regression Analysis

In regression analysis, this study assumed that the returns of a given market timing strategy can be explained by the average returns of the markets as given by SBH and the prevailing risk-free rate. The market timing ability was determined by adding a dummy variable, which evaluates if a market timing strategy can generate returns in excess of mean returns from the market.

4.4.3.1 Henrikson and Merton Model

Using the HM model of 1981, the strategies' market timing abilities were determined as shown in Table 4. 14. All three market timing strategies have positive and statistically significant γ values. However, all the strategies equations are supported by weak Adjusted R2. Furthermore, the residuals for all their strategies contain serial correlation, are heteroscedastic and are not normally distributed. Whereas the violation of normality assumption has no significant on the coefficient the violation of the other two implies that the coefficients estimated are no longer efficient.

Table 4. 14: Henrikson and Merton Model

	Fixed Regressor		SBH-RF		Dummy (SBH-RF)		Adjusted R^2	Model P value	DW
Strategy	α	p	β_1	P	γ	P			
HMM	-0.0125	0.0065	0.0087	0.5737	0.5251	0.0000	0.14	0.0000	0.0850
RSI	0.0230	0.0000	0.0912	0.0000	0.0523	0.0000	0.48	0.0000	0.0092
SMA	0.0264	0.0000	0.1733	0.0000	0.1172	0.0003	0.18	0.0000	0.0390

	HM-Residual Diagnostics					
	White-Test		LM-Test		Jarque-Bera	
Strategy	F-Statistic	P	F-Statistic	P	JB-Statistic	P
HMM	28.5746	0.0000	20531.40	0.0000	2117492	0.0000
RSI	1032.26	0.0000	182093.3	0.0000	41.44	0.0000
SMA	101.0616	0.0000	46840.54	0.0000	268291.4	0.0000

4.4.3.2 Modified Henrikson and Merton Model

To merit the residual diagnostic problems from the ordinary least squares regression, this study estimated the HM model using the autoregressive distributed lag model (ARDL).

From the summary result in Table 4. 15 it can be shown that the ARDL model specification is able to capture at least 90% of variations in any given market timing strategy, with a significant portion being explained by autoregression. For all the strategies the P value is less than alpha(0.05), which means that all the regressions for each given strategy are statistically significant.

From the regression analysis conducted, the market timing ability is determined by the parameter γ. A positive and statistically significant γ implies that a strategy has the ability to time the market.

Table 4. 15: ARDL Model Estimation Out-put

	Fixed Regressor		Lagged Returns		SBH-RF		Dummy (SBH-RF)		Adjusted R2	Model P value	DW
Strategy	α	p	β_1	P	β_2	P	γ	P			
HMM	0.0023	0.0006	0.9575	0.0000	-0.0073	0.1017	0.0387	0.0735	0.92	0.0000	1.9771
RSI	0.0003	0.0095	0.9898	0.0000	0.0015	0.00006	-0.0004	0.6693	0.99	0.0000	1.9831
SMA	0.0005	0.4846	0.9807	0.0000	0.0037	0.1591	0.0023	0.7159	0.96	0.0000	1.9805

MHM-Residual Diagnostics						
	White-Test		LM-Test	Jarque-Bera		
Market Timing Strategy	F-Statistic	P	F-Statistic	P	JB-Statistic	P
HMM	13.5658	0.0000	1.6548	0.1913	3.86E+08	0.0000
RSI	229.2304	0.0000	0.2694	0.7638	9.85E+05	0.0000
SMA	5.3513	0.0000	0.37	0.6908	2.53E+08	0.0000

From the results, the γ parameter for RSI is negative, implying that the strategy has no market timing ability. For both SMA and HMM, the parameter is positive which means that the strategies have positive market timing abilities. However, for both strategies γ generated lacks statistical significance. The P-value of HMM (0.0735) however conveys greater significance compared to SMA (0.7159). This implies that of the three strategies, HMM's market timing ability was the best.

The residual diagnostics for both models are presented below the models' estimation outputs. Pertaining to the regressions of market-timing strategies, the null hypothesis for homoscedasticity is rejected in all three instances for all models. This means that the error terms for the models are not homogenous. Though heteroscedasticity is undesired in regression analysis, the presence of heteroscedasticity does not affect coefficients' unbiasedness and consistency. This means that the deductions made on γ will still hold.

The Lagrange Multiplier (LM) tests for serial correlation in the residuals. From the LM tests conducted for all the three strategies, the P-value is less than 0.05 in the ordinary Henrikson and Merton model. This means that the null hypothesis of no serial correlation is rejected. It can, therefore, be concluded that the residuals in the model are serially correlated. However, when autoregression is accounted for the serial correlation problem ceases to exist.

The last residual diagnostic test conducted was a normality test on the model residuals. For all the three strategies the null hypothesis of normally distributed disturbances is rejected in both models. The subsequently implies that the error terms are not normally distributed. Given that the analysis was based on financial returns the results do not deviate from the expected due to the fat tails inherent to financial time-series. Violation of the normality assumption is largely inconsequential and therefore the deductions drawn from such regression remain unaltered.

4.5 Checks for Strategies' Robustness.

To evaluate the validity of the models' performance, returns were evaluated using four criteria; simulation, sub-period test, random stock selection, and portfolio performance.

4.5.1 Simulation

To evaluate the validity of the market-timing strategy, this study conducted a simulation scenario. Geometric Brownian motion principles were followed in a Monte-Carlo simulation of NSE-20 stock prices over 3728 days equivalent to the number of the days considered in the study. The returns based on the simulated prices were then determined following the three market timing strategies under consideration. The results were as shown in Table 4. 16.

Table 4. 16: Sharpe Ratio from simulated Prices

	SBH	**RSI**	**SMA**	**HMM**
Annualized Returns	0.32%	10.55%	3.55%	11.23%
Annualized Standard Deviation	0.0116	0.0029	0.0103	0.0031
Average Risk-Free Rate	8.36%	8.36%	8.36%	8.36%
Sharpe-Ratio	**-6.9602**	**7.4274**	**-4.6527**	**9.2615**
Modified Sharpe Ratio	**-0.0009**	**7.4274**	**-0.0005**	**9.2615**

Source: Researcher

By following the NSE-20 simulated share-prices between over 3728 days, the HMM strategy gave the maximum returns with the least standard deviation and subsequently the highest Sharpe ratio of 9.2661. The next best-performing strategy was RSI whose standard deviation and mean annualized return almost equaled those of HMM strategy. The strategy's Sharpe Ratio was 7.5753, 1.6908 points lower that of HMM. Both SMA and SBH gave negative Sharpe Ratios. Where Sharpe Ratios are negative, direct comparison is not applicable. To merit this shortcoming Modified Sharpe ratio is applied. Using Modified Sharpe ratio as a comparison basis the ratio of SMA (0.0005) is greater than that of SBH (0.0058), therefore SMA proved to be a better strategy than SBH.

4.5.2 Sub-Period Test

If the markets are fractal in nature their patterns should remain irrespective of the time horizon chosen. This study followed a deductive approach to test for the existence of fractal behavior in NSE. Given that the market timing strategies are based on the existence of repetitive patterns, the profitability of market timing strategies in sub-periods would infer fractal nature in price behavior. For sub-period testing, the study split the period into two halves and proceeded to test for the profitability of the market timing strategies in the latter half of 2011 to 2018. As an alternative index, the sub-period testing used the returns of NASI whose returns are not statistically different from those of NSE-20. The findings were as tabulated in Table 4. 17.

Table 4. 17: Sub Period Sharpe Ratios

	SBH	RSI	SMA	HMM
Annualized Returns	15.54%	15.21%	15.83%	15.04%
Annualized Standard Deviation	0.0174	0.0079	0.0062	0.0040
Average Risk-Free Rate	8.36%	8.36%	8.36%	8.36%
Sharpe-Ratio	**4.13**	**8.68**	**12.12**	**16.76**

Source: Researcher

By sub-period evaluation, the results show that SMA had the best average returns followed by RSI and HMM. However, on consideration of standard deviation, the risk-adjusted returns of HMM rank highest followed by SMA and then RSI. In all the cases of average returns and risk-adjusted returns the returns of SBH realized are lower than those of all the market timing strategies.

4.5.3 Randomized Stock Selection

The next model validation test considered in this study was based on trading based on a random selection of shares to trade. From the entire population of sixty-four companies listed in NSE, a sample of five companies was systematically randomly selected. The five companies selected were East Africa Cable Limited (CABL), Co-operative Bank (COOP), Eaagad (EGAD), East Africa Brewery (EABL) and Safaricom (SCOM). The turning points as determined by the market index was used as the trading points for all the companies selected and their profitability as determined by the strategies compared. The findings were as illustrated in Table 4. 18.

Table 4. 18: Sharpe Ratios of the Market and Five Selected Companies (2011-2018)

	CABL	COOP	EGAD	SCOM	EABL	Average	NSE-20	NASI
HMM	(0.00009)	18.7018	(0.0314)	17.7615	11.9784	**9.6820**	15.6439	16.7552
RSI	(0.00055)	(0.0001)	(0.0003)	11.0239	2.9182	**2.7882**	3.5559	8.6772
SMA	(0.00012)	12.9792	(0.0005)	15.5355	11.0630	**7.9154**	7.6611	12.1179
SBH	(0.03882)	(0.0183)	(0.0004)	15.3186	(0.0205)	**3.0481**	(0.0017)	(0.3329)

Source: Researcher

The result shows that in the exception of EGAD, in all the other instances, first, the returns of all the market timing strategies exceeded the returns of SBH. Second, on an inter-comparison basis among the market-timing strategies, HMM performed best. On average the HMM Sharpe ratio for the five companies was 9.6820, the HMM strategy was followed by SMA with a ratio of 7.9154. The SBH returns for all the companies were all negative for all the companies and market indices except for Safaricom. The performance of the strategy in Safaricom can be explained by the fact that Safaricom was the only company which showed a dominant upward trend from 2011 to 2018 as shown in Appendix 13 This scenario can also be used to explain why Zakamulin (2018) concluded that the returns of SBH and SMA were almost indistinguishable, with SMA performing marginally better than SBH. For Safaricom the returns of SBH and SMA closely match the findings of Zakamulin (2018), however, this only holds when the trend is upward and not cyclic in nature. By failing to account for structural breaks in the USA the period considered by his study would generally give an upward trend which explains his findings.

4.5.4 Performance of Market-Timing Strategies in a Selected Portfolio

After evaluating the performance of the strategies based on individual stocks randomly selected this study went further to analyze how the strategies perform in a portfolio setting. The portfolio selected was based on equity shares traded in NSE. Five metrics were considered in the construction of the portfolio; liquidity, market capitalization, price earnings ratio, price to book value as well as the dividend yield. These are considered important determinants when investors are deciding on whether to invest in stock markets,(Kheradyar, Ibrahim, & Nor, 2011; Musallam, 2018). For each metric, this study selected the companies had the highest, lowest and median values, which translated to three companies for each metric a total of fifteen companies. Where a company appeared in two metrics, the company was substituted with a company which ranked next to it. Liquidity was based on the volume of the shares traded, while the rest of the metrics were based on the financials as evidenced in Appendix 7. The performance of the strategies was evaluated based on the average log return over the period 2011-2018 and Sharpe ratio as well. The results are as presented in Appendix 9.

The strategies performance in the constructed portfolio closely mirror the results of the selected individual stocks. The returns of HMM ranked first with an annual average return of 19.12% and a Sharpe ratio of 8.5025. SMA ranked second with an annual return near that of HMM strategy at 18.24% however the difference in Shape-ratio was much bigger. The buy and hold strategy was the least profitable trading strategy with an annual return of approximately 4% and a risk-adjusted return of 1.4298.

Table 4. 19: Summary Ranking of Market Timing Strategies

Test	**HMM**	**RSI**	**SBH**	**SMA**
Planned Contrast Test	1	3	4	2
Risk Adjusted Returns	2	1	4	3
Regression Analysis	1	3	4	2
Sub-Period Test	1	3	4	2
Simulation	1	2	4	3
Randomized Selection	1	4	3	2
Portfolio Performance	1	3	4	2
Average	**1.4**	**2.6**	**4**	**2.3**
Rank	**1**	**3**	**4**	**2**

Source Researcher

This study conducted three main tests to evaluate the performance of the select market timing strategies and an additional four supporting tests. To gauge the superiority, the performance of all the strategies were ranked based on all the six tests and mean ranking obtained. The results showed that the best performing strategy was the HMM strategy, where it was only outdone once in terms of risk-adjusted returns. The SMA strategy returns ranked second closely followed by the returns of RSI strategy. For all the tests conducted there is no single point that the SBH outperformed the market timing strategies analyzed.

4.6 Significance of Market Timing to Kenyan Fund Managers

The final objective of this study sought to understand the significance attached to market timing strategies by fund managers is Kenya. In this respect, significance was implied by the extent to which the market timing strategies are applied by the fund managers. The survey was conducted online and received a response rate of 68.2%. The responses were received from one chief investment officer, three investment managers while the remainders were financial analysts and advisors.

Given that market timing falls under technical analysis, the study's first interest was to determine how relevant technical analysis is among the fund managers in Kenya. From the survey, 60% of the respondent reported that their investment decisions are majorly informed by fundamental analysis of the 60%, where in most cases it accounts for over 80% of all equity investment decisions. 26.7% reported that their investment decisions are majorly informed by technical analysis while the remaining 13.3% use the two methods of analysis in equal weights.

4.6.1 Determinants of Entry and Exit points in NSE

This study sought to understand what determines traders' decisions to buy or dispose of equity holding in NSE. Three factors were considered; the prevalence of bull and bear markets, the necessity to alter portfolio weights and ad hoc basis. The feedback was as provided in Table 4. 20.

Table 4. 20: Factors Influencing Entry and Exit points in NSE

Factor	Weighted Average	Standard Deviation	Rank
Prevalence of Bull and Bear Markets	3.37	0.8	2
Need to Adjust Portfolio Weights	4.00	0.86	1
Ad-hoc Basis	1.67	0.31	3

Source: Survey

From the survey results, the fund managers decisions are majorly driven by the need to adjust portfolio weights. The prevalence of bull and bear markets play a moderate role in determining the treading points in NSE. The ad-hoc basis is rarely used. If the fund managers believed that the market follows the random walk hypothesis the reliance on ad hoc basis would have been higher than what was reported.

On the level of market efficiency, 71.4% of the respondents believe NSE efficiency lies in the Semi-strong form, while the rest believe that NSE is in the weak form. After determining how the fund manager perceive the efficiency of NSE, this study explored whether their assessment is congruent with their practices in terms usage of technical analysis vis a viz fundamental analysis. This study found that no single applied either technical or fundamental analysis exclusively. 60% of the respondents reported that they place heavy reliance on fundamental analysis, 26.7%, on the other hand, indicated that they rely more on technical analysis compared to fundamental analysis while 13.3% indicated that their level of application of either strategy was equal.

4.6.2 Significance of Market Timing Strategies

The survey sought to understand how much significance the fund managers attached to market timing. The respondents were requested to respond to how significant the perceived market timing to be in NSE. Their responses are tabulated in Table 4. 21

Table 4. 21: Significance of Market-timing to Fund Managers

Significance	Very Low	Low	Average	High	Very High	Weighted Average
Market timing	6.7%	0%	33.3%	20%	40%	3.87

Source: Survey

The fund managers in Kenya do not attach high significance to market timing but rather, the significance which is just slightly above average. This is congruent with the finding that in the determination of trading points, the prevalence of market patterns is given moderate consideration.

The study went further and interrogated the tentative level of usage of the various market timing strategies. The findings were that of the four investing strategies considered in this study SBH is the most applied strategy. This can be rationalized by the fact that the majority believe that NSE is semi-strong and therefore according to the EMH theory this would be the expected behavior.

SMA ranks as the second most applied strategy closely followed by the RSI strategy. The HMM concludes the ranking as the least applied trading strategy by fund managers in Kenya.

Table 4. 22: Application Levels of Market Timing Strategies

Strategy	Standard Deviation	Average	**Rank**
HMM	0.18	1.83	**4**
RSI	0.08	2.58	**3**
SBH	0.23	3.23	**1**
SMA	0.17	2.66	**2**

Source: Survey

4.7: Comparison of Primary Data Findings with Secondary Data Findings

The secondary data shows that from a wide perspective the behavior of asset prices follow cyclic repetitive patterns. As such the data shows that it is possible to determine profitable trading opportunities by choosing a model that best fits the cyclic nature. This study focused on three strategies that can be used to determine such trading opportunities and then compared the profitability of trading on points so determined. As shown in Table 4. 19, HMM was the best performing strategy followed by SMA, RSI and in the final rank was SBH. When these results are compared to how the frequencies at which fund manager utilize them, the SBH ranks as the most utilized strategy while HMM ranks as the least applied strategy. For the other two strategies, the results are similar, SMA ranks second followed by the RSI strategy. Just as noted under secondary data analysis the difference between the levels of application of these two strategies is also marginal.

The fund managers regard NSE efficiency as semi-strong efficient. In line with this theory, market timing based on historical prices is deemed futile in markets which are efficient. This can explain why the fund managers tend to huddle towards the buy and hold strategy. However, according to the analysis of the past prices, this study shows that the financial markets do exhibit patterns which can be used to trade profitably. According to this study, these patterns can be determined using the moving averages or using the probability theory as applied in HMM strategy.

This study was based on the long run where the trading periods were based on prices over periods equal or exceeding twelve months. The secondary data showed that the buy and hold strategy was the least profitable strategy in the long run. Whereas most of the respondents indicated that rely on the buy and hold strategy their evaluation criteria were based mostly on a weekly basis or continuous. This may point out the buy and hold strategy may be a profitable strategy where the holding period is in terms of weeks.

CHAPTER FIVE

DISCUSSIONS, CONCLUSION, AND RECOMMENDATIONS

5.1 Introduction

The objective of this study was to conduct a comparative assessment of how three market timing strategies; HMM, RSI and SMA performance in NSE and also evaluate how their respective performance compares to the SBH strategy. Following research analysis done this chapter presents a discussion of this study's finding, the conclusions which can be drawn, limitations of the study and finally the recommendations.

5.2 Summary of the Findings

5.2.1 Profitability of the Market Timing Strategies

The first objective of this study sought to determine the performance of RSI, SMA and HMM strategies when applied in NSE. The evaluation of the strategies' performance was conducted at three levels; average annual returns, risk-adjusted returns and finally using parametric regression. At each level of evaluation, SBH was used as the benchmark.

5.2.1.1 Performance based on Average Annual Returns

At a bracket point of view, the findings of this study were that all the market timing strategies' raw returns were significantly different from those realized in the absence of market timing. These results are congruent with Ghobadi (2014), Glabadanidis (2015) and Rousis & Papathanasiou (2018) who all agreed that with appropriate strategies trading based market timing was more profitable than the buy and hold strategy.

The performance based on the raw returns of NSE-20 showed that HMM strategy was the most viable, followed by SMA and then RSI. Interestingly all the strategies' returns were above ten percent, which mirrors the findings of Kole & Dijk (2017) who concluded that market timing gave returns above ten percent and well above the returns of buy and hold strategy. As shown by Tukey-HSD test the returns from the select market-timing strategies are statistically different when compared to the SBH strategy. The returns of the SBH strategy were less than one percent, on an approximate basis the returns of the market timing strategies were fifty times more than those of the SBH strategy. These findings are contrary to Borri & Cagnazzo (2018) and Metcalfe (2018) where the two studies concluded that trading based on market timing strategies was not profitable.

5.2.1.2 Performance Based on Risk-Adjusted Returns

Returns alone are not enough to make investment decisions. The investors are concerned with the level of risk associated with a given level of returns. This study applied the Sharpe ratio as a gauge of the risk-adjusted returns. In the time span, 2004-2018 RSI had the best Sharpe ratio. This can be explained by the fact that the strategy had the least trading points and consequently the least standard deviation. HMM, the strategy had the second-best returns and SMA closed the list of the strategies with positive Sharpe ratio. Just like the case of raw returns SBH was the worst performer with negative Sharpe ratio of a magnitude similar to that of RSI.

For the subsequent validation tests; simulation, sub-period testing and randomized stock selection the HMM strategy outperformed the rest based on the Sharpe ratio. While agreeing with Ghobadi (2014) that market timing strategies lack consistency as noted in the case of RSI and SMA this study provides evidence that the performance of the HMM strategy is fairly consistent, this is supported by similar findings by Artur (2014).

5.2.1.3 Performance as Measured by Market Timing Ability

In regression analysis, this study evaluated the strength of market timing ability of the strategies under consideration. The first approach was parametric regression of the modified capital asset pricing as outlined in Henriksson & Merton (1981). The comparative results were comparable to those of the raw return comparison. The results showed that all the market timing strategies had positive market timing abilities. Though all the strategies had positive performance, HMM had the best performance followed by RSI and finally SMA.

This study revealed that by estimating the HM equation the resultants models have low explanatory power and furthermore the residuals of the said models are serially correlated and heteroscedastic. The presence of the two latter problems implies that the coefficient parameters are no longer efficient. To remedy these Shortcomings this study modified the HM regression model by estimating the equation using the ARDL regression model instead of the classical linear regression model. By so doing this study showed that the explanatory was increased to at least ninety percent for all the models. In addition, serial correlation problem was eliminated altogether.

The results of the ARDL model showed that both HMM and RSI had positive market timing abilities, while RSI had negative market timing ability. Though all the determinant coefficient were statistically non-significant HMM had the positive coefficient which had the least P-value. It can, therefore, be concluded that HMM conveys the best market timing ability compared to the other two strategies.

Most of the studies on market timing ability have been limited to evaluation of whether fund managers possess positive or negative market timing abilities, (Chang & G Lewellen, 1984; Gao, O'Sullivan, & Sherman, 2017; Henriksson & Merton, 1981; Paramita, Jafar, & Siregar, 2017; Treynor, & Mazuy, 1966). This study contributes to the field of market timing by extending the market timing principles applied in these studies to evaluate the performance of market timing strategies as opposed to the performance of specific funds or fund managers.

5.2.2 Model Superiority Analysis and Validation

The model validation tests evaluate whether a model performs as is purported to. To validate the performance of the market timing strategies under consideration, this study employed a Monte-Carlo simulation to mimic the NSE 20 returns over the years 2004-2018. The simulated prices' returns were then subjected to the three market timing strategies.

The results showed that based on raw returns HMM had the best performance (11.73%) followed very closely by RSI (11.11%), while SMA had a way lower return of 4.12%. The three strategies returns were still higher than those of SBH whose returns were still below 1%. Sharpe-ratio comparative results were similar to those of raw returns comparison. HMM had the highest Sharpe ratio of 9.27 followed by RSI with 7.57. However, unlike using the actual returns under the simulation analysis the ratio of SMA fell into negative. The ratio of SBH was also negative but way lower compared to the ratio of SMA. The dismal performance of SMA under the simulation can be explained by the Ghobadi (2014) who found out that profitability of the graphical market timing strategies lacked consistency.

Glabadanidis (2015) argues that robustness checks for market timing strategies can be achieved through subperiod tests this argument is supported by other literature like Shen (2002) and Nguyen & Roberge (2008). In line with his argument, this study split the study period into two equal parts and focused on the latter half running from 2011 to 2018. The returns of NSE generated by NSE proxied by NASI were then evaluated for each market timing strategy. The findings showed that the returns in the subperiod for all the market timing strategies and SBH as well were slightly higher than when the of the entire period returns are considered. Similar to the evaluation based on the entire sample period, the subperiod returns of all the market timing strategies were at least twice those of SBH. This implies that irrespective of the period chosen the considered market timing strategies deliver superior returns to those of SBH. This confirms robustness in the select market timing strategies.

This adds on to the study Dyck et al. (2013) whose study focused on investment strategies in developed and emerging markets by addressing the performance of market timing strategies in NSE, a frontier market. Similar to the findings of Dyck et al. (2013) in developed markets and Naidoo (2017) in South Africa, this study found that trading informed by active market timing gave returns far superior to those of the passive buy and hold strategy.

5.2.3 Significance of Market Timing Strategies to Kenyan Fund Managers

The final objective of this study was to determine the level of significance placed on the market timing strategies by Kenyan fund managers. All the investor considers historical prices in their investment analysis, the level of reliance on historical prices was determined to be moderate. In line with their assessment of the level of market efficiency(semi-strong), the usage of technical analysis is quite low.

The trading points in NSE according to the Kenyan fund managers are majorly driven by the necessity to alter portfolios, while market regimes play a moderate role. This is no different from some findings in other financial markets; Kole & Dijk (2017) in USA and Frøystad, Johansen, & Zakamouline (2017) in Norway. The SBH is the most was determined to be the strategy mostly relied upon, this in disharmony with other many studies like Glabadanidis (2015) and Cohen & Cabiri (2015) who reported SMA and RSI to be the popular trading strategies, respectively. Comparing this with the profitability this study shows that there is discord between the strategy's high level of reliance, yet the strategy's profit is the lowest compared to all the other strategies. Likewise, there is a disharmony between the profitability of HMM whose performance was best among all the strategies, yet it was the least applied trading strategy. The relative usage of the market timing strategies in NSE can be related to when the market timing strategies, the oldest market timing strategy is the SMA formulated at the beginning of the twentieth century, followed by RSI in 1978 and finally HMM in 1989. From this research, it is evident that reliance on a particular strategy is linked to how long the strategy has been in use.

5.3 Conclusion

The objectives of this study were first, to determine the individual performance of RSI, SMA, and HMM as market timing strategies and second perform a comparative analysis of all the three strategies. The results of this study based on actual simulated and results conclude that trading based on market-timing strategies is indeed more profitable compared to the passive buy and hold strategy. For any given test this study showed that the market timing strategies will always outperform the passive buy and hold strategy. This analysis relied on the theory of moving average in two respects. One in relation to Dow's Theory this study focused on modeling the primary trend and the second for each estimation method moving averages were considered to smoothen the Two strategies have shown persistent strong performance; SMA and HMM. In comparing the two the SMA strategy is outperformed by the HMM strategy. Therefore, this study concludes that of the three market timing strategies, HMM performs best.

This study has proven that it is possible to earn above average market returns by trading using market timing strategies. The market timing strategies are fundamentally based on repetitive patterns. As shown by the sub-period test this study shows that the market patterns remain fundamentally unaltered irrespective of time span considered. This is in line with the fractal nature of financial markets as explained by fractal Brownian motion. This study concludes that it is possible to profit from trading based on the patterns of historical prices' patterns. This essentially casts doubt on EMH theory and seconds the FMH as a more relevant theory in explaining the behavior of prices in equity markets.

The last objective of this study was to find the level of usage of the market timing strategies in the industry and determine if the level of usage was in alignment with the strategies' performance. This study showed that investors in Kenya are majorly fundamentalist and in line with that majority rely on the buy and hold strategy confirming herding behavior in NSE. Given the method is used by a majority of the investors explains why the strategies return remain low.

5.4 Recommendations

5.4.1 Recommendation to Fund Managers and Individual Investors

This research showed that the majority of fund managers in Kenya tend to follow the buy and hold strategy. This study has clearly shown that the passive buy-and-hold strategy performs poorly in NSE relative to the market timing strategies. As such for a fund manager who would like to outperform the other players this study recommends that such fund managers rely more on market timing strategies particularly the HMM strategy as opposed to the buy and hold strategy. This study suggests that such individuals should afford themselves the knowledge of how market timing strategies work and apply the same when making investment decisions.

5.4.2 Recommendations to Capital Market Policy Makers

The CMA has the mandate to disseminate investor education to Kenyans. In the authority strategic plan investor education has mostly been considered a crucial pillar. The authority has in its review pointed out that investor education in Kenya has been unsatisfactory and has not been able to achieve significant improvement in the number of Kenyans investing in NSE. This study recommends a different approach, where the potential investors are trained on how to identify trading points based on market timing as well as the shortcoming of such approaches. Given that NSE and CMA do conduct trading challenges especially for the university students. This study would recommend that participants are equipped with knowledge regarding trading strategies before the students can begin their virtual trading challenges.

This study was based on the index returns of NSE-20. This study showed that trading based on securities that track the market indices in NSE can be profitable. This research, therefore, makes a recommendation to NSE and CMA to establish index traded funds. Such funds will help investors avoid security selection cost while earning at the very least the average market returns.

5.4.3 Recommendation to Researchers and Academics

The final recommendations go to scholars and researchers, particularly in finance. For over half a century these individuals have placed and continue to place great reliance on EMH theory. However, the many unrealistic assumptions of the theory make it an impractical theory. Given that the findings of this study negate the premises of the EMH theory, the study recommends that the persons in the field should now shift focus to more realistic theories like Complexity, FMH and non-linear dynamics theories.

Lastly, this study recommends that future researchers interested in market timing abilities evaluate the same using ARDL model as opposed to the ordinary regression model. The ARDL model can capture the variation in asset prices better while ensuring that the assumptions of the efficient estimator are met.

5.5 Limitations of the Study

A major limitation of this study was that the analysis was based on smoothed data. Though so doing helps eliminate noise, the natural structure of the data is altered. The alteration also ends up tranquilizing the volatility observed during market crises. This research was conducted on an ex-post basis. This implies that the results are backward looking, however, the investors' concerns tend to lean more towards the future rather than the past. This implies that the results of this study may have reduced interest to future-oriented investors.

5.6 Plausible Areas for Further Research

By deductive reasoning, this study showed that the financial markets are made up repetitive patterns. Given so, it is imperative to say that the market crashes that happen from time to time are not just random events. This assertion is supported by Chaos theory which posits that non-linear dynamical systems are from time to time faced by huge perturbations which are nonetheless encapsulated in the system. This study, therefore, recommends further market timing study focusing on the modeling of market crashes, which were not addressed in this study.

This study has demonstrated that autoregressive HMM has great ability in capturing the behavior of systems that follow a cyclic nature. This study would, therefore, call on future researchers to look for other areas that can be model can be applied. These areas could include modeling economic variables like inflation, gross domestic product (GDP) or financial variables like interest rates.

From interaction with practitioners in Kenyan fund managers firms, this study found that in given cases the investments in equity markets were primarily driven by dividend income. From the findings of this study, it is possible to earn capital gains in NSE by market timing strategies to decipher optimal buying and selling points. It would, therefore, be important to undertake a comparative study comparing the income generated from capital gains versus the dividend income for select companies in NSE.

By randomly selecting stocks and subjecting them to market timing strategies, this study showed that thought the market timing strategies ordinarily deliver superior profits to buy and strategy the profitability varies from one company to another. This shows that stock selection is an important step when it comes to stock selection. Given that the focus of this research was on entire NSE, this study recommends a further study to evaluate whether returns of investments based on stock selection will exceed the returns arrived at in this study.

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APPENDICES

APPENDIX 1: Letter of Introduction

Strathmore
UNIVERSITY

20 March, 2019

TO WHOM IT MAY CONCERN

Academic Reference for Ng'anga Judah Waweru Student No. 73581

Ms Ng'ang'a Judah Waweru is a postgraduate student in our Master of Commerce (MCom) programme. In partial fulfilment of the MCom degree, students are required to carry out a research project and write a thesis on a contemporary subject within their field of specialisation. Among other activities, the project involves data collection and analysis.

Judah is requesting to gather information to be used in his research. The information he will obtain from your organization will be used for this academic purpose only and will be kept confidential. The results of the survey will be in summary form and will not disclose any individual, company name or company information in any way.

The research study is entitled **"An Assessment of Marketing Timing Strategies' Performance in Nairobi Securities Exchange."**

We hope that your organization can assist by providing information to the above named student.

Yours faithfully,

Quindos Karanja
Coordinator – Master Programmes
Strathmore University Business School
Email: qkaranja@strathmore.edu

APPENDIX 2: Ethical Review Board Approval

Strathmore
UNIVERSITY

13th May2019

Mr. Ng'ang'a, Judah
P.O. Box 59857-00200,
Nairobi.
jwaweru@strathmore.edu

Dear Mr. Ng'ang'a

REF **Protocol ID:** SU-IERC0432/19 **Student NO:** 73581

AN ASSESSMENT OF MARKET TIMING STRATEGIES' PERFORMANCE IN NAIROBI SECURITIES EXCHANGE

We acknowledge receipt of your application documents to the Strathmore University Institutional Ethics Review Committee (SU-IERC) which includes:

1. Study Protocol submitted 29th April 2019
2. Cover letter listing all submitted documents 29th April 2019
3. Proposal declaration Page signed by supervisors 29th April 2019

The committee has reviewed your application, and your study *"An Assessment of Market Timing Strategies' Performance in Nairobi Securities Exchange"* has been granted **approval.**

This approval is valid for one year beginning **13th May 2019** until **13th May 2020**

In case the study extends beyond one year, you are required to seek an extension of the Ethics approval prior to its expiry. You are required to submit any proposed changes to this proposal to SU-IERC for review and approval prior to implementation of any change.

SU-IERC should be notified when your study is complete.

Thank you

Sincerely,

STRATHMORE UNIVERSITY INSTITUTIONAL ETHICS REVIEW COMMITTEE (SU-IERC)
13 MAY 2019
TEL: +254 (0)703 034 000
P. O. Box 59857 - 00200
NAIROBI - KENYA

Prof. Florence Oloo
Secretary
Strathmore University Institutional Ethics Review Committee

Ole Sangale Rd, Madaraka Estate. PO Box 59857-00200, Nairobi, Kenya. Tel +254 (0)703 034000
Email admissions@strathmore.edu www.strathmore.edu

APPENDIX 3: Questionnaire

PART: ONE: GENERAL INFORMATION

Name of the firm ……………………………………...

Please state your role in the firm………………………

PART TWO: MARKET TIMING

1. In making investment decisions, does your firm consider past prices of financial instruments?

   YES [ ]   NO [ ]

2. If you chose 'YES' to the question above, please indicate the level of reliance on past prices patterns?

   High Reliance [ ]   Moderate Reliance [ ]   Low Reliance [ ]

3. What level of market efficiency would you attach to Nairobi Securities Exchange?

Form of Efficiency	Tick as appropriate.
Weak	
Semi-strong	
Strong	

4. For the following investment strategies, what proportions apply in decision making regarding investments in equity trading

Technical Analysis	Fundamental Analysis	Please tick
100%	0%	
80%	20%	
60%	40%	

50%	50%	
40%	60%	
20%	80%	
0%	100%	

5. What significance would you attach to the following when it comes to the determination of appropriate entry & exit times in equity markets? Where 5 if the highest level of significance and 1 the least level of significance

	5	**4**	**3**	**2**	**1**
Need to alter portfolio weights					
Prevalence of either bull or bear markets					
Ad- Hoc basis/ Non-planned					

6. What significance do you attach to market-timing, when it comes to trading decisions in NSE? Where 5 if the highest level of significance and 1 the least level of significance.

	5	**4**	**3**	**2**	**1**
Significance of market-timing					

7. Please indicate the relative levels of usage of the following techniques in equity trading.

Strategy	**High**	**Medium**	**Low**	**Never**
Simple Moving Averages (, SMA)				
Relative Strength Index (RSI)				
Hidden Markov Strategy				
Buy and Hold Strategy				

Others; (indicate below)				

8. How would you rank the profitability of trading based on the following strategies?

Strategy	**High**	**Medium**	**Low**	**Cannot Tell**
Simple Moving Averages (, SMA)				
Relative Strength Index (RSI)				
Hidden Markov Strategy				
Buy and Hold Strategy				
Others; (indicate below)				

9. According to your experience, please indicate the frequency at which market-timing strategies are applied in financial asset trading?

Frequency of Application	**Weekly**	**Monthly**	**Quarterly**	**Bi-Annually**	**Annually**	**Continuously**
Please tick as appropriate						

10. Please add (if any) additional comments regarding market-timing strategies

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Thank you very much.

Your assistance is much appreciated.

APPENDIX 4: Registered Fund Managers in Kenya in 2018.

	REGISTERED FUND MANAGERS - 2018	TELEPHONE	PHYSICAL LOCATION
1	African Alliance Kenya Investment Bank Limited	2762000	4th Floor, Kenya Re Towers, Upper Hill
2	Allan Gray Kenya Limited	205147016	2nd Floor, Eaton Place.
3	Alpha Africa Asset Managers Limited	2595448	Crawford Business Park, 4th Floor Suite 26, State House Road
4	Amana Capital Limited	2351738	Block C, Suite C5, Saachi Plaza, Argwings Kodhek Rd
5	Apollo Asset Management Company Limited	3641000	Apollo Centre, Ringroad, Westlands
6	Britam Asset Managers Ltd	2833000	Britam Centre, Upper Hill
7	CBA Capital Limited	2884444	CBA Centre, Mara & Ragati Roads
8	CIC Asset Management Limited	2823000	8th Floor, CIC Plaza II, Mara Road
9	Co-op Trust Investment Services Limited	3276000	Co-operative Bank House'
10	Dry Associates Limited	4450520	Dry Associates House, Brookside Groove, Waiyaki Way
11	Fusion Investment Management Limited	2738460	1st Floor, ACK Garden House, 1st Ngong Avenue
12	Get Africa Asset Managers Limited	2323343	1st Floor, Arlington Block, 14 Riverside Drive, Westlands
13	Genghis Capital Limited	0709185000	1st Floor, Purshottam Place, Westlands
14	ICEA Lion Asset Management Limited	2221652	ICEA Lion Centre, 4th Floor, Riverside Park, Chiromo Road
15	Kenindia Asset Management Company Limited	316099	Kenindia House, Loita Street
16	Madison Asset Management Services Limited	2864502	Madison Insurance House, Upper Hill Road
17	Nabo Capital Limited	2286000	7th Floor, International House.
18	Natbank Trustees and Investment Services Ltd	2828356	13th Floor, National Bank Building, Harambee Avenue

19	Old Mutual Investment Group Ltd.	2829000	Old Mutual Building, Corner, Mara
20	Sanlam Investments EA Ltd.	4967000	Africa Re Centre, Hospital Road.
21	Stanlib Kenya Limited	3268508	Liberty House, Mamlaka Road
22	Zimele Asset Management Ltd.	2246273	Fedha Towers, Muindi Mbingu Street

APPENDIX 5: 91-day Treasury Bills 2004-2018

Year	Rate
2004	8.29%
2005	8.07%
2006	5.73%
2007	6.87%
2008	8.59%
2009	6.82%
2010	2.28%
2011	18.30%
2012	8.30%
2013	9.52%
2014	8.58%
2015	9.81%
2016	8.44%
2017	8.01%
2018	7.76%

APPENDIX 6: A Graph of NSE-20 Share price between 2004-2018

APPENDIX 7: 2018 Financials of NSE Listed Companies

CODE	Price	Mkt.Capitalization	P/E	P/BV	Dividend Yield	Volume Traded
ARM	5.43	20,677,731,250.00	(3.76)	0.65	0.06%	DNT
ADSS	1.05	12421955517*	51.17*	10.3*	0.06%	DNT
BAMB	155.13	63,517,873,125.00	10.70	1.85	7.40%	1,200.00
BBK	11.75	73,882,489,600.00	5.26	1.87	7.40%	241,100.00
GLD	1,220.0	N	N	N	N	DNT
BAT	612.50	78,500,000,000.00	17.08	0.35	5.40%	5,000.00
BKG	30.53	231421955517*	51.7*	10.3*	0.06%	DNT
BOC	86.00	1,991,550,000.00	11.56	1.16	5.09%	100.00
BRIT	12.08	25,199,405,894.00	7.90	1.43	230.00%	31,000.00
C&G	23.00	1,336,776,960.00	33.55	0.33	1.50%	300.00
CARB	10.75	4,319,741,197.00	8.88	1.59	4.10%	4,900.00

ICDC	34.75	30,610,321,650.00	3.04	0.78	0.06%	6,200.00
CIC	4.45	1,621,638,874.00	8.84	2.07	1.69%	9,200.00
COOP	16.33	88,007,693,310.00	5.65	1.79	4.40%	103,200.00
BERG	68.75	23367807343*	66.15	10.3*	0.06%	600.00
DCON	1.60	12421955517*	4.83	10.3*	0.06%	DNT
DTK	171.00	452,744,589,635.00	5.86	1.18	1.40%	500.00
EGAD	17.80	3204813120*	2,250.	10.3*	0.06%	DNT
EABL	215.00	240,427,016,576.00	17.63	6.51	2.00%	898,900.00
CABL	3.70	4,100,625,000.00	(2.82)	89.00	3.09%	28,100.00
PORT	19.30	5,175,000,000.00	0.50	0.26	0.06%	DNT
EQTY	45.20	148,111,080,800.00	5.61	2.05	5.00%	1,649,200.00
EVRD	1.59	640,500,000.00	0.88	0.74	0.06%	100.00
XPRS	6.03	159,317,055.00	1.94	0.46	0.06%	1,000.00
FTGH	3.43	65755527871*	3.53	10.3*	88.00%	7,600.00
HFCK	7.86	1,053,663,832.00	(1.21)	1.44	0.06%	10,400.00
HAFR	0.83	7,841,270,841.00	3.45	10.3*	0.06%	54,500.00
I&M	106.25	39,236,203,900.00	6.42	1.16	3.50%	DNT
JUB	453.00	31,888,098,000.00	11.59	1.56	1.76%	2,100.00
KUKZ	345.00	3204813120*	10.43	10.3*	0.06%	400.00
KAPC	83.00	3204813120*	(13.57)	10.3*	0.06%	1,000.00
KCB	45.25	172,437,140,544.00	4.08	2.28	3.50%	1,016,000.00
KENO	17.90	14,128,907,520.00	9.89	1.61	2.60%	1,000.00
KQ	8.90	6,734,110,658.00	(32.00)	10.3*	0.06%	53,900.00

KEGN	7.23	20,334,843,468.00	5.23	0.17	7.00%	172,900.00
ORCH	47.30	65755527871*	287.88	0.02	0.06%	DNT
KPLC	5.53	35,809,420,275.00	2.02	4.80	0.06%	740,400.00
KNRE	15.13	14,698,930,428.00	4.43	0.67	3.60%	40,600.00
KURV	1,500.0	65755527871*	(13.16)	1.10	0.06%	DNT
CFCI	12.25	16,216,338,874.00	9.82	2.60	0.06%	DNT
LIMT	550.00	3204813120*	434.43	10.3*	0.06%	DNT
LKL	5.50	1,096,875,000.00	7.20	10.3*	3.33%	21,600.00
MSC	0.68	65755527871*	(0.36)	0.53	0.06%	73,200.00
NBV	1.78	12421955517*	52.67	10.3*	0.06%	8,300.00
NSE	17.05	4,816,968,750.00	8.31	10.3*	1.98%	7,400.00
NMG	85.88	36,011,576,626.00	6.73	3.95	6.17%	17,300.00
NBK	6.43	31,677,306.00	(1.68)	0.44	0.06%	400.00
NIC	31.45	14,565,238,058.00	3.28	0.55	2.30%	30,400.00
OCH	2.85	250,000,000.00	(2.93)	10.3*	0.06%	5,000.00
SCOM	26.75	6,771,055,733,200.00	18.89	17.76	4.50%	3,679,200.00
FIRE	2.51	104,378,974.00	(45.00)	0.42	0.06%	100.00
PAFR	22.25	8,640,000,000.00	(56.98)	315.9	0.06%	DNT
SASN	20.25	3204813120*	8.26	10.3*	0.06%	1,800.00
CFC	95.50	32,614,035,135.00	5.28	0.85	6.50%	600.00
SCBK	209.00	60,286,105,230.00	9.01	1.46	8.70%	1,100.00
SGL	29.13	2,288,463,912.00	6.10	0.89	0.06%	200.00
FAHR	10.15	1,936,403,610.00	-	0.53	8.84%	DNT

TOTL	30.75	11,489,149,859.00	6.63	0.61	4.20%	7,700.00
TPSE	27.50	4,554,350,000.00	11.84	0.34	0.06%	1,100.00
TCL	3.86	2,312,346,927.00	(96.00)	0.29	0.06%	1,000.00
UCHM	1.52	3,266,388,563.00	(0.30)	2.91	0.06%	3,200.00
UMME	8.95	27,524,732,185.00	9.67	0.02	207.69%	DNT
UNGA	37.50	3,539,301,595.00	7.40	0.56	2.12%	DNT
WTK	157.00	3,204,813,120.00	6.86	0.43	5.46%	100.00
SCAN	15.30	11,365,953,060.00	15.18	1.29	167.00%	1,600.00

Source: NSE *Based on Industry Average

APPENDIX 8: Tukey HSD Homogenous Subset Tabulation

Returns

Strategy		N	Subset for alpha = 0.05		
			1	2	3
Tukey HSD[a]	ZSBH	3728	-.2881		
	RSI	3728		10.3225	
	SMA	3728		10.4720	
	HMM	3728			11.6252
	Sig.		1.000	.974	1.000
Ryan-Einot-Gabriel-Welsch Range[b]	ZSBH	3728	-.2881		
	RSI	3728		10.3225	
	SMA	3728		10.4720	
	HMM	3728			11.6252
	Sig.		1.000	.892	1.000

APPENDIX 9: Portfolio Performance

Firm	Metric	SBH	RSI	SMA	HMM
BOC	Returns	-2.67%	9.74%	7.95%	6.58%
	Sharpe Ratio	(0.0001)	6.4321	(0.0000)	(0.0001)
AFR	Returns	-3.89%	6.83%	24.30%	20.87%
	Sharpe Ratio	(0.0038)	(0.0003)	8.0317	14.5722
ORCH	Returns	42.76%	-40.17%	96.62%	96.71%
	Sharpe Ratio	3.0586	(0.0277)	10.6497	11.5234
BAT	Returns	12.77%	15.35%	12.28%	14.31%
	Sharpe Ratio	3.1177	5.6772	4.1338	6.8065
SGL	Returns	-0.65%	6.77%	11.87%	11.69%
	Sharpe Ratio	(0.0010)	(0.0001)	8.1336	14.0344
TOTL	Returns	4.29%	9.12%	17.97%	14.13%
	Sharpe Ratio	(0.0006)	1.8143	8.8860	7.9999
I&M	Returns	-0.20%	9.43%	9.80%	10.78%
	Sharpe Ratio	(0.0006)	3.7132	1.9925	3.7520
TCL	Returns	-18.16%	1.29%	-9.72%	4.54%
	Sharpe Ratio	(0.0062)	(0.0006)	(0.0036)	(0.0004)
TPSE	Returns	1.20%	0.80%	0.96%	0.83%
	Sharpe Ratio	(0.0024)	(0.0004)	(0.0002)	(0.0004)
BRIT	Returns	2.34%	10.42%	25.78%	27.62%
	Sharpe Ratio	(0.0018)	4.4655	12.5250	14.7519
DTK	Returns	7.29%	9.07%	22.18%	23.28%
	Sharpe Ratio	(0.0002)	1.2054	12.6904	15.8882
NBK	Returns	-19.05%	1.94%	7.05%	9.10%
	Sharpe Ratio	(0.0233)	(0.0005)	(0.0001)	1.7463
COOP	Returns	2.33%	5.31%	13.42%	13.74%
	Sharpe Ratio	(0.0010)	(0.0001)	12.9792	18.7018
SCOM	Returns	45.80%	18.10%	31.82%	30.90%
	Sharpe Ratio	15.3186	11.0239	15.5355	17.7615
EGAD	Returns	-14.48%	5.07%	1.33%	1.70%
	Sharpe Ratio	(0.0058)	(0.0003)	(0.0005)	(0.0004)

	Portfolio Sharpe-Ratio	**1.4298**	**2.2868**	**6.3702**	**8.5025**

APPENDIX 10: NSE 20 correlogram

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.363	0.363	492.23	0.000
		2	0.230	0.113	690.41	0.000
		3	0.091	-0.028	721.34	0.000
		4	0.010	-0.044	721.73	0.000
		5	-0.022	-0.021	723.53	0.000
		6	-0.036	-0.016	728.49	0.000
		7	-0.036	-0.010	733.36	0.000
		8	-0.024	0.000	735.51	0.000
		9	0.019	0.039	736.85	0.000
		10	0.005	-0.012	736.94	0.000
		11	0.020	0.011	738.43	0.000
		12	0.012	-0.001	739.00	0.000
		13	0.012	0.004	739.53	0.000
		14	0.018	0.013	740.76	0.000
		15	0.019	0.010	742.05	0.000

APPENDIX 11: Univariate GARCH Output

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000178	0.000184	0.969379	0.3324
AR(1)	-0.562781	0.227681	-2.471792	0.0134
AR(2)	0.352265	0.119473	2.948490	0.0032
AR(3)	0.150456	0.043941	3.423997	0.0006
MA(1)	0.861271	0.228355	3.771634	0.0002
MA(2)	0.054642	0.108097	0.505495	0.6132
		Variance Equation		
C	1.11E-05	6.89E-07	16.12192	0.0000
RESID(-1)^2	0.149966	0.009106	16.46820	0.0000
GARCH(-1)	0.599966	0.016133	37.18964	0.0000

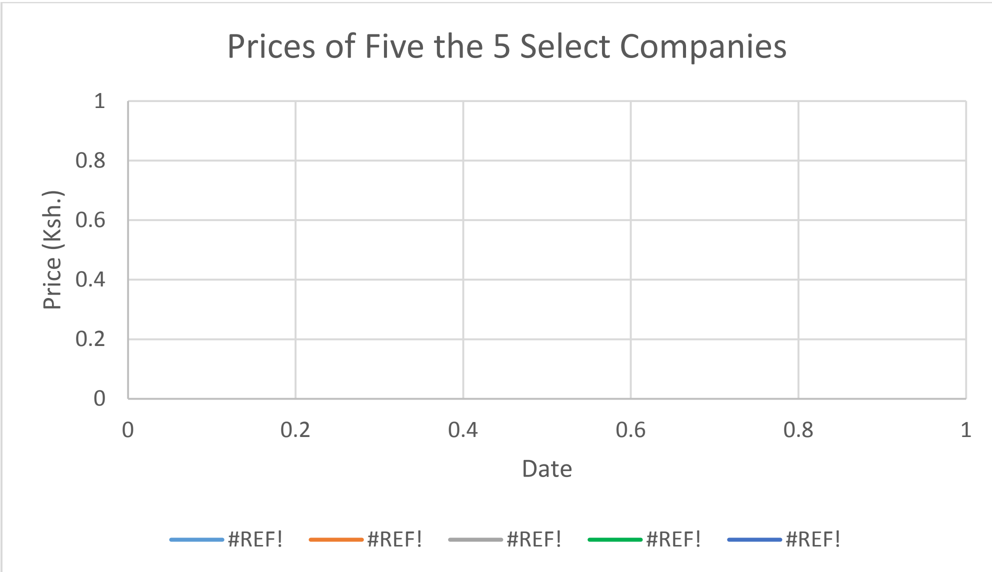
R-squared	0.142440	Mean dependent var	4.17E-05
Adjusted R-squared	0.141287	S.D. dependent var	0.008297
S.E. of regression	0.007688	Akaike info criterion	-7.177737
Sum squared resid	0.219821	Schwarz criterion	-7.162702
Log likelihood	13377.54	Hannan-Quinn criter.	-7.172389
Durbin-Watson stat	1.943566		

Inverted AR Roots	.56	-.35	-.77
Inverted MA Roots	-.07	-.79	

APPENDIX 12: Multicollinearity Test

Variable-1	Variable-2	VIF
(HMM-SBH)	Dummy1	1.00
(RSI-SBH)	Dummy2	1.00
(SMA-SBH)	Dummy3	1.00

APPENDIX 13: Prices of Five the 5 Select Companies



*For comparison purpose, the price of EABL share has been divided by ten.

APPENDIX 14: Commands of Non-Linearity Test

```
import "C:\Users\Judah\Desktop\EndGame!\Data\Relevant\Kenya NSE 20 Historical Data-
ARMA Test..csv" ftype=ascii rectype=crlf skip=0 fieldtype=delimited delim=comma colhead=1
eoltype=pad badfield=NA @id @date(date) @smpl @all
change__.sheet
change__.correl
change__.correl(12)
change__.correl(15)
{%equation}.ls(optmethod=opg) c ar(1) ar(2) ar(3) ma(1) ma(2)
{%equation}.ls(optmethod=opg) c ar(1) ar(2) ar(3) ma(1)
{%equation}.correl
{%equation}.hist
{%equation}.ls(optmethod=opg) c ar(1) ar(2) ar(3) ma(1)
{%equation}.arch(optmethod=opg, optmethod=opg) c ar(1) ar(2) ar(3) ma(1)
{%equation}.arch(optmethod=opg, fixedlag=32, optmethod=opg) c change__
{%equation}.correl
{%equation}.arch(optmethod=opg, fixedlag=32, optmethod=opg) c ar(1)  ar(2) ar(3) ma(1)
ma(2)
```

```
{%equation}.arch(optmethod=opg, fixedlag=32, optmethod=opg) c ar(1)  ar(2)
{%equation}.arch(optmethod=opg, fixedlag=32, optmethod=opg) change__ c ar(1)  ar(2) ar(3)
ma(1) ma(2)
{%equation}.white(c)
{%equation}.correl
{%equation}.arch(optmethod=opg, fixedlag=32, optmethod=opg) change__ c ar(1)  ar(2) ar(3)
{%equation}.arch(optmethod=opg, fixedlag=32, optmethod=opg) change__ c ar(1)  ar(2) ar(3)
ma(1) ma(2)
{%equation}.arch(optmethod=opg, fixedlag=32, optmethod=opg) change__ c ar(1)  ar(2) ar(3)
ma(1) ma(2) ma(3)
{%equation}.arch(optmethod=opg, fixedlag=32, optmethod=opg) change__ c ar(1)  ar(2) ar(3)
{%equation}.arch(optmethod=opg, fixedlag=32, optmethod=opg) change__ c ar(1)  ar(2) ar(3)
ma(1) ma(2)
{%equation}.hist resid.sheet resid.bds resid.sheet
{%graph}.line
close RESID
price.sheet price.uroot(dif=1) close PRICE
```

APPENDIX 15: E-views HMM Estimation Commands

```
import "c:\users\Judah\desktop\endgame!\data\kenya nse 20 historical-eviews.xlsx"
 range="Kenya NSE 20 Historical Data" colhead=1 na="#N/A" @id @date(date) @smpl @all
{%equation}.switchreg(type=markov, seed=981278271) _200_days___returns c
{%equation}.transprobs
{%equation}.rgmprobs 1 2
{%equation}.rgmprobs(type=smooth) 1 2
{%equation}.rgmprobs(type=smooth, view=sheet) 1 2
{%equation}.correl
```