Adaptive Market Hypothesis and Calendar Anomalies in Selected African Stock Markets

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DECLARATION

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DEDICATION

This thesis is dedicated to my late mother, Madam Dorcas Arike Obalade, and my wife, Mrs Grace Oluwafunmilayo Obalade.

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ABSTRACT

It takes a theory to beat a theory. However, whether the adaptive market hypothesis (AMH) offers better explanations for stock return behaviour than the popular efficient market hypothesis (EMH) still remains a question for serious empirical investigation. This question informed the analyses of efficiency and calendar anomalies in the selected African stock market, namely the Nigerian Stock Exchange (NGSE), the Johannesburg Stock Exchange (JSE), the Stock Exchange of Mauritians (SEM), the Casablancan Stock Exchange (MOSE) and the Tunisian Stock Exchange (TSE) with the sample period spanning from January 1998 to February 2018. The first objective of this study is to investigate whether market efficiency changes in cyclical version over time, according to the AMH. The second objective is to evaluate the effect of market conditions (up, down, bull, bear, normal) on return predictability. The third objective is to analyse whether calendar anomalies disappear and reappear over time. The fourth objective is to determine how the anomalies behave under different bull and bear market conditions.

Various linear testing tools such as the variance ratio test, the autocorrelation test, the unit root tests and the nonlinear of BDS were implemented in rolling window approach to track time-variation in efficiency. A dummy regression model was used to evaluate the market condition effect on return predictability. This study also explored rolling window analyses of several alternative variants of nonlinear models of the GARCH family, to track variation in the behaviour of days-of-the-week (DOW), months-of-the-year (MOY) and intra-month effects. Lastly, the study modelled the switching behaviour of the calendar anomalies under bull and bear conditions by using the Markov switching model (MSM), which is able to generate regime-specific regression results for the calendar anomalies under consideration.

Findings from the various linear and nonlinear tests revealed that there are cycles of significant linear and nonlinear dependence and independence in each of the five markets, suggesting bouts of predictability and unpredictability. The regression analyses of return predictability against series of market condition dummies revealed that high

predictability is associated with the bull, volatility and financial crisis periods, especially in NGSE, SEM and TSE and not in others. It suggests that the effect of market condition cannot be generalised for all markets. Further, rolling GARCH estimations showed that calendar anomalies disappear and reappear over time in line with the AMH. The evaluation of calendar anomaly under AMH provides a clearer picture of the behaviour of African stock markets as adaptive. Finally, the empirical results revealed that regime-switching is an important feature of calendar anomalies and that a calendar anomaly that is found in a bull regime tends to disappear or weaken in a bear regime and *vice versa*, depending on the market and the calendar anomaly in question.

This study adds to the extant literature on the AMH in Africa and global markets. First, it shows that African stock markets are adaptive. Thus, it is more appropriate to describe African markets as adaptive markets rather than inefficient markets. Secondly, it provides empirical evidence of efficiency cum market condition in African stock markets. Thirdly, the study represents a timely contribution on calendar anomalies under AMH in African stock market. Fourthly, by evaluating DOW, MOY and HOM effects under AMH, this study extends the existing works on Monday and January effects in developed markets. Additionally, this study shows the usefulness of MSM in evaluating calendar anomalies under AMH.

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LIST OF ABBREVIATIONS

ACF	Autocorrelation function
ADF	Augmented Dickey-Fuller
AMH	Adaptive market hypothesis
ANOVA	Analysis of variance
AR	Autoregressive
ASEA	African Securities Exchanges Association
ATLFH	Africa Tax, Law, Finance Hub
BDS	Brock-Dechert-Scheinkman
BF	Behavioural finance
CA	Calendar anomaly
CIVET	Colombia Indonesia, Vietmen Egypt, Turkey and South Africa
DOF	Degree of freedom
DOW	Day-of-the-week
EGARCH	Exponentialgeneralised autoregressive conditional heteroscedasticity
EMH	Efficient market hypothesis
EAP	East Asia and Pacific
EU	Euro area
FOREX	Foreign exchange
GARCH	Generalised autoregressive conditional heteroscedasticity
GED	Generalised error distribution
GJR	Glosten, Jagannathan and Runkle
HAC	Heteroscedasticity and autocorrelation consistent
HOM	Half of the month or intra-month
I.I.D	Independent and identically distributed
IGARCH	Integrated generalised autoregressive conditional heteroscedasticity
JALSH	JSE All Share Index
JB	Jarque-Bera
K	Kurtosis
KPSS	Kwiatkowski, Phillips, Schmidt, and Shin
KW	Kruskal-Wallis

LAC	Latin America and Caribbean
LB	Ljung-Box
LM	Langrage multiplier
MCAP	Market capitalisation
MOSENEW	Casablancan Stock Exchange all Share Index
MOY	Month of the year
MSM	Markov switching model
NGSEINDX	Nigerian Stock Exchange All Share Index
NYSE	New York Stock Exchange
OLS	Ordinary least square
PP	Philip and Perron
RWH	Random walk hypothesis
RWM	Random walk model
S	Skewness
SSA	Sub-Sahara African
SEMDEX	Stock Exchange of Mauritians All Share Index
TGARCH	Threshold generalised autoregressive conditional heteroscedasticity
TUSISE	Tunisian Stock Exchange All Share Index
VR	Variance ratio

LIST OF PUBLICATIONS

Published Articles

- **Obalade, A. A.,** & Muzindutsi, P-F. (2018). Are there Cycles of Efficiency and Inefficiency? Adaptive Market Hypothesis in Three African Stock Markets. *Frontiers in Finance and Economics*, *15*(1), 185-202.
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Submitted Articles under Review

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CHAPTER 1: INTRODUCTION

1.1 Background to the Study

Over the years, the investigation of the behaviour of stock returns has piqued the interest of scholars in the field of finance. At the centre of the investigations is the efficient market hypothesis (EMH). The hypothesis is traceable to Louis Bachelier (1900) who, in his dissertation, "begins the mathematical modelling of stock price movements and formulates the principle that the expectation of the speculator is zero" (Courtault, Kabanov, Bernard, Crépel, Lebon & Marchand, 2000 p. 343). Fama (1965) formalised the EMH theory and the theory has been extensively examined ever since. An efficient market is one in which sufficient rational investors compete to predict the expected prices of individual assets and where participants have free access to important current information (Fama, 1965). In such a market, the rivalry among various rational investors results in a situation where information based on past, present and future events is already incorporated in prices of individual assets (Fama, 1965). There is a rapid adjustment in the stock markets prices such that it would be difficult for anybody to consistently gain return higher than the market.

Three types of efficient market exist, namely the weak-form, semi-strong-form and strong-form. Weak-form hypothesis implies that the price reflects all previous information; the semi-strong hypothesis means that prices incorporate all information available to the public while the strong-form, in addition to public information, also reflects the insiders' information (Fama, 1965). The most debated of the three forms is the weak-form efficiency (Urquhart, 2013). Ching, Munir and Bahron (2014) note that the violation of this least restricted form of EMH is tantamount to the violation of other forms of EMH. Consequently, this study focuses on the examination of weak-form efficiency. The implication of EMH is that no one can consistently earn a return above the market average return, except if one is lucky (Helena, 2009). Thus, no amount of security analysis based on past information could result in consistent higher profit.

According to Urquhart (2013), the main argument of the EMH is that stock returns or changes in stock prices are independent and unpredictable.

Earlier studies, such as Samuelson (1965), Fama (1965, 1970) and Roberts (1967), provide evidence in support of the efficiency of stock market. As time passed, submissions from studies of market efficiencies began to cast doubt on the validity of EMH. Several deviations and various types of patterns have been discovered in asset returns, which are at variance with the EMH and, hence, are termed efficient market anomalies[1] (Bodie, Kane & Marcus, 2011). Lo, Blume and Durlauf (2007) identified three main categories of anomalies, namely fundamental anomalies, technical anomalies and calendar anomalies. Fundamental anomalies are market anomalies (for example size and value effect), which cause security prices to depart from their intrinsic values (Gabrielė, 2015), while a technical anomaly is one in which the study of past market data results in an estimate of anticipated price trends (Lo *et al.,* 2007). Alagidede (2013) defines calendar anomalies as the likelihood that returns on financial securities would exhibit systematic patterns during a particular time of the day, week, month or year. The hype of calendar anomalies is as a result of investors seeking gainful trading strategies in order to take advantage of any identifiable pattern. A calendar anomaly is the most renowned market anomaly (Evanthia, 2017). It is examined in this study because it is an indication of weak-form inefficiency. Calendar effect, calendar anomaly, seasonal effect, or seasonal anomaly can be used interchangeably. There are different types of calendar anomalies or effects but the notable amongst them consist of the day-of-the-week (DOW), end-of-the-week, January or month-of-the-year (MOY), intra-month or half-of-the-month (HOM) (Floros & Salvador, 2014 and Kumar, 2017). To justify the presence of various anomalies or contradictions of EMH, behavioural explanations have been provided. Consequently, anomalies have been placed under the umbrella of behavioural finance (BF) (Kapoora & Prosad, 2017), which has to do with the study of psychological influence on the financial

[1]systematically predictable price patterns that are exploitable through investment strategies (Meier, 2013)

practitioner's behaviour and markets. BF thus comes with the introduction of emotions and irrationality in the field of finance and hence, it is usually regarded as the opposite end of the EMH.

EMH and BF are two contradictory theories. A new explanation for the behaviour of market returns emerged in the early 2000s, called the adaptive market hypothesis (AMH), a middle of the road approach between EMH and behavioural school of finance. Lo (2004, 2005) holds that market efficiency is not an all or nothing phenomenon as the stock market evolves over time and periods of inefficiency alternate efficiency subject to changing profit opportunities, market conditions as well as nature and number of market participants. AMH states that markets are not always efficient and that inefficiencies do exist as market conditions change. Lo (2017) argues that market is adaptive and investors are neither rational nor irrational but *satisficing*[2]. Thus, AMH marks a turning point in the history of market efficiency by changing the emphasis from absolute to varying efficiency (Anatolyev & Gerko, 2005; Lim, Brooks & Hinich, 2006; Noda, Ito & Wada, 2012) and, more recently, to the effect of market conditions on market efficiency (Kim, Lim & Shamsuddin, 2011; Soteriou & Svenssion, 2017). Market conditions could be bullish or bearish (Fabozzi & Francis, 1977); up, down or normal (Klein & Rosenfeld, 1987); social, cultural, political, economic and natural environments (Lo, 2017), all of which may affect the efficiency of the market. The validity of AMH has been documented in certain markets from its introduction in 2004. However, the subject is still recent and remains largely underrepresented most especially from the point of view of small and emerging markets such as the African stock markets.

Stock markets in Africa are relatively smaller than those in the more advanced regions. As of 2005, the total market capitalisation (MCAP) for Sub-Sahara African (SSA) stock markets is US$605,113; compared to US$1,212,704 in East Asia and Pacific (EAP); US$1,028,157 in Latin America and Caribbean (LAC) and US$6,357,326 in Euro Area

[2] Satisfice is a combination of two English words; satisfy and suffice; which means good enough. Lo (2017) argues that the investors make good enough decision based on best guess.

(UA) (WDI, 2012). The figures had risen to US$951,930; US$4,638,422; US$2,274,194 and US$5,482,967 respectively in 2011. In addition, the total number of listed companies stood at 911, 3,931, 1,504, and 6,737 in SSA, EAP, LAC and EA respectively in 2005 and 932, 5,181, 1,446, and 6,250 in 2011. Additionally, most of the African stock markets have below $50 billion MCAP and less than 10 listings as of the year 2013 (Africa Tax, Law, Finance Hub (ATLFH), 2016). In terms of MCAP and listing, the biggest markets in the region are in South Africa with above $970 billion MCAP and 388 listing; Nigeria with above $114 billion MCAP and 190 listing; Morocco with 54.8 billion MCAP and 75 listing and Egypt with $54.3 billion MCAP and 232 listing (ATLFH, 2016). Mauritius and Tunisia stock markets are smaller markets with about $8.5 billion and 8.6 billion MCAPs respectively. Smallest markets are found in Sierra Leone, Cameroon and Mozambique with less than $2 billion MCAP as of 2013 (ATLFH, 2016). The JSE remains the oldest existing (after Egypt) and largest stock exchange in Africa. As at December 2017, the MCAP stood at $1.01 trillion, $36.99 billion, $67.03 billion, $7.21 billion and $7.23 respectively for South Africa, Nigeria, Morocco, Mauritius and Tunisia (Bloomberg, 2017). In the small markets such as the African stock market, studies are required to contribute to the mounting empirical evidences on the AMH, as the theory continues to attract the interest of researchers all over the world. Verheyden, De Moor and Van den Bossche (2013, p. 20) assert that “the AMH theory needs more empirical validation”. Thus, an evaluation of AMH, with a view to bringing out its relevance in explaining the behaviour of stock returns and calendar anomalies in the African stock markets constitutes the focus of this study.

1.2 Statement of the Problem

The significance of valid financial theories and models cannot be overemphasised, as economic managers, regulatory authorities and investing public usually act upon academic theory. Verheyden *et al.* (2013) observe that reliance on academic theory usually works out for the best as in the Markowitz theory[3], which explains that portfolio diversification has concomitant synergistic effect. However, the longstanding controversy between the proponents of EMH and BF is a major debate on financial market studies. By the beginning of the 1990s, the debate had split researchers into two camps: believers of the EMH on the one hand and proponents of BF on the other. The former holds that in an efficient market, prices adjusted quickly to new information, that systematic forecast of security returns is impossible and expectation of speculators is zero**.** The latter holds that markets are inefficient, otherwise, no one would analyse the stock or trade since no profit would arise. This leads to a lack of consensus as to the behaviour of stock returns and the lack of consensus poses a serious problem for asset allocation and portfolio management. The EMH, for instance, creates passive investors who fail to take advantage of profit opportunity even when it exists, while BF, on the other hand, creates active investors (Bryne, 2016) whose irrational exuberance[4] could result in fundamental loss or crisis.

The new AMH cyclical market efficiency might offer a better explanation for stock return behaviour compared to the two earlier schools of thought. AMH has sparked reinvestigation of market efficiency from 2004. The earlier empirical investigations that accompanied AMH have concentrated on varying efficiency of developed and other emerging markets. Interestingly, majority of the so-called efficient markets in the developed world, which were adjudged efficient in absolute form, are now found to exhibit cycles of efficiency and inefficiency when examined within the AMH framework. African markets possess certain features which differentiate them from others. With little exception, the markets are believed to be relatively small in size, illiquid, prone to speculation and adjudged inefficient (Ntim, 2012; Vitali & Mollah, 2015). Given these features, findings from developed markets do not always provide a good approximation

[3]It suggests by investing in more than one stock, an investor can reap the benefits of diversification, particularly a reduction in the riskiness of the portfolio (Markowitz, 1952)

[4]Irrational exuberance refers to investor enthusiasm that leads to market bubble (i.e. drives asset prices up to levels that aren't supported by fundamentals). Inefficiency or irrational decision of the crowd could lead to stock market disaster (Mackey, 1932).

of what is obtained in smaller markets. It is crucial to examine these so-called inefficient markets within the new framework of AMH.

Similarly, consideration of calendar anomalies in absolute form, as it is usually the case, could be misleading. In the wake of the AMH, which supports the disappearance and reappearance of market efficiency over time, a new way of investigating calendar anomalies is also suggestive, which is to examine how patterns in stock return during calendar periods change over time or behave under different market conditions. Efficiency and anomalies could be viewed as two sides of the same coin; hence, if the market is efficient, it cannot be anomalous. If AMH states that efficiency is time varying, is calendar anomaly also time varying? If efficiency is affected by market conditions, is calendar anomaly equally affected by market conditions? These are important questions or matters, which require empirical investigation. It remains to be seen whether market efficiency and calendar anomalies switch over time or how they behave under different market conditions in small or less-developed markets such as the African stock markets. Thus, AMH provides ideal opportunity for evaluating weak-form efficiency and calendar anomaly in African stock market.

1.3 Research Objectives

Given the motivations in the background to the study and the problem statement, the main objective of this study is to test for market efficiency and calendar anomalies within the AMH framework in the selected African stock markets. The specific objectives of this research work, therefore, are to:

i. Investigate whether market efficiency changes in cyclical version over time in the selected African stock markets according to the AMH;
ii. Evaluate the effect of market conditions (up, down, bull, bear, normal, financial crisis, volatility) on return predictability in the selected African stock markets as propounded by the AMH;
iii. Analyse whether calendar anomalies disappear and reappear over time in the selected African stock markets as postulated by the AMH;

iv. Determine how calendar anomalies behave under different market conditions in the selected African stock markets.

1.4 Research Questions

Consequent to the issues raised in the previous sections, it is imperative to provide answers to the following research questions:

i. Does market efficiency of the African stock markets change in cyclical version over time according to the AMH?
ii. What is the effect of market conditions on return predictability in African stock markets?
iii. Do patterns in calendar anomalies conform to the AMH in the African stock markets?
iv. How do calendar anomalies behave under different market conditions in the African stock markets?

1.5 Methodological Scope

A quantitative research approach is employed in this study. Secondary data on stock returns are collected on selected African stock markets, namely South Africa, Nigeria, Morocco, Mauritius and Tunisia over a period of 20 years (1998:1-2018:2) based on data availability. The approach involves the employment of different models to achieve the objectives of the study. To investigate whether market efficiency changes in cyclical version over time, the study uses the rolling variance ratio (VR) test to examine linear dependence and rolling Brock-Dechert-Scheinkman (BDS) (1987; 1996) test to examine non-linear dependencies respectively. Rolling approach is a form of overlapping sub-sample analyses, which take into account the probable time-varying nature of weak-form efficient markets. The study proceeds to evaluate how the market conditions affect market efficiency in the African stock markets using dummy regression models. These models are able to show the condition that is associated with high or low predictability (inefficiency) (Urquhart & McGroarty, 2016). The study further analyses variations in patterns of calendar anomalies, namely DOW, MOY and HOM using rolling GARCH methodologies. The rolling estimation is able to show whether the parameter of a time series model observed in absolute form, is persistent over time (Springer, 2006). Moreover, the study also estimated the Markov switching model (MSM) to incorporate the bull and bear market condition into the calendar anomaly equations. Basically, MSM is not a common model for the investigation of calendar anomalies as conventional calendar anomaly models have been estimated presuming only one state subsists. However, regime switching model provides for the existence of at least two regimes which could provide invaluable insight into the effect of bull and bear markets on behaviour of calendar anomaly and into the relevance of the MSM in testing AMH.

1.6 Justification for the Study

Being a relatively new theory, this thesis presents a timely investigation of AMH in the African stock markets, owing to the need for its validation, especially in relatively small stock markets. In addition to providing inferences towards resolving the longstanding controversy between the proponents of EMH and supporters of BF, establishment of AMH in the African stock markets removes the confusion associated with the notion of absolute efficiency or inefficiency, which involves believing that a market remains efficient or not, at all times. This is particularly important when it is considered that the majority of African markets have been adjudged inefficient over the years. Unlike few available African studies on market efficiency, the combination of linear and non-linear methodologies also overcomes the possibility of wrong inference. This study ranks among the foremost studies, to investigate changing efficiency-cum-market conditions. The study, therefore, provides useful information for investors as to whether different markets display similar/different return behaviour at the same period of time or should be treated or viewed differently. The study becomes one of the few studies to examine fluctuation in calendar anomalies in the context of AMH and to analyse whether some calendar anomalies disappear with market conditions in the African stock markets. Knowledge of the effect of market conditions would assist both local and international investors in timing their investments in the selected African stock markets. It would also inform regulator on the need to take market conditions and possibility of adaptive behaviour into consideration in their effort to enhance market efficiency.

1.7 Organisation of the Study

Chapter 1 centres on the background to the study and the problem statement. The essence of the chapter is to provide motivation for the study. The main research questions are raised and the objectives and justification for the study are provided.

Chapter 2 provides an extensive review of the major theories on the behaviour of stock returns over the year, namely the EMH, BF and the new AMH. The purpose of this chapter is to lay the theoretical foundation for the current study, provide links and identify dissimilarity between the theories and to provide a theoretical framework for the current study.

Chapter 3 further provides a detailed review of the empirical literature, the purpose being to present and interact with the conclusions of existing researches on the subject matter and to identify gaps in the literature. The progression of the various empirical tests of market efficiencies and anomalies is presented from the absolute point of view of EMH to the examination of AMH.

Chapter 4 contains a full description of the methodology and empirical models employed to achieve the objectives of the study. The purpose of the chapter is to explain the sources of data collection and procedure for sample selection. The evolution of the various methodological kits for the testing of market efficiencies and anomalies are traced. The chapter also describes the various linear tests (VR, autocorrelation tests and unit root tests) and non-linear (BDS) test of dependence. This chapter discusses the dummy regression procedure for capturing the effect of market conditions, explains the use of various GARCH models to evaluate calendar anomalies in rolling windows and describes how the MSM is used to explore the regime-switching behaviour of calendar anomalies.

In Chapter 5, results of the various estimated models are presented. The purpose of the chapter is to present and interpret the results as well as testing the hypotheses associated with each model. The results and interpretation are done in the order of the objectives.

Chapter 6 is devoted to the discussion of the main findings from the tests of hypotheses with the aim of establishing whether the findings conform to the AMH and the conclusions of existing empirical works. Finally, chapter 7 provides the summary of the thesis, implication of findings, limitations and suggestions for further study.

CHAPTER 2: THEORETICAL REVIEW

2.1 Introduction

The foremost concept amongst earliest traditional theorists is the theory of expected utility[5] in which individuals' satisfaction from the consumption of goods and services is measured in terms of utility (Bernoulli, 1954). The advent of the concept of *homo economicus*, a perfectly rational economic being by Mill (1844) suggests that individuals attempt to make the most of his utility subject to certain constraints. This economic man is assumed to be perfectly rational, guided by perfect self interest and having perfect information (Kapoora & Prosad, 2017). These suppositions become the bedrock for different classical theories, including the Markowitz (1952) portfolio selection model, CAPM[6] and the EMH. A large number of asset pricing models are based on the assumption of market efficiency and Fama (1965), defines an efficient market as one in which all available information is at all times wholly reflected in stock prices.

The debate on the EMH has been going on for many decades and for many reasons, which are associated with its assumptions. Amongst others, the EMH opines that the arrival of new and free information occurs randomly, investors at all times behave rationally, adjustment of stock prices to new information occurs instantaneously and movement in stock prices occurs randomly; hence, price changes are unpredictable (Shleifer, 2002). It implies that the market is an unbiased estimate of the true investment value. However, the literature has provided instances (anomalies) such as values and size strategies, momentum and reversals and calendric patterns in which asset prices are predictable (Banz, 1981; Keim, 1983; Haugen & Lakonishok 1988; Fama & French, 1992, 1993; Lakonishok, Shleifer & Vishny, 1994). Such instances have been given behavioural explanations, which lead to the advent of behavioural school of finance. In

[5]The theory states that the investors' decisions under risk involves weighing expected utility values of the available alternatives and the best choice is one with highest satisfaction (Aleskerov & Monjardet, 2002)

[6]CAPM describes the relationship between systematic risk and expected return for assets, particularly stocks. (Rossi, 2016)

contrast to the EMH, the behavioural school believes that market is not always efficient and investors make decisions that are not rational (De Bondt & Thaler, 1994). Furthermore, Lo (2004), in an effort to bridge the gap between EMH and BF, recently introduced the AMH, which explains that efficiency and anomalies can alternate cyclically due to changes in investment environments.

This chapter begins with the history of EMH, its different forms and implications. This is followed by the responses from the critics, arising from violations of the EMH and the subsequent establishment of BF. Lastly, the emergence of AMH is introduced as the basis for the recent spark in the investigation of efficiency in financial markets all over the world. Emphasis is placed on the AMH theory since the theory provides the framework for the cycles of efficiency and anomalies, which are examined in this study. Hence, the study is underpinned by the AMH.

2.2 History of Efficient Market Hypothesis

One of the foremost mathematical models of stock market prices has its origin in the world of gambling and it is not surprising because investment of money and gambling both entail computing trade-offs between return and risk (Lo 2017)[7]. The model emerged from the gambling principle formulated by Cardano (1565:198) who states,

> the most fundamental principle of all in gambling is simply equal conditions, e.g., of opponents, of bystanders, of money, of situation, of the dice box, and of the die itself. To the extent to which you depart from that equality, if it is in your opponent's favour, you are a fool, and if in your own, you are unjust.

[7] The review in this section is based on the history of EMH (Sewel, 2011) and history of RWH (Lo, 2017)

The idea of a fair game, which neither favoured you nor your rival, is known as a martingale[8] (Lo, 2017). Martingale suggests that winnings or losses cannot be estimated by considering past performance; otherwise the game would be unfair by creating profit opportunity at the opponent's expense. The idea of fair game or martingale eventually becomes the basis for the evaluation of market efficiency. Bachelier (1900) presented a proposition that the market uses martingale measures to evaluate securities, making it mathematically unrealistic to beat the market. He observed that a stock market transaction has to be a fair trade because it involves buyers and sellers, none of which wants to be a fool. Bachelier (1900), in his dissertation, begins the mathematical modelling of stock price movements and formulates the principle that 'the expectation of the speculator is zero'. His effort seems to be one of the first attempts towards the establishment EMH but the effort was neither formalised nor immediately recognised.

Some years later, Bachelier's argument was supported by subsequent researchers such as Pearson (1905) who introduced the concept of random walk, Einstein (1905) and von Smoluchowski (1906) who advanced Brownian motion equation and Barriol (1908) and de Montessus (1908) who published financial transactions and probability texts (Sewel, 2011). Martingale thereby represents the earliest and most significant theory of security pricing. The theory holds that systematic forecasting of security returns is impossible. In other words, changes in security prices should be random, independent and identically distributed processes (Urquhart, 2013). Consequently, any efforts to forecast expected security prices will be futile. Taking random walk hypothesis (RWH) through history, Lo (2017, pp 18-19) put thus:

> *The game could be something as simple as a coin flip. In a fair game, past performance is no guarantee of future outcomes. After each turn, you'll either win some money (heads) or lose*

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[8] In probability theory, a martingale is a sequence of random variables for which, the conditional expectation of the next value, given all prior values, is equal to the present value (Seetharam, 2016).

> *some money (tails). Now imagine playing this fair game repeatedly, but with a twist. Visualize your winnings and losses physically by taking a step forward or backward with every flip of the coin. (You might need to do this on a sidewalk, or in a hallway).The unpredictable nature of this fair game will reveal itself in a precarious two- step dance, as you lurch back and forth like a drunk driver attempting to walk a straight line at a sobriety checkpoint. Any fair game like a martingale will produce wins and losses in a random pattern like a "drunkard's walk"— and as Bachelier discovered, so do the prices in the stock market. Today, we call Bachelier's discovery the Random Walk Model (RWM) of stock prices.*

Bachelier's work lay unnoticed for decades before it was found by Paul Samuelson in the mid 1960s and it became a popular subject in the finance literature following its rediscovery. Samuelson (1965), focusing on Martingale, delivered the first recognised economic argument for efficient markets. He showed, by induction, that the entire information relating to security's historical price changes are incorporated in the current security price. The price at present accounts for or comprises all the existing information regarding the asset until that point in time. So, historical price information cannot be used to estimate the security's expected price. The main argument is that stock returns or changes in stock prices are unpredictable. In an informationally efficient market, all participants' expectations are reflected in current prices such that the subsequent price returns would the impossible to predict. What is called the EMH today is summarised by Samuelson (1965).

While Samuelson tends towards the idea of martingale, Fama is more familiar with the notion of random walk. Almost simultaneously, Fama (1965) studied stock price movement and introduced the efficient market for the first time and brought the then evolving notion of random walks to the financial analyst environment. Fama (1965) defines the efficient market as one in which sufficient numbers of rational investors compete to predict expected prices of individual assets and where participants have free access to important current information. In such a market, rivalry among various rational investors results in a situation where information based on the past, present and future events are incorporated already in prices of individual assets (Fama, 1965). It means there is a rapid adjustment in the stock markets prices such that it will be difficult for anybody to enjoy persistent higher return. Thus, in an efficient market, prices reflect all available information. Fama (1965) formalised EMH and the theory has been extensively examined; and yet, remains a theory to beat in a financial market.

2.3 Forms of EMH

The basic EMH conceives that no one can beat the market since it integrates all vital determinative information into present share prices; hence, the market is deemed efficient as a whole. By following the work of Roberts (1959) and taking the degree of information that is reflected in the prices into consideration, Fama formulates three different forms of market efficiency, namely the weak-form, semi-strong-form and strong-form. These forms of efficiency are varying degrees of the basic EMH. Although, the weak-form is the focus of the present study, other forms are described briefly for sake of clarity.

2.3.1 Weak-Form Hypothesis

Weak-form hypothesis implies that all previous data are already incorporated in the prevailing prices. It means that today's stock prices already reflect all past information such as the previous price and volume of the trading (Urquhart, 2013). Based on the weak-form EMH, those who trade with the chart method, which relies on analysing price histories to beat the market cannot provide above normal profits because all information would have been instantaneously incorporated into the market price. By the way of illustration, since historical share price information is in the public domain and almost attracts no cost to acquire, if such information ever depicts reasonable signs regarding expected performance, all participants would have already learned to take advantage of the signs. In the end, the signals lose their value, as they become public knowledge.

However, if fundamental analysis is applied in a market that is only weak-form efficient, overvalued and undervalued assets can be ascertained and traders can earn above-average return by exploring a company's financial report. A weak-form efficient market denotes that security returns will follow the random walk (Abraham & Achma, 2013; Maximillian, 2015) and be free of technical anomalies (Ching *et al*., 2014). In other words, there is absence of successive dependence or serial correlation and exploitable patterns such as calendar anomaly in price changes.

2.3.2 Semi-Strong-Form Hypothesis

This type of efficiency holds that asset price incorporates all information made known to the public. In addition to the historical price data, most of the public information about the firm is made available in the financial statement and the market data, and are used in the calculation of the current security price. Therefore, analysts cannot rely on technical and fundamental methods to detect whether a security is undervalued or overvalued (Helena, 2009). Since these data are available in the public domain, the semi-strong-form hypothesis holds that the information is instantaneously incorporated into security prices as soon as the information gets to the investors (Abraham &Achma, 2013). Examples of public available information are fundamental information on the company's product line, management quality, statement of affair composition, patents hold, earning projections and accounting policies (Maximillian, 2015) and economic situation (Fama, 1965). Therefore, no trading strategy, which relies on analysis of public information, will yield abnormal returns. The semi-strong-form implies that there is no learning lag in the distribution of public information. Therefore, relying on public information such as company's sales, earnings and book-to-market ratios in selecting assets is also worthless. The advocate of this version of EMH, however, believes that above market average profits can be earned when investors have access to this information that is private or not publicly available. By implication, a semi-strong efficient market is a weak-form efficient market.

2.3.3 Strong-Form Hypothesis

A market is strong-form efficient where, in addition to past price information and all publicly available information, the price of security fully reflects even the insiders or private information (Fama, 1970). The private information, otherwise known as the insiders' information is that only known to the managers regarding the firm's prospects but which have not been made available to the public. In the face of this type of efficiency, the insider trading will fail to earn above-normal profit by relying on private information (Abraham & Achma, 2013). A market that is efficient in strong form is automatically efficient in semi-strong and weak forms. The supporters of this version of efficiency believe that investors cannot make above-normal market returns, irrespective of the types of information analysed. It is difficult to test this form of efficiency since the makeup of private information is difficult to determine.

Although, prices may fluctuate over time, EMH holds that it is not possible to identify the trend. A large number of empirical investigations accompanied EMH with many of the earlier tests confirming the efficient market hypothesis. Some of the earliest empirical studies in support the EMH include Fama and Blume (1966) who, estimating the path and extent of dependence in price changes, point out that serial correlation is probably as powerful as the Alexandrian (1961, 1964) filter rules. Similarly, Mandelbrot (1966) provided some of the first theorems revealing how, in competitive markets with rational risk-neutral investors, returns are unpredictable and security values and prices follow a martingale. In essence, if a market is efficient, available information will be incorporated in security prices and no amount of stock analysis will result in abnormal profits (Dyckman & Morse, 1986). Further, Fama, Fisher, Jensen and Roll (1969), who examined a sample of 940 stock split prices from 1927:1 to 1959:12, showed that all existing information is mirrored in prices on the day of announcement and that the knowledge of the occurrence cannot be exploited. Hence, Jensen (1978) proudly wrote that no existing proposition in economics, other than the EMH, had more solid empirical proof. According to him, "[a] market is efficient with respect to information[9] set θt if it is impossible to make economic profits by trading on the basis of information set θt." (Jensen, 1978, p. 3) while Malkiel (1992) states that a stock market is efficient whenever the prices of stocks remain unchanged, despite information being revealed to each and every market participant.

Concluding on the role of Samuelson (1965) and Fama (1965, 1970) in the evolution of EMH, the two, irrespective of the difference in their approach, have a common ground for what they view as efficient market, which is "the more efficient the market, the more random the sequence of price changes in the market and the most efficient market of all is one in which price changes are completely random and unpredictable" (Lo, 2017, p. 38).

2.3.4 Early Aftermath of EMH

It was observed that most of the earliest (notably from 1960 to 1980) studies support EMH, while subsequent (1980-2004) findings cast doubt on its validity (Kim, Lim & Shamsuddin, 2011). Kemp and Reid (1971) observe that most of the earlier studies used only the U.S. stock market as a sample and by considering the UK setting, showed that changes in stock prices stray from the RWH and violate Fama's (1965,1970) proposition. In an extensive survey of the literature, Ball (1978) submits that steady surplus returns follow the public broadcast of companies' earnings, which obviously contradicts the EMH in its semi-strong form. Another violation of EMH was documented by Shiller (1979) who established that the observed volatility is higher than that expected under expectations models, meaning some degree of predictability of long-term interest rates. In reality, if markets were efficient, no one would analyse the stock or trade since no profit would arise, then the market would end up being inefficient (Grossman & Stiglitz, 1980). Hence, market efficiency has to do with market participants

[9]Information is defined as anything that influences prices in a way unknown in the present, appearing randomly in the future (Helena, 2009).

who, being aware of inefficiency in the market, believe that buying and selling of securities will result in substantial gain (Shleifer, 2000). Thus, Grossman and Stiglitz (1980) became the most plausible piece of contradicting evidence against EMH.

2.4 Establishment of Behavioural Finance

The EMH appeared to enjoy huge experiential success in the first 10years of its formation. Thereafter, scholars began to spot a wide range of anomalies, which essentially violate the EMH and signal inefficiency. To mention but a few, French (1980) discovered calendric patterns in stock prices, Ball (1978) and Fama and French (1992, 1993) discovered that securities having high price-to-earnings and book-to-market ratio earn beyond average return, while Keim (1983) showed that small capitalisation companies perform very well. Jegadeesh and Titman (1993) discovered that past performing stocks have a tendency to repeat satisfactory performance in the later years and *vice versa*. Hence, the anomalies are encapsulated "in the form of stock market bubbles, market overreaction or under reaction and momentum and reversals" (Kapoora & Prosad, 2017, p. 52). These anomalies are evidence that investors' decision making is not only informed by the rationality assumption. Gradually, BF began to evolve in an attempt to provide behavioural arguments for the anomalies. Unlike the EMH, the BF states that the market is not efficient and investors are not always rational. By definition, BF involves the examination of psychological influences on the investors' behaviour and the consequent impact of the influence on the market (Kofarbai & Subaru, 2016; Kapoora & Prosad, 2017).

BF comes from the psychological theories, which explain consumer behaviour; hence, psychologists play prominent roles in the advancement of BF. Selden (1912) delved into stock market psychology and based his text on the conviction that the changes in market prices depend, to a large extent, on the mental approach of the investing and trading public. While market participants are presumed to be rational in financial theory, they, however, make certain decisions quickly, without enough information or time. Thus, factors such as fears, desires and emotions influence investors' decisions (Helena, 2009). In practice, investors take their feelings into consideration and as a result, market may not reflect economic fundamentals under certain situations (Goedhart, Kolle & Wessels, 2005). One of the situations is irrational behaviour. The EMH portrays that investors will always maximise their expected utility, based on rational expectations (Tan, 2013). These EMH assumptions have been challenged by the proponents of BF who argued based on the tendency that investors may think irrationally by failing to form rational expectations or by having unalike expected utility (Tan, 2013). Cognitive psychologists believe that attitude guides behaviours and that a combination of feelings and facts guide investors' decisions (Zanna & Rempel, 1988; Fazio, 1990). The seemingly inconsistency of rationality and EMH to human decision making is inherent in typical behavioural biases and heuristics[10].

BF, therefore, explains the impact of psychological biases and their consequences on investors' decision making. Biases and heuristics have been used synonymously as practical principles that provide shortcuts to systematic estimation (Gigerenzer, 2014). Kahneman, Slovic and Tversky (1982) portray that people rely on some heuristics to make quick decisions under uncertainty and the use of these heuristics usually results in systematic errors, known and vital errors, which are not random. Two types of biases have been identified, namely emotional and cognitive biases. The former occurred when decision making is informed by feelings as opposed to facts, while the latter occurred as a result of the imperfections in human perception of reality (Sarpong, 2017). Heuristics may cause systematic departure from rationality even though there is still some existing controversy on whether or not some of these heuristics are truly irrational (Baker & Ricciardi, 2014). The mainstream theories, namely the prospect and overreaction, and other behavioural biases are highlighted and expounded in the following sub-sections.

[10]Behavioural biases can be described abstractly, in the same way as systematic errors in judgment (Pompian, 2006), whereas a heuristic is any kind of 'rule of thumb' or a simple rule of behaviour through which a problem is solved (Cartwright, 2014).

2.4.1 Prospect Theory

Prospect theory is the pioneering theory of BF. It is a behavioural economic theory that illustrates decisions between two or more options that entail risk. It was credited to two psychologists, Kahneman and Tversky (1979) who formulated prospect theory as a substitute for expected utility theory (Bernoulli 1738; von Neumann & Morgenstern 1944; Bernoulli, 1954) after critiquing the latter as a descriptive model of decision making under risk. The term prospect was used originally to refer to lotteries or gambles. Kahneman and Tversky (1979) report that people underweight outcomes that are unlikely, in contrast with outcomes derived with assurance. This theory allocates value to losses and gains as opposed to the final value of the assets; the decision weights replace probabilities. Decision weights are generally lower than the corresponding probabilities, except in the range of low probabilities. Kahneman and Tversky (1979) demonstrated that value allocated to a loss is much higher than the value allocated to a gain using the hypothetical value function. It implies that individuals have unalike risk attitude. In other words, the theory suggests different types of risk attitudes: risk aversion for gains of moderate to high probability and losses of low probability and risk seeking for gains of low probability and losses of moderate to high probability. Loss aversion is inherent in the prospect theory. It means preferring possible gain to possible loss. Tversky and Kahneman (1991) wrote a reference-dependent model of riskless choice, relying centrally on the assumption of the theory of loss aversion, which presumes that profit and benefits have smaller effects on preferences than losses and disadvantages. Decision making by individuals is based on the effect of the decision outcome on the reference (present level of wealth). The hurt of loss is higher than gain of equal magnitude.

2.4.2 Overreaction

Overreaction is the emotional reaction to new information concerning a stock, which arises out of greediness or fear. DeBondt and Thaler (1985) describe overreaction as the predictability of good (bad) future performances from bad (good) previous return while underreaction is the foreseeability of good (bad) potential performances from good (bad) previous return. When investors overreact to news, it leads to overbuying or overselling of the stock, pending when it reverts to its intrinsic value. The earliest remarks concerning overreaction in markets was made by J. M. Keynes: "... day-to-day fluctuations in the profits of existing investments, which are obviously of an ephemeral and nonsignificant character, tend to have an altogether excessive, and even an absurd, influence on the market" (pp. 153-154). De Bondt and Thaler (1985) provided shocking and insightful evidence of the stock market being weak-form inefficient when they found that people usually overreact to unexpected and dramatic news events. Overreaction suggests that people have a tendency to underweight prior news and overweight recent information (De Bondt & Thaler, 1985). In support of overreaction to recent news, Williams (1956) asserts that the reliance of prices on recent earning power is far higher than on future dividend-paying ability of the companies. For instance, broadcast of suddenly high earnings can cause buying panic and drive up share price beyond reasonable extent while the announcement of low earning will have the opposite effect. Similarly, Veronesi (1999) presented a dynamic, rational expectations equilibrium model of asset prices in which, among other features, prices overreact to bad news in good times and under-react to good news in bad times. Overreaction is thus a contradiction of rationality.

2.4.3 Other Behavioural Biases

2.4.3.1 Framing

Framing has been identified as another key behavioural incident. Tversky and Kahneman (1981) established framing bias and argued that people respond differently when the same event is framed differently. Thus, “the frame that a decision maker adopts is controlled partly by the formulation of the problem and partly by the norms, habits and personal characteristics of the decision maker” (Tversky & Kahneman, 1981, p. 453). They showed that the psychological principles that govern the perception of decision situation and the assessment of chances and outcome do change depending on how the problem is presented. In other words, the way a problem is described or posed, affects the choices that consumers make. For instance, investors may be favourably disposed to a particular investment when they are told that there is 95 percent chance of success than when they are told that there is 5 percent chance of failure, even though the outcome is the same or identical. Hence, investors' decisions could be influenced depending on positive or negative frame. Unfortunately, people are usually provided with options within the context of only one of the two frames

2.4.3.2 Mental Accounting

Mental accounting is another topic in the field of BF. This model of investors' behaviour was propounded by Thaler (1985) and it tries to illustrate the method employed by individuals and households to code, organise and evaluate events or keep track of their financial activities (Thaler, 1990). The proponents of this behavioural bias state that individuals group their assets into a number of different mental accounts (Shefrin & Thaler, 1988). Shefrin and Thaler (1988) further showed that people have different categories of income and marginal propensity to spend differs among the categories. Thaler opines that individual's process a mixture of outcomes as opposed to individual events and that this leads to irrational financial behaviour.

Mental accounting was explained by Tversky and Kahneman (1981) using the following analogy:

> (a) Imagine that you have decided to see a play and have paid the admission price of ₤10 per ticket. As you enter the theatre you discover you have lost the ticket. The seat was not marked, and the ticket cannot be recovered. Would you pay ₤10 for another ticket? OR (b) Imagine you have decided to see a play where the admission is ₤10 per ticket. As you enter the theatre, you discover that you have lost a ₤10 note. Would you still pay ₤10 for a ticket for the play?

According to Tversky and Kahneman (1981), less than 50 percent of the interviewees answered yes to (a), while almost 90 percent of them answered yes to (b). Economically speaking, one would expect identical responses. However, many would feel that it is too much to pay twice for the play but treat the money lost in isolation to the play (Davies, 2003). Thaler (1999) reviewed the studies on mental accounting and submitted that the bias controls choice. To overcome the irrationality embedded in this bias, a rational, economic being would view money as perfectly fungible when they are being allocated for different purposes and value a Rand the same whether it is received as a gift or earned. Therefore, a dollar dividend income should not be viewed as different from a dollar capital gain income or the former should not be viewed as disposable when the latter is not.

2.4.3.3 Endowment Bias

An investor would want to be paid a higher price for the shares owned by them than they would be ready to pay to acquire the same share. This is known as the endowment or divestiture aversion, which Kahneman, Knetsch and Thaler (1991) describe as ownership effect in the field of social psychology (Beggan, 1992). The bias holds that individuals attach more value to items owned by them (Morewedge & Giblin, 2015). The bias involves two paradigms. First, the bias has to do with a valuation paradigm in which individuals will be predisposed to pay more to have continuous possession of something owned by them than to buy something they do not own even where there is no reason for the attachment or where the item in question is newly acquired. Second, the bias has to do with an exchange paradigm, in which individuals, when given an item, are cautious to swap it for another item of equal worth. For instance, Knetsch (1989) gives an illustration of participants who, when first given chocolate, were hesitant to swap it for a mug of coffee. On the other hand, those who were first given the mug of coffee were equally cautious to exchange it for the former. In the stock market context, many portfolio managers have had dealings with clients who are indisposed to sell stocks willed to them because they perceived selling the asset as a sign of disloyalty (Pompian, 2006). This behavioural bias contravenes the reference-independence supposition of rational choice theories and where crowds are influenced by this bias, they cannot be said to be rational.

2.4.3.4 Overconfidence

Overconfidence is a behavioural phenomenon in which investors have unfounded trust in their own instinct, opinion, calculation and cognitive abilities and skills as opposed to rational processing of information. This bias has its source from various experiments and research in cognitive psychology where people overrate their prediction abilities. Fuller (1998) explains that people who claimed to be 90 percent sure of the truism of a statement or occurrence of an event, are more often than not, only 70 percent right. Studies have traced the root of wars and strikes, litigations and market bubbles to overconfidence bias (Moore & Healy, 2008). By experiments, Camerer and Lovallo (1999) showed that excessive business entry is caused by overconfidence and optimism while Barber and Odean (2001) discovered that men trade 45 percent more than women do because of overconfidence.

There are two types of overconfidence bias, namely the miscalibration and better-than-average effects (Hilton, 2001). Miscalibration means excessive trust in one's accuracy, while better-than-average effect implies overestimating one's performance relative to others (Moore & Healy, 2008). The miscalibration results from underestimating or overestimating events. A fund manager for instance, asked to make a prediction on the Dollar/Euro exchange rate in six months may be 90 percent sure that the rate will be within 0.64 and 0.74 dollars. Stephan (1998), applying this method, found that 71 percent of foreign exchange dealers failed exchange rate projection. Further, analysts who are 80 percent confident that a particular security will rise are only right about 40 percent of the time. Better-than-average bias may occur, for instance, when the majority of people deem themselves better than the average driver when questioned about their driving ability. People unrealistically overestimate their ability (Merkle & Weber, 2011; Harris & Hahn, 2011). When considering the effect of overconfidence on the investors' behaviour, it is a self-deception bias, which has resulted in significant increases in trading volume the world over (Shefrin, 2000). Consequently, the trading volume in the world stock exchanges is much higher than what EMH would imply. It also increases market depth and decreases average returns of overconfident investors.

2.4.3.5 Herding

It is widely believed that herding occurs among investors in the stock market (Devenow & Welch, 1996). Herding is the tendency for market participants to flock together in their trading decisions, in the same manner as a herd (Sarpong, 2017). Hwang and Salmon (2004, p. 585) state, that "[h]erding arises when investors decide to imitate the observed decisions of others or movements in the market rather than follow their own beliefs and information." In other words, it is the penchant to copy other investors, which makes a collection of investors to take similar actions (Lemieux, 2004). Herding may be spurious or intentional (Bikhchandani & Sharma, 2001). Spurious herding occurs when investors confronting identical problem or information sets, make similar decision. This type of heading may not violate market efficiency. Intentional herding, on the other hand, arises out of the intent of traders to mimic one another's action even when they are faced with different problems, which may lead to market inefficiency. However, Bikhchandani and Sharma (2001) note that differentiating the two types of herding might be difficult in reality since there are so many factors that determine investment decisions.

The tendency of investors to mimic each other's actions has attracted the attention of researchers. A study of this bias by Nofsinger and Sias (1999) revealed that herding by institutional investors affects prices more than herding by individual investors does. Similarly, Sarpong and Sibanda (2014) established that herd habit is common among professional mutual fund managers in South Africa. For example, Lakonishok *et al.* (1991) are of the opinion that professional investors involve themselves in herding purposely to "window dress"[11] their portfolio. On the other hand, Cont and Bouchaud

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[11]strategy used by portfolio managers close to the year end to enhance fund's performance outlook by selling loosing and buying gaining stocks which are then reported as part of the investments' holdings.

(2000) held that uninformed investors are susceptible to the herding habit, which affects stock prices while the behaviour is rare amongst professional investors.

This behavioural bias is normally used to explain correlations in trades arising out of relationships among market traders (Chiang & Zheng, 2010, p. 1911). It is also one of the commonly mentioned reasons for stock return volatility as Christie and Huang (1995) and Teh and De Bondt (1997) posit that stock return volatility can be affected significantly by herding. It means that the effect of investor herding practices can move prices farther than their fundamental values (Tan *et al.*, 2008) and this poses questions on the general efficiency of the market (Lux, 1995). Thus, it is a common argument that financial crises are an outcome of extensive herding amid market traders (Chari & Kehole, 2004, p.128).

2.4.3.6 Affect Heuristic

Affect is a psychological notion which means emotional response (Cherry, 2018). The concept was first introduced in a 1978 paper by Fischhoff, Slovic and Lichtenstein (1978), who introduced affect bias, which can be seen as a fast good or bad emotional reaction to a stimulus; shorter and different from a mood. It involves a mental shortcut that individuals apply when making automatic decisions, which depend majorly on current emotional conditions as opposed to taking the time to think about the future implications of the decision (Cherry, 2018). Current emotions of people, for example fear, surprise and pleasure influence mental shortcuts. This bias can be negative or positive and this influences your awareness of the benefits and risks of a stimulus. Positive affect educes a high benefit, low risk view and *vice versa* (Fischhoff *et al.*, 1978). It means that the higher the perceived benefits, the lower the perceived risk**.**

Affect-based judgments are quick, involuntary and usually depend on experiences (Slovic, Finucane, Peters & McGregor, 2007). Interestingly, stimuli do not generally spur identical emotion, as someone who had a dog bite as a child and another who owns a dog may have different views of a dog. The immediate emotional response to a stimulus will drastically change how we interpret later events and choose to act. Finucane, Alhakami, Slovic and Johnson (2000) opine that observed positive correlation between perceived benefit and risk could be traced to affect heuristic. The affect bias expects an inverse relationship between risk and return for unfamiliar stocks and a direct correlation between risk and return for familiar stocks (Sarpong, 2017). For instance, best stocks may perhaps be ignored by an investor, notwithstanding its return because of the indirect relation of affect heuristic and judgment (Hassan *et al.,* 2013), while Su, Chang and Chuang (2010) showed that negative financial information affects a firm's corporate image or investors' stock buying intention. This emotional reaction more often leads to wrong judgment. People are prone to this heuristic when they have no opportunity for reflective assessment or are under pressure, hence, cannot base decisions on assessment of risk return tradeoff between available alternatives.

2.4.3.7 Anchoring and Adjustment Bias

In numerical prediction, when a relative value (an anchor) is given, individuals make estimates by starting from an initial value (the anchor) that is adjusted to yield the final answer (Tversky & Kahneman, 1974). The bias influences investors when they are unnecessarily preoccupied with a given set of information to which inadequate subsequent modifications are made regardless of the availability of new information (Neumann, Roberts & Cauvin, 2011; Bokhari & Geltner, 2011). Supposing one is estimating values of unknown magnitude, people tend to anchor on information that comes to mind and amend until they arrive at a reasonable estimate. In the original formulation, the starting information, or anchor, has a tendency to exert drag on the ensuing adjustment process, ending up with estimates not significantly different to the initial anchor. Wansink, Kent and Hoch (1998) showed that people are likely to buy more items from a shop when each price refers to numerous goods, for instance $2.00 for 4 items, instead of one good, such as $0.50 for each item. The final decision is biased by the anchor, which is the quantity of goods described in the price, such as four cans or one can. A fan who is required to estimate the number of goals scored by Ronaldo (a footballer) a year may have his judgment biased by any numbers they had recently observed. An investor may also be over-influenced by the earliest information received when making a buying decision and driven to a conclusion towards the anchor. This bias prevents investors from making rational investment decisions by basing decisions on irrelevant anchors instead of considering the pros and cons of each option.

2.4.3.8 Availability Bias

The availability bias is a principle, whereby an individual evaluates the probability of an event by the extent to which it is readily recollected (Tversky & Kahneman, 1973); it is a cognitive heuristic in which people consider information that is readily available rather than examine further alternatives (Sewel, 2007). It occurs when one, who is asked to judge the rate of recurrence or the probability of an event, tends to do so by the ease with which instances or occurrences can be brought to mind (Tversky & Kahneman, 1973). This heuristic is a common mental shortcut that makes people rely on immediate information or examples that occur to them first when gauging a particular decision. It is based on the assumption that what can be remembered must be very important relative to options that cannot be easily remembered. This could generate a bias concerning the hottest news, events, experiences or memories (Bebbington, 2010). For instance, “Most investors, if asked to identify the “best” mutual fund company, are likely to select a firm that engages in heavy advertising” (Pompian, 2006, p. 96). According to Goetzmann, Kim and Shiller (2016), while historical statistics indicate relatively low probability of occurrence of extreme stock market crashes in a single day, surveys of market participants in the past 26 years in the United States (US) revealed that they judged the likelihood to be far higher, simply because of the ease with which the term is brought to mind.

2.4.3.9 Representativeness Bias

In making judgments under uncertainty, Tversky and Kahneman (1974) state that individuals judge the probability that an object A belongs to group B, by the extent to which A is representative of or looks like B. Tversky and Kahneman define representativeness as "the degree to which [an event] (i) is similar in essential characteristics to its parent population, and (ii) reflects the salient features of the process by which it is generated". This heuristic could lead to wrong judgment since the fact that something is more representative does not really make it more likely. There are two main categories of representativeness bias relevant to investment decision making, namely base-rate neglect and sample-size neglect (Pompian, 2006). Base-rate neglect bias occurs when investors try to ascertain probable success of, say, a security of firm A by putting the company in an easily understood classification scheme. For instance, firm A could be classified as size stock and the reward and risk will be evaluated within such classification. Doing so, other variables or diligent information analyses are ignored in the investment evaluation. Sample-size neglect occurs when individuals incorrectly treat small sample size as a representative of large pool of data. This heuristic is employed for the reason that it is an easy computation, but there is the danger of overestimating its accuracy.

2.4.3.10 Regret Aversion Bias

Instead of weighing all alternatives *vis-a-vis* their probable outcomes, people tend to ponder on the worst possible outcome and how they would feel (regret), hence, they end up picking options that reduce regret even if it is not optimal. Investors succumbed to this bias when they fail to make any decisive decision because they fear that the action will be sub-optimal and in order to avoid the hurt of regret, which accompanies a poor decision (Prince, 2017). In his retirement decision, Harry Markowitz, a Nobel laureate in economics, was a victim to regret aversion stating, “I visualized my grief if the stock market went way up and I wasn’t in it—or if it went way down and I was completely in it. My intention was to minimize my future regret, so I split my retirement plan contributions 50/50 between bonds and equities” (Pompian, 2006, p. 227). The bias could make investors hold onto losing positions for a long time or make investors afraid of considering markets that have experienced loss in recent times or behave like herds by thinking that joining large wagons will reduce possible future regrets (Pompian, 2006).

2.5 Contradiction between EMH and Behavioural Finance

Sharma (2014) describes the contradictions of the two investment concepts (EMH and BF), which include the investors' rationality, the role of emotions, information accuracy and demographic factors. Table 2.1 shows the detailed explanation of these contradictions. Table 2.1 summarises the tenets of EMH, which includes how accurate processing of information by rational or intelligent agents determine stock market behaviour. The BF counterpart, however, brings into play how psychological and emotional factors, other than information, inform the individuals' behaviour and shape the stock market. Thus, psychological and emotional characteristic of the participants, which contradict rationality, have roles to play and rational analyses do not at all times provide acid test for investors' decision-making processes (Sharma, 2014). Therefore, objective processing of information does not always hold because investors may act irrationally since they are social and emotional beings. Underlining the role of emotion, Pompian (2006) argues that human behaviour is more the result of subjective impulses than logic. Further, the EMH impressions of investors always having equal access to all information, which is immediately reflected in prices have been considered practically impossible by the BF.

In response to that, Pompian (2006) aptly states "[i]n the world of investing, there is nearly an infinite amount to know and learn and even the most successful investors don't master all disciplines". Consequently, the market price may not represent a factual reflection of accurate information processing. Moreover, EMH fails to distinguish investors, treating them as equally rational in the decision-making process, while BF holds that differences in sex, age, education and other demographic factors impact on the attitude of investors. Conclusively, if markets were efficient, bubbles and crises, which have been said to arise out of the irrationality of market participants, would not occur in the stock market.

Table 2.1: Contradictions between EMH and BF

Basis	EMH	BF
Investor rationality	EMH assumes that investors in the financial markets are at all times rational in respect of analysis of information and decision making	BF discipline portrays that investors are not always rational. Most of the time their behaviour shows they are irrational
Role of emotion	Emotion has no place in decision making process according to EMH	BF has incorporate emotion and psychology too in the investment behaviour study
Informational accuracy	Strong-form EMH says that all the investors have equal access to all information and the stock price reflect that	BF refutes the equal access to information principle of EMH and says that stock prices do not always reflect all information
Demographic factors	EMH does not make any distinction between a new and experienced investor	BF makes distinction between investors as per age, sex, income, education level and experience.
Interdisciplinary base	EMH is mainly based on the principles of Economics.	BF includes the theories of psychology, sociology and other disciplines too in some cases.
Market crisis	If EMH actually exists, there would not have been any market crisis or market bubbles, as EMH believes that the investors always act rationally.	Market crisis/bubbles are better described by BF. In decision making process the investor rationality is not the only ground, other issues should be analysed.

Source: Sharma (2014)

2.6 Consequences of Behavioural Biases

Since various behavioural biases provided reasons while investors (even the well informed) tend to respond differently to the same information, the BF has been identified as the most plausible reason for many stock market anomalies in the literature (Tan, 2013). An event is considered anomalous when it is hard to explain rationally with the existing theories or logical assumptions. Schwert (2002) and Hassan, Syed and AsadSaleem (2015) view anomalies as an observed situation, which is inconsistent with asset pricing theory or where a return on shares exhibits patterns, which negate common asset pricing models. In other words, anomalies can be described as market inefficiencies through which investors can earn some abnormal returns by using well-planned strategies within many observed market movements that cannot be explained by efficient market hypotheses. Stock market anomalies, therefore, represent the existence of abnormal patterns of stock returns in the stock markets (Sedeaq, 2016). Lo, Blume and Durlauf (2007) hold that market anomalies present an important challenge to the EMH because they are a regular pattern in an asset's returns, which is reliable, common and inexplicable. The regularity and reliability of the pattern implies a degree of predictability and the common knowledge of the regularity implies that many investors can exploit it. It is a price or profit distortion, which is an evidence of inefficiency within the financial markets (Magnus, 2008).

Furthermore, Akkaya and Cimen (2013), and Guler and Cimen (2014) opine that financial anomaly is synonymous to abnormal return, which implies a deviation from the average return. It is usually a result of structural factors such as unfair competition, lack of transparency in the market or behavioural biases by various economic agents, which form the bedrock of BF. According to Vandana (2016), stock market anomalies are the observable patterns based on publicly available information that could result in consistent abnormal returns. Hassan *et al*. (2015) also conceive anomaly as an abnormal return, which can influence investors' decision in the choice of an investment strategy and portfolio management. Stock market anomalies may be calendar, fundamental or technical anomalies. Lo *et al.* (2007) categorised anomalies into fundamental anomalies, technical anomalies, calendar anomalies and others. However, since technical analysis is essentially a form of human pattern recognition (Lo & Hasanhodzic, 2010), calendar anomalies have been identified as an important member of the technical anomaly family (Ching, 2014). The fundamental anomalies are described briefly, but this study concentrates on the weak form of EMH by examining the RWH and calendar anomalies.

2.6.1 Fundamental Anomalies

Fundamental analysis consists of analysing all publicly available information (e.g. financial statements) about a certain stock to infer important insights that can be used to make a profit in the stock market (Kothari, 2001; Verheyden et al., 2013). Fundamental market anomalies are said to occur when the price of an asset is different from its intrinsic value (Gabrielė, 2015). According to Lo *et al.* (2007), fundamental analysts pay attention to economic information and have their decisions based on the examination of the industry and some other variables of the company that guide the analyst to have an estimate of intrinsic value of his investment. Fundamental anomalies include value effect, size effect, high dividend yield, low price to earnings (P/E) and low price to sales (P/S), (Karz 2011; Pandey & Samanta, 2016).

The most common fundamental anomalies are related to stocks with low price-to-book ratio. Value anomaly results from investors' underestimation of the future prospects of companies' (those with high book-to-market ratios) returns and earnings (Graham & Dodd, 1934). Value effect, otherwise known as the price-to-book effect or book equity-to-market equity (BE/ME) involves the idea that securities with a low price-to-book ratio (high BE/ME) and low valuation generate, on average, superior returns compared to growth stocks, stocks with a high valuation and high price-to-book ratios (Fama& French, 1992, 1993). Another well-known fundamental anomaly is related to the company's size, which has been revealed from the empirical investigation of asset pricing model (Berk, 1995). For instance, Banz (1981) found an inverse correlation of size to returns, meaning that small firms' returns are considerably bigger than those of larger firms. Size effect implies that small stocks and small cap companies do better than index on an average or perform better than bigger firms do. The critics viewed the extension of the asset pricing model to include both size and value variables, as recognition of existence of anomalies but Fama and French (1992) argue that additional return from the two factors are compensation for the risks associated the small companies, which are also higher.

There are various other kinds of anomalies. For instance, companies with low price-to-sale and price-to-earnings ratios, high dividend yield and neglected (less known) tend to outperform the others in the market (Guin 2005; Basu, 1977; Chan, Hamao & Lakonishok, 1991; Levy & Post, 2005). However, the commonest and widely-studied fundamental anomalies have been described.

2.6.2 Technical Anomalies

For a market to be weak-form efficient, it must pass RWH tests and the technical market anomalies must be absent (Ching, *et al.*, 2014). Technical anomalies are the anomalies derived from the reading of technical analysis, used in making investment decisions by considering past patterns of price movements. Technical analysis consists of investigating time series of past prices and returns of a stock in order to ascertain patterns that can be extrapolated in the future to make profitable predictions of future price movements (Brown & Jennings, 1989; Verheyden *et al.*, 2013). Lo *et al.* (2007) view technical analysis as involving the investigation of past market information such as trading volume and prices of stocks, that leads to an estimate of forthcoming price trends. There are different forms of technical anomalies, namely the momentum, mean reversal, volatility clustering[12], technical rules and calendar anomalies (Ching, *et al*., 2014).

[12] Volatility clustering describes the tendency of large changes in asset prices (of either sign) to follow large changes and small changes (of either sign) to follow small changes (Brooks, 2014, p. 386).

The momentum strategy as a kind of technical anomaly in the stock market entails long positions in the past (historical) best performing stocks and short positions in the past (historical) worst performing stocks. Momentum effect implies that there is a positive relationship between a security's past returns and future returns (Pandey & Samanta, 2016). In other words, momentum effect is typically defined as a positive relation between the return of a stock in a certain period with its lagged return. Hence, stocks with high returns in the recent past promise higher future returns than stocks with low past returns. Based on this, investors would adopt buying past winners and selling past loser's strategy (Jegadeesh & Titman, 1993; Bundoo, 2011). It is difficult for EMH to explain momentum strategy because a rise in security price, in and of itself, should not guarantee further rise. The anomaly is believed to be caused by cognitive bias such as investors' underreaction to new information.

Mean reversion is the likelihood of security with low current returns to generate high returns in the future and *vice versa* (Hubbard, 2008). The long run effect is present when the past years (say 3-5 years) biggest losing stock tends to become the biggest gaining stock in the subsequent years (say 3-5 years) (DeBondt & Thaler, 1985; Guin, 2005). Short run effect is present when previous short-term (say 1-month) underperforming securities tend to outperform the subsequent month (and *vice versa*). Hence, the previous performance serves as the basis for determination of present or future performance. Short and Long run return reversal is a consequence of investors' underreaction and overreaction to recent news. In defence of EMH, Fama and French (1988) argue that the anomaly may not portend reliable predictability or promise repeated abnormal return and that the anomaly will disappear with the activities of the arbitrageurs.

Volatility refers to the tendency of security prices to vary or move in a trading range[13] gradually during a long period, in which high volatility and low volatility are portrayed by

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[13]Trading range can be referred to as the distance between a stock's established high and low prices over a period of time (Thomsett, 2006, p. 226).

a wide trading range with broadly varying price trends and a thin trading range with stable price trends, respectively (Thomsett, 2006). From the EMH viewpoint, stock price changes only occur on the arrival of new information or when there is anticipation of dividends. However, stock returns are often characterised by volatility clustering, which can be exploited by market participants to forecast expected security prices. Shiller (1981) and LeRoy and Porter (1981) have shown that stock volatilities are much higher than the changes in discounted values of expected dividends, while Oran (2008) opines that observed high stock market volatility cannot be explained from an EMH point of view. Herding behaviour of the investors has been held responsible for this anomaly

Technical anomalies also cover trading range brakes and moving averages (Gabrielė, 2015). The former exists when investors decide to sell at maximum or resistance stock price level and buy when the prices are at the minimum or support level (Brock, *et al.,* 1992; Karz, 2010). The latter involves observing stocks' past performance and dividing them into groups according to it; comparing short-term averages and long-term averages results; buying if long-term averages are higher than short-term averages; and selling if otherwise (Arshad, Latif, Farooq & Fatima, 2011).

2.6.3 Calendar Anomalies

Calendar anomaly is another form of (technical) anomalies found in the financial market. The investigation of this anomaly is relevant, since this type of anomaly is not in agreement with the weak-form EMH. Consequently, Muhammad, Rehana and Muhammad (2013) describe calendar anomalies as unswerving movement in stock returns that cannot be explained by the rational finance theories, while Rossi (2007) defines it as anomalies that create higher or lower returns depending on the time, which cannot be explained by traditional asset pricing theories. In essence, calendar anomalies are those that show deviations from normal behaviour and return patterns during particular time periods continuously during the day, week, month or year (Archana, Safeer & Kevin, 2014). Alagidede and Panagiotidis (2006) and Alagidede (2013) define it as the likelihood that returns on financial securities would exhibit systematic patterns during a particular year, month, week, day or time of the day, while Guler and Cimen (2014) view it as anomalies in stock returns, depending on the time period at calendar. Thus, the anomaly is used to describe a situation where changes in stock returns display high or low patterns at certain calendar periods (Nur, Zuraidah & Carolyn, 2014).

In the literature, different terminologies have been used to describe calendar anomaly, yet its meaning remains the same. Hence, calendar effect, calendar anomaly, seasonal effect and seasonal anomaly have been used interchangeably. Dragan, Martin and Igor (2012) used calendar effects as calendar-related economic effects, which affect the changes of stock market returns. In the same vein, Phaisarn and Wichian (2010) and Martin (2011) used seasonal effects as cyclical anomalies in the form of financial market returns in which the cycle is based on the calendar. Basically, stock market calendar anomaly is the presence of patterns in stock market returns, which relate to the calendar period, such as the DOW, the MOY, or holidays (Hansen & Lunde, 2003 and Gugten, 2010). If the market is efficient in weak form, the knowledge of the existence of calendar anomaly would lead to its disappearance. However, strong evidences have been provided in support of this anomaly in the literature, such that it has become a stylised fact (Alagidede, 2009) that cannot be discarded.

2.6.4 Types of Calendar Anomalies

Calendar patterns in stock returns are of different types and have been credited to a collection of factors notable among which are psychological or behavioural in nature (Malkiel, 2003). Explained below are the different types of calendar anomalies, but the emphasis is very much on the DOW and MOY being the most prominent effects and HOM effect as one of the earliest calendar effects. Although there seems to be no consensus on the reasons for these anomalies, some of the reasons for each calendar effect are also identified and discussed.

2.6.4.1 DOW/Weekend Effect

Common calendar patterns in stock returns have to do with weekdays. Weekdays' effect involves the existence of higher returns than normal on certain days of the week, often in a recurring pattern over the year (Magnus, 2008). The DOW effect is the tendency for returns on stock to be abnormally greater on certain weekdays than on other days (Hassan *et. al*., 2015). It explains that the expected or standardised returns are different for all weekdays. For instance, the Friday anomaly compares the previous trading day's closing price return; say Thursday to Friday's closing price and similarly for the other days (Hansen & Lunde, 2003). According to the DOW effect, the returns on some days of the week are substantially different from the returns on other days of the week (Brooks & Persand, 2001). In other words, the distribution of security returns is not identical for all days of the week and it might vary based on the day (Rossi, 2007).

Further, Pandey and Samanta (2016) state that the DOW effect is evidenced by notably different returns on certain days of the week, notably larger Friday returns and lower Monday returns. One well-known discovery among market participants and academics is the tendency of stock prices to fall on Mondays. Monday effect states that Monday returns are generally negative and lower than those on Tuesday through Friday (French, 1980). Monday effect is where the returns are significantly lower over the first trading day of the week (Yuan *et al*., 2006; Levy & Yagil, 2011; Floros & Tan, 2013). Results of the studies on DOW effect worldwide have generally indicated higher Friday and lower Monday returns, hence the use of weekend effect. Scholars (Dragan, Martin & Igor, 2012) have defined DOW effect to mean the same as weekend effect.

Weekend effect is otherwise known as the DOW effect (Dragan *et al.,* 2013). It holds that securities displayed much lower returns over the period between Friday's close and Monday's close (Gibbons & Hess 1981, Mills & Coutts 1995, Al-Loughani& Chappell 2001). Weekend effect suggests that returns on Monday are significantly different from returns on Friday with the likelihood of security to display relatively high returns on last, compared to those on first days of the week (Phaisarn & Wichian, 2010 and Martin, 2011). Alagidede and Panagiotidis (2006) argue that the effect occurs where returns on

Monday are appreciably lesser relative to other days of the week. Ideally, the returns on Monday should account for investment over 72 hours from Friday close till the opening on Monday, hence greater than the 24 hours returns expected for other days in the week (Dragan *et. al.,* 2013). In other words, the anomaly presents a puzzle, as Monday returns cover three days, one would anticipate higher returns for other days in the week, as the longer period amounts to higher risk. It is safe to conclude that Monday effect, Friday effect and weekend effect are all subsets of or embedded in the DOW effect. There are several explanations for the DOW/weekend effect, ranging from investors' psychology hypothesis, pattern of information flow and information release hypothesis, information processing hypothesis and settlement regime hypothesis.

Reasons for DOW/Weekend Effect

Amongst the several explanations for weekday effect, the primary one is the short selling[14], as stated by Singal (2004). The author argues that this effect comes from unhedged short sellers that take a lot of risk. and this way they need to monitor their positions closely to avoid losses, which they cannot do in non-trading hours, therefore, they become highly exposed to risk as new information can arrive to the market and they cannot trade. This type of investor would want to close their positions before the end of the trading days, but because of the costs to do that, they would only close[15] their positions on Fridays because the weekend is a period with more hours of non-trading, so they will have more risk if they left their positions open. Singal (2004) found evidence of the hypothesis, where the stocks with higher levels of short selling have stronger presence of this effect; additionally, this author states that this effect is more intense with institutional investors since individual investors do not execute short selling that often.

[14]A short position, is selling first and then buying later. The trader's expectation is that the price will drop; the price they sell at is higher than the price they buy it later, for profit.

[15]Closing a short position in a security would involve buying it back.

Investors' psychology hypothesis may play a significant role in explaining DOW effect. Rossi (2007), Rystrom and Benson (1989) point out that investors may sometimes act irrationally; therefore, their economic decisions may be influenced by moods, emotions etcetera. In addition, if these moods differ across the days of the week it can very well produce differing degrees of optimism and pessimism across the days of the week, hence, differing returns to assets. Rystrom and Benson (1989) argue that if investors feel more pessimistic on Mondays than on other days of the week, they sell their securities and depress prices. In contrast, on Fridays, optimistic investors buy securities and create upward pressure on prices. In other words, Monday is seen as a bad day and investors are less positive. Hence, they will be more likely to sell and less likely to buy.

Pattern of information flow and information release hypotheses have also been used to explain DOW/weekend anomalies. Niederhoffer (1971) argues that stock markets react to both good and bad news headlines. According to Dyl and Maberly (1988), information flow over the weekend is the cause of weekend effect. Negative information flows on weekend days and the two non-trading days enable investors to absorb the information before reacting with trading activity. That is, the pattern of information flows, according to Damodaran (1989) and Lakonishok and Maberly (1990), who state that bad or unfavourable news tends to be released on Fridays or during the weekends and this leads to low demand or negative returns on Mondays. Consequently, Pettengill (2003) argues that investors would avoid purchasing securities on Mondays as a result of fear of the possible loss from trading with well-informed traders whose decision to sell might be based on bad information they have received during the weekend. Firms and government usually release bad news on weekends (Saturday and Sunday) and generally release good news between Monday and Friday. Hence, the bad news explains negative Monday returns while good news explains higher Friday returns (French, 1980; Rogalski, 1984; Damodaran, 1989; De Fusco, 1993).

Similarly, there is the information processing hypothesis, which postulates that while it is costly for all the investors to collect and analyse information, it is more costly for the investors to do so during weekday trading hours when they are engaged in other activities (Miller 1988; Lakonishok & Maberly, 1990). Therefore, weekends provide a convenient, low-cost opportunity for individual investors to reach investment decisions. Consequently, individual investors might be expected to be more active when markets reopen; although, they may put some buying orders through during other days of the week based on the recommendations of stockbrokers, for selling orders they rely on their own analysis. This causes the selling pressure to exceed the demand on Monday. On the other hand, the trading volume of institutional investors remains depressed on Monday morning. Osborne (1962) further explained that the decrease in trading activity of institutional investors is based on an industry-wide practice of using the early trading hours of Monday as an opportunity to plan strategy for the upcoming week. Simply put, individual investors make their financial planning during weekends and become more active on Mondays (mostly with selling orders) and institutional investors would make their planning on Mondays, thus, they would be less active in the market.

Another explanation for the negative weekend effect is that the delay between the trade date and the settlement date creates an interest-free loan until settlement. Friday buyers get two extra days of free credit, creating an incentive to buy on Fridays and pushing Friday prices up. The decline over the weekend reflects the elimination of this incentive. This hypothesis is supported by the intra-week behaviour of volume and returns: Friday is the day with the greatest volume and the most positive stock returns. Gibbons and Hess (1981), Lakonishok and Levi (1982) report that the waiting period before the cash settlement for an asset can result in an increase in asset return on certain days owing to the additional credit arising out of the two weekend days. Overall, Lukas (2012) submits that there has been no convincing justification than the psychological cause of DOW effect.

2.6.4.2 MOY/January Effect

When stock returns on a particular month are higher than other months of the year, the result is the MOY effect (Olowe, 2010; Oba, 2014). This is described by Rahele, Fereydoun and Mohammad (2013) as monthly effect, which holds that the average return for stock depends upon the month of the year. Large numbers of empirical results on this effect have indicated the presence of higher returns in January than other months of the year, hence, the name January effect. The effect is the likelihood that security returns in January are larger than or exceed those of other months of the year (Alagidede & Panagiotidis, 2006; Aylin, 2014). January effect is the foremost and the most important calendar anomaly because January has an important implication in predicting the movement of the stock market for the rest of the calendar year (Haugen & Jorion, 1996; Rossi, 2015). Jayen (2016) showed that mean raw returns of January month are relatively greater than mean returns of the remaining 11 months of the year.

The MOY and January effects have also been used interchangeably with the turn of the year (TOY) effect in the literature to explain the possibility of estimated returns being larger in the January month. This is particularly so in the first few trading days of the month than the returns obtainable in other months of the year (Rozeff & Kinney, 1976; Keim, 1983; Gultekin & Gultekin, 1983 and Alagidede 2013). The TOY effect refers to the anomaly, which causes the stock prices to rise between 31st December and the end of the first week of January (Ana, Luís & José, 2015). Thus, the effect considers the last trading day of the previous year to the fifth trading day of the new year. The effect is characterised by an upsurge in purchase of stock by year ending at a lower price, for sales in January to generate profit from the price differences (Karadžić & Vulić, 2011).

Reasons for MOY/January/TOM

One of the explanations provided for the January effect is rooted in tax-loss-selling hypothesis. This hypothesis states that the investors put up for sale shares that perform poorly at the closing stages of the tax year in order to realise capital losses. This is done to make up for profits on other shares and in so doing cut investor’s tax liability. Given that most countries have December as the tax year end, tax-loss-selling leads to a decrease in prices towards the end of the year. As soon as investors begin acquiring stocks again in January, there would be a price increase and the January effect occurs (Branch, 1977; Dyl, 1977; Aylin, 2014; Márcio, 2015). In other words, as most investors sell securities towards the end of the year, the pressure leads to a fall in prices at year ending. In January, when this downward pressure is relieved, securities rise back up to their equilibrium values, thereby creating higher returns. That is as investors invest their money in January, the pressure on the prices leads to a rise thereby generating higher returns (Elton & Gruber, 1995). Since taxation of capital gains is common in all developed countries, Africa can act as a counter example because capital gains are usually free of taxes. Hence, tax-motivated selling may not be observable on the African Stock Exchanges. Turn of the year or January effect effects could also be explained by liquidity hypothesis. The liquidity hypothesis of Ogden (1990) postulates that individual investors receive additional cash via holiday bonuses and annual salary benefits at year ending and plow this money into the stock market, leading to an increase in demand, prices and stock price changes at the turn of the year.

Another well-known explanation for the January effect is the window dressing hypothesis developed by Lakonishok, Shleifer, Thaler and Vishny (1991). This theory states that institutional managers, who are evaluated based on their performance, sell poorly performing stocks at the end of the year to make their portfolios look safe and successful. Then, in January, after the year-end evaluations, they buy back the loser stocks. Because of these window dressing actions, prices go down in December, which causes the December returns to be low; and up in January, which causes the January returns to be high. This means that at the end of the year many professional fund managers decide to sell those stocks that have performed badly during the year in order to avoid their existence in annual reports. At the beginning of the year, managers buy a lot of stocks that have performed extremely well in order to make their funds attractive for investors (Sharpe, Alexander & Bailey, 1999).

Apart from the window dressing hypothesis, Merton (1987) formulated investor recognition of new information hypothesis, which was studied by Chen and Singal (2004). In line with this hypothesis, investors are inclined to acquire more stocks once companies release new information, for the reason that this kind of information boosts their consciousness. Because new information is normally released at the start of the year, investors are persuaded to put more buy orders in this time and, consequently, the stock returns in January months are drastically bigger. The investor recognition hypothesis holds that the frequency at which stocks are bought and sold is higher in January than in December for the reason that dealers will delay investments until the beginning of new year, when many companies will make new information public (Aylin, 2014).

A risk-based argument for the January effect was offered by Rogalski and Tinic (1986). They opine that nearly all investigations on seasonality in stock returns erroneously presumed that risk remains unchanged all through the year. It was argued that the stock returns in January are greater than in any other month, as is the risk. Investors, therefore, need superior rates of return in January to pay them compensation for the bigger risk assumed in this month. Hence, the January effect is not a valid anomaly, other than a matter of risk measurement. Earlier studies on the risk-based explanation of the January effect such as Tinic and West (1984, 1986), Keim and Stambaugh (1986), Hillion and Sirri (1987) and Chang and Pinegar (1988) offered more proof to support the risk-based argument. However, later studies have not always established this hypothesis (Seyhun, 1993; Sun & Tong, 2010). In essence, there has been no convincing justification than the psychological cause of MOY effect (Malkiel, 2003 and Lukas, 2012).

2.6.4.3 Turn of the Month and Intra-month Effects

Another anomaly, which has been discovered in the literature, is that turn of the month (TOM) has a significantly higher return compared to the rest days. This is called TOM effect and it is particularly strong (Urquhart, 2013). Karadžić and Vulić (2011) view TOM effect as the tendency for stock prices to rise in the last two days and the first three days of each month, while Urquhart (2013) used TOM to describe the presence of particularly high returns in the last day of a month and the first three days of the following month. It simply refers to the patterns of stock returns on the last days and the first days of a given month (Muhammad *et al.,* 2013). On the other hand, Pandey and Samanta (2016) postulate that the TOM effect means that returns are higher over the first fortnight of the month. His own definition is similar to semi-monthly, HOM or intra-month effect. Intra-month effect shows the changes in return within a month as the days elapse and reflects the tendency of market to generate higher returns on the early days than the rest of the month. Mainly, the intra-month effects involve the existence of positive/higher returns only in the first half of the month (Martin, 2011).

Reason for TOM/HOM

Liquidity hypothesis has been identified as the possible cause of this calendar effect. Liquidity hypothesis is associated with Ogden's (1990) study, which holds that most investors have access to cash receipt at the end of the month and become liquid. This liquidity encourages them to invest more in shares, thereby creating an increase in demand, which in turn leads to a rise in prices and hence, higher returns at the turn of the month (Márcio, 2015). The rise in cash flow at the turn of the month and year can explain the so-called January, turn of the year, MOY and turn of the month anomalies. Others have attributed it to macroeconomic news announcement.

2.6.4.4 Other Calendar Effects

Apart from the groups of calendar anomalies described above, which are the focus of this study, there are other types that include the holiday effect, lunar effect and Halloween effect. Holiday effect refers to the tendency of the market to generate higher returns on any day that precedes a holiday (Lakonishok & Smidt, 1988; Martin, 2011; Brishan, 2012; Pandey & Samanta, 2016). Holiday effect can be explained by the investor's psychology hypothesis. This hypothesis states that investors tend to buy shares before holidays because of 'high spirits' and 'holiday euphoria' (Brockman & Michayluk 1998; Vergin & McGinnis 1999; Marrett & Worthington, 2006). Further, a lunar effect is synonymous to moon effect. It is a situation whereby the average returns around the new moon are higher than the mean returns around the full moon (Yuan, Zheng & Zhu, 2006; Nur, Zuraidah & Carolyn, 2014). According to Dichev and Janes (2001), strong lunar cycle effects in stock returns are usually indicated by higher returns in the 15 days around the new moon dates, than the returns in the 15 days around the full moon dates. It is believed that the moon has a natural power and tends to influence investors' psychology and human decision (Levy & Yagil, 2011). This affects investors' mood and while new moon is associated with optimism and energy, full moon is associated with pessimism, depression and sadness, which translates to the market. Moreover, Halloween effect is a calendar anomaly, which is characterised by the tendency of average stock market returns to be lower over a period of winter and higher over a period of summer. Here, the average daily return of the summer is compared with the average daily return from winter (Gugten 2010; Ana, Luís, & José, 2015). Halloween indicator is used to describe the truth in the old market wisdom "Sell in May and go away". The implication of the statement is for the investors to divest in May, after which the price will fall and reinvest in November.

Essentially, financial economists are now aware that stock prices are determined by both rational and irrational investors. Black (1986) termed irrational participants as *noise traders* who are always present in the market. This category of investors has a notable influence on stock prices despite changes in their sentiments bear no relationship with market fundamentals (De Long, Shleifer, Summers & Waldmann, 1990). While the EMH supporters have defended their position over the years, Lo (2005) notes that the end of the disagreement is not in view and that there is little or no knowledge of the likely winner between the supporters of EMH and BF. Lo (2005) went ahead to review the merit and demerit of EMH and came up with a new framework − the adaptive markets hypothesis − "in which the traditional models of modern financial economics can coexist alongside behavioural models in an intellectually consistent manner" (p. 1).

2.7 Adaptive Market Hypothesis

In an effort to accommodate efficiency and inefficiency, Lo (2004) proposes the AMH to reconcile or unite economic theories, notably the EMH and BF, through the application of the principles of evolution to financial interactions: competition, adaptation and natural selection. The assumptions and implication of the AMH are discussed below.

2.7.1 Conceptualisation of AMH

The AMH can be described as a new form of the EMH, formed from evolutionary ideologies (Lo, 2005). The main constituents of the AMH entail the ideas that: (i) Market participants or investors act in their own self-interest; (ii) Market participants or investors make mistakes; (iii) Market participants or investors learn and adapt; (iv) Competition drives adaptation and innovation; (v) Natural selection shapes market ecology; and (vi) Evolution determines market dynamics.

The advent of AMH seems to end the controversy between the proponents of EMH and BF. In line with time-changing level of market efficiency of Campbell, Lo and MacKinlay (1997) and by drawing insight from evolutionary principles, Lo (2004) presented a framework called the AMH, which accommodates the coexistence of EMH and BF in an intellectually consistent manner. Using principles of evolution, AMH explains that the extent of market efficiency has a force to bear with environmental factors characterising market ecology, which include the number and nature of market competitors (such as pension funds, retail investors, market-makers and hedge-fund managers) and the degree of profit opportunities as well as adaptability of the market participants (Lo, 2005). The AMH is rooted in Wilson's (1975) and Simon's (1982) concepts of socio-biology and of bounded rationality. It implies that investors satisfice[16] (make good enough decision by best guess) and learn via trial and error. Factors such as loss aversion (preference for possible gain to possible loss), overconfidence (overestimation of one's qualities, judgment or probability of occurrence of event), overreactions to information and other biases that form the bedrock of behavioural school found relevance in evolutionary model of participants acclimatising to dynamic environment via simple heuristics (Lo, 2005). Lo (2012) states that investors are intelligent but fallible and they learn and adapt to dynamic economic environments. Thus, markets are not

[16]Because optimisation is costly and humans are naturally limited in their computational abilities, they engage in something he called "satisficing," an alternative to optimisation in which individuals make choices that are merely satisfactory, not necessarily optimal (Lo, 2005).

efficient at all times but are usually competitive and adaptive, varying in their magnitude of efficiency as the environment and participants vary through time.

Like EMH, AMH portrays that market participants' act in their self-interest. Unlike EMH, which holds that individuals operate in a stationary and equilibrium market environment and, hence, do not make mistakes, AMH holds that individuals make frequent mistakes, but they have the capability to learn from them and adapt their behaviour accordingly (Lo, 2005). AMH explains that competitive forces in the market drive innovation and adaptation and that the interaction among competitors is governed by the survival of the richest (natural selection) (Lo, 2005). Lastly, the stages beginning with selfish individuals through competition, adaptation and natural selection to environmental conditions describe the market dynamics. In other words, the stages in the biology theory of evolution are used to describe market ecology.

AMH is a new version of market efficiency theory, which states that prices reflect as much information as dictated by the mixture of environmental conditions and the number and nature of competitors (species), profit opportunities (food/water) and adaptability (Lo, 2004; 2012). Profit opportunities lead to an increase in the number of competitors; as they compete among themselves; it will get to a point when the profits will be exhausted. At that point, the market becomes efficient. Some participants will leave the market, resulting in a decline in the level of completion. Another cycle will start when a profit opportunity is created when market conditions change. In addition to the new entrants, some of the participants who left will return while some will go into extinction (Lo, 2005). The cycles will continue with efficiency alternating inefficiency.

Evolutionary analogy can be used to derive market dynamics, interactions and innovation. An important insight of the AMH, derived directly from theory of evolutionary biology, is that convergence to equilibrium is unguaranteed or unlikely to occur at any point in time due to factors such as institutional changes or entry and exit of participants (Lo, 2005). Hence, the idea that evolving systems must march inexorably toward some ideal stationary state is a mirage. Investment strategies will undergo cycles of profitability and loss as a result of changes in business situations, the number of participants entering and leaving the market as well as changing type and degree of profit opportunities (Lo, 2005). As opportunities shift, so too will the affected populations; that is, the population of investors tends to change as opportunities change.

2.7.2 Implications of AMH

The new AMH has four main implications (Lo, 2005). First, AMH implies that the stock risk premium is unstable, changing with time-varying and path dependent as a result of factors like changing market size, competitors' preferences and regulations (Lo, 2005). Therefore, natural selection determines who participates in market interactions, as participants who suffered significant losses in the past tend to leave the market, resulting in different participants today compared to previous years. Whether or not prices fully reflect all available information, the particular path that market prices have taken over the past few years influences current aggregate risk preferences. Secondly, Lo (2005) states that arbitrage opportunities exist from time to time, otherwise there will be no price-discovery because there will be no rationale for participants to process information (Grossman & Stiglitz, 1980). Based on the evolutionary explanation, active liquid markets ecology requires the existence of profit opportunities, which will evaporate as soon as they are exploited (Lo, 2017). However, new profits will be created continuously as certain participants leave, as others enter and as regulations and business conditions change. Instead of the rising trend toward higher efficiency expected by the EMH, the AMH explains relatively complex market dynamics, characterised by cycles, trends, panics, manias, bubbles, crashes and other common features of real market (Lo, 2005).

Thirdly, investment strategies under AMH may be profitable in one environment and unprofitable in another environment. Unlike EMH where profit opportunities are eliminated by competition, the AMH implies that strategies may fail and then return to profitability when environmental conditions favour it (Lo, 2005). While EMH does not rule out such cycles, EMH studies have failed to investigate these dynamics in practice, assuming rather a perpetually stationary and equilibrium market (Lo, 2005). The last implication of AMH is that features such as value and growth may behave like risk factors, off and on (Lo, 2005). This means that value and growth assets may result in higher future profits at times when those attributes are favourable. For instance, growth securities provided better performance compared to value securities during the 1990s technology bubble in US and reversed thereafter. Such non-stationarity is a major challenge for EMH in which a characteristic is either a risk factor or not but AMH is open in terms of what can constitute a risk factor (Lo, 2005). The pricing of a particular characteristic is dependent on the nature of the population of participants at the time; a growth-factor risk premium occurs if majority of market participants are favourably disposed to growth assets at the expense of others (Lo, 2005). Reduction in number of this category of growth-favoured investors is tantamount to reduction in the growth premium and other features may replace it (Lo, 2005).

2.8 Conceptual Framework

This study attempts to provide a structure for the AMH in order to aid proper understanding of the objectives of the study. The explanations for stock return behaviour are found in the various theories of market efficiency. EMH states that the current price or return is independent of previous values; otherwise, the market will be inefficient and predictable. This supposition is captured by the upper part of Figure 2.1. On the other hand, AMH argues that market efficiency does fluctuate over time, owing to changes in market conditions among others. The argument is expressed in the second lower part of Figure 2.1. As Figure 2.1 shows, if the analysis of return behaviour shows that current prices and returns depend on their historical values, the implication is that the market is not efficient. If there is variation in market efficiency or if dependency in stock returns varies over time, the market is adaptive.

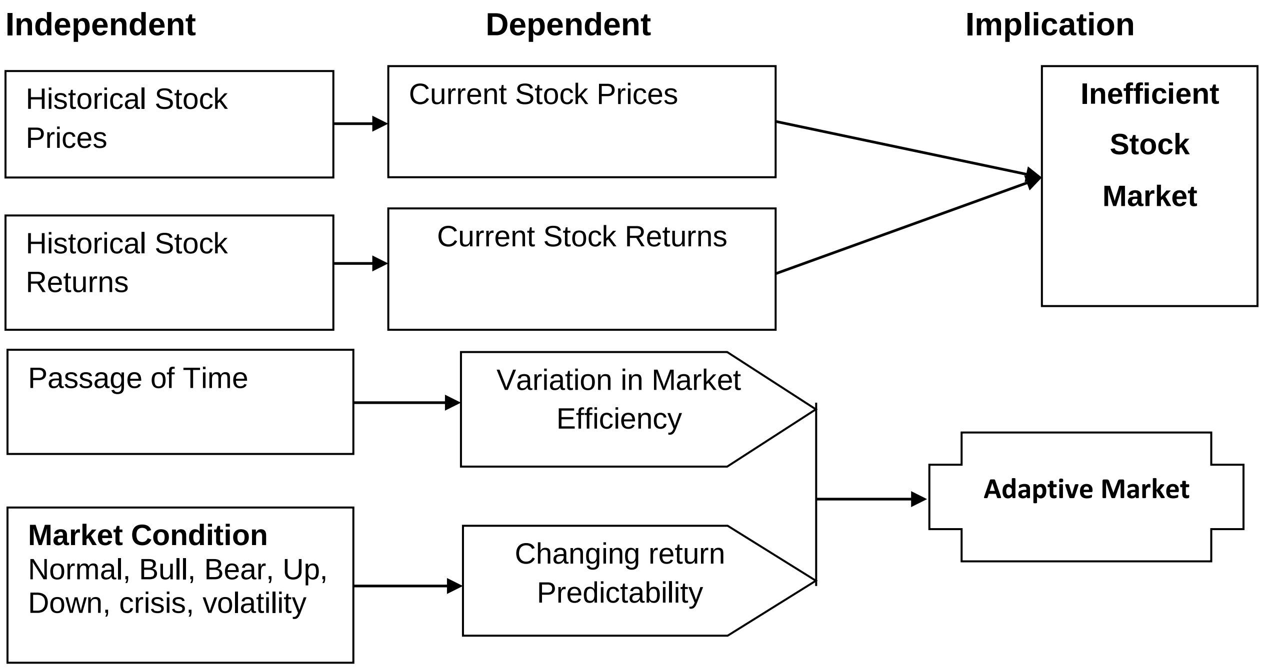

Figure 2.1: Market Efficiency and AMH

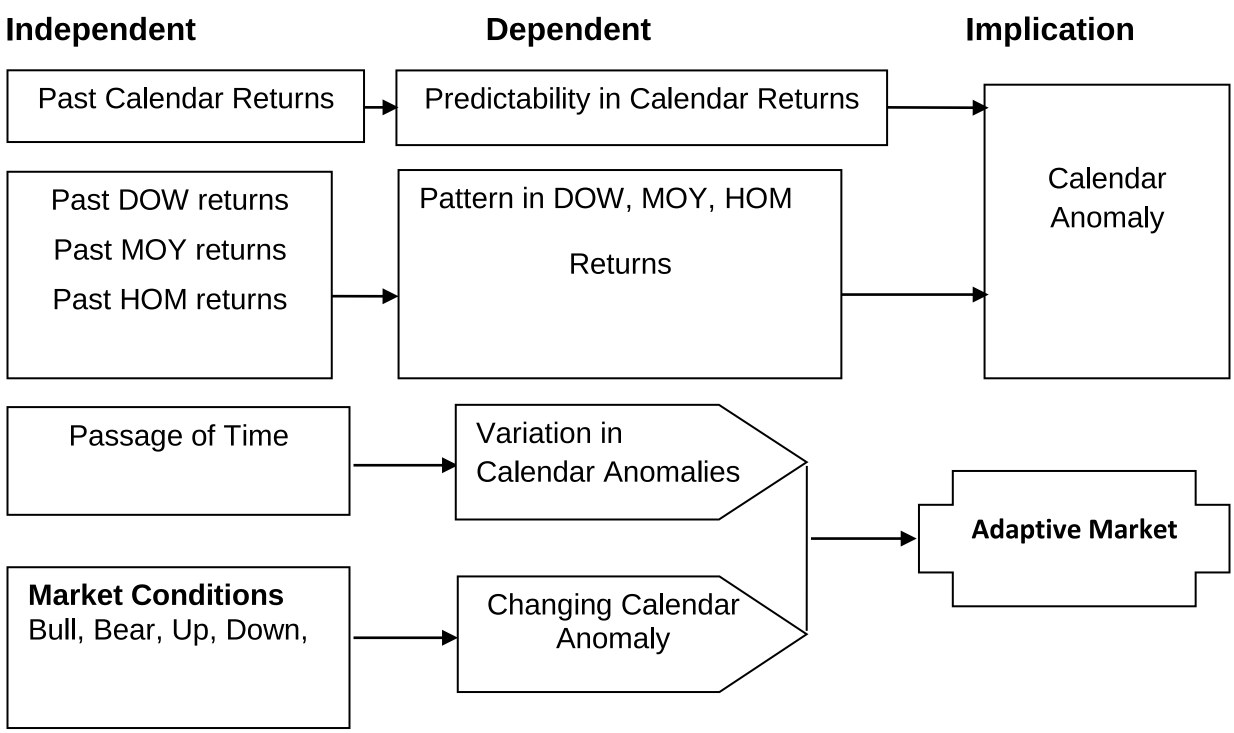

Figure 2.2: Calendar Anomalies and AMH

Source: Author's Design (2019)

If the predictability in stock returns is influenced by market conditions, the market is said to support an AMH. Calendar anomaly is the tendency for return to show regular patterns in certain calendar periods. In the light of AMH, the calendar anomaly is expected to display cyclical patterns and is affected by changes in market conditions as depicted in Figure 2.2. From Figure 2.2, if varying patterns in calendar anomalies are revealed when DOW, MOY and HOM returns are analysed in rolling windows and under different market conditions, it implies that AMH provides better explanation for calendar anomalies in the selected African stock markets. In line with the new AMH, researchers are responding with growing empirical studies. The revived focus being to see how AMH provides a better framework for behaviour of market returns from both efficiency and an anomaly point of view.

2.9 Summary and Concluding Remarks

The EMH put forward that the security return is basically unpredictable. The conjectures of investors' rationality and the informational efficiency connote that it is not possible to beat the market and no participant is in a better position to predict future stock markets. The EMH became the mainstay of modern financial theories and has a huge support, principally in the academic society, especially in the 1960s and 1970s. EMH remains an important theory in the academic financial literature, although it now has many critics due to many observed patterns such as return dependence that cannot be explained by rational theory. BF brings in the fact that investors may react or behave irrationally because their investment decisions are based on the mixture of fact and feelings. Thus, the EMH continues to generate controversies as market participants continue trying to better average returns with their stock selections. Consequently, theorists began to consider the development of a more suitable model for the explanation of stock return or price behaviour.

It is now the right time for an evolutionary alternative to market efficiency and this is the path followed by Farmer and Lo (1999), Farmer (2002), Lo (2002, 2004) to birth AMH; capable of accommodating efficiency and anomaly in an intellectually consistent manner.

AMH provides argument that market efficiency changes in a cyclical version due to changing market conditions. Lo (2017) asserts that it takes a theory to beat a theory. To this end, investigation and modelling of cyclical dependence or efficiency and anomaly should be considered in line with the market conditions. The following chapter presents the review of empirical studies on the weak form of EMH and calendar anomaly in the stock market since the presence of this anomaly is an attestation to the weak-form market inefficiency and *vice versa*.

CHAPTER 3: REVIEW OF EMPIRICAL STUDIES

3.1 Introduction

From the 1980s, the argument has been whether the behaviour of stock market returns is random or independent and identically distributed and whether there are significant calendar anomalies in stock markets. Vast numbers of empirical investigations have been conducted and they are inconclusive as to whether stock markets are efficient or inefficient. The first section of this chapter presents the conclusions from some existing research on the weak-form efficiency of stock markets from the absolute point of view. Having identified calendar anomaly as the most popular contradiction to the weak-form efficiency of the stock market, the second section presents the empirical evidence on calendar anomalies, where it is viewed as all or nothing. Moreover, the third section shows the new submissions of the recent researches about efficiency and calendar anomalies from AMH point of view, in other words, taking time-variation and market conditions into consideration**.** Lastly, this chapter has a summary and the concluding remarks.

3.2 Empirical Studies on Weak-form EMH

Large numbers of empirical studies have been carried out in testing the weak form of EMH or random walk in developed and developing stock markets. These studies focus on the relationship between successive price changes to determine whether they are dependent or predictable. Some studies examine linear dependence (Samuelson, 1965; Fama, 1965, 1970; Roberts, 1967; Cooper, 1982; Borges, 2008) in stock returns, while others focus on non-linear dependence (De Gooijer, 1989; Peters, 1989; Serletis & Shintani, 2003). The types of dependence and the development of the markets examined seem to impart the conclusion from these studies, hence, the empirical review is presented below taking cognisance of the two categories (linear and non-linear) of dependence.

3.2.1 Linear Empirical Studies from Developed and Emerging Markets

The linear dependence tests constitute the earliest test of weak form of EMH and they are still in use today. There are four major linear tests employed in testing weak-form efficiency in the literature, namely the autocorrelation/partial autocorrelation tests, VR, run and unit root tests (Urquhart, 2013). In most cases, studies of weak-form efficiency have combined various linear estimation tools. Hence, this study presents a general empirical review of linear test-based studies, since having to separate a single study where various linear tests are combined may be cumbersome.

The first set of researchers used the linear serial correlation tests, which test RM3[17] (i.e. the least restrictive hypothesis) to establish non-correlation of returns. The presence of serial correlation in return series implies weak-form inefficiency. Studies such as Working (1934); Kendall (1943); Osborne (1962); Samuelson (1965) and Fama (1965, 1970) and Roberts (1967) provide support for the efficiency of the developed stock market due to insignificant magnitude of autocorrelation. Kendall (1953) investigated weekly indices and the idea of serial correlation was debunked in the US. Although serial correlation was found in the UK, it was considered insignificant. Serial correlation was also found in the US share index by Moore (1962) but it was adjudged to be insignificant. In addition, low serial correlation was found by Jennergren and Korsvold (1974) whose study was based on the Swedish stock market. Where significant serial correlations were reported earlier, it was dismissed on the ground of spuriousity. Hence, most of the above studies do not really reject weak-form EMH. However, Niederhoffer and Osborne (1966) debunk the notion that stock price changes are independent and identically distributed and state that investors are aware of the possibility of price reversal and exploit it for abnormal profits.

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[17] RWH1 implies independently and identically distributed successive price increments; RWH2 implies independent increments; while RWH3 implies dependent but uncorrelated increments

Additionally, some studies have employed runs[18] test as another popular serial correlation test of changes in stock prices with additional benefits of being non-parametric test. Here, the actual and expected numbers of runs of a series are compared. Using this approach, Fama (1965) provided minor support for return dependence in the US while Cooper (1982), using different frequencies of stock return series from 36 countries, submitted that the United Kingdom (UK) and the US are efficient and in conformity with EMH. Apart from the autocorrelation and run test, another linear dependence test is the VR test, which has become the commonest test (Lim & Brooks, 2011; Verheyden, 2013) for determining whether price changes are not serially correlated. The test assumes that if changes in asset price are consistent with RWH, the variance of the *p*-period change must be *p* multiplied by the variance of *1*-period change. Applying their own VR test, Lo and MacKinlay (1988) found that the RWH does not hold for weekly stock market returns. Also, Smith and Ryoo (2003) used the multiple VR to examine the randomness of European emerging stock markets and found significant violation of the weak form of market efficiency.

The forth group of linear tests of weak-form efficiency are known as the unit root tests, which are used to examine the stationarity of stock returns, based on the argument that stock returns follow a random walk if they reject stationarity or have a unit root (Lim & Brooks, 2011). Unit root test and other linear tests are employed in a study of 16 developed markets, namely Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the UK and four emerging markets, namely Czech Republic, Hungary, Poland and Russia by Worthington and Higgs (2004) in European equity markets using daily returns. Results of the emerging market showed that only Hungary is characterised by a random walk and, hence, is weak-form efficient, while in the developed markets only Germany, Ireland, Portugal, Sweden and the UK conform to the most strict weak-form efficiency criteria.

[18] a run is 'a succession of identical symbols which are followed or preceded by different symbols' (Siegel, 1956, p. 15).

In addition, autocorrelation test and the VR test were employed by Lovatt, Boswell and Noor (2007) to test firm level and market-wide randomness in the UK from 1992 to 1998. Results from the two tests depict significant dependence of daily stock returns in the UK. On the basis of run test, Borges (2008) showed that RWH cannot be rejected in UK (daily and monthly data), Spain, France and Germany (monthly data). Konak and Şeker (2014) supported the efficiency of the UK FTSE 100 based on the findings of unit root tests. Drawing from many of the available studies (Samuelson, 1965; Fama, 1965, 1970; Roberts, 1967, Cooper, 1982; Borges, 2008) in the developed economies, the notion of weak-form efficiency has hardly been rejected (Vitali & Mollah, 2010). In contrast, findings from the emerging economies are contradictory with some supporting and some rejecting weak-form efficiency. For instance, evidence from Asian, Latin American and European emerging markets and the Middle-East are all contradictory (Vitali & Mollah, 2010). Kim *et al.* (2011) state that there is vast proof of predictable patterns from past price changes, particularly in the emerging financial markets.

3.2.2 Linear Empirical Studies from African Markets

While the African region studies are not as much as others are, the JSE seems to have received more attention than other African markets in the investigation of market efficiency. The JSE has been identified as the most developed in the league of African stock markets and it has been noted that the market behaves more like those in developed economies. A review of JSE studies by Thomson and Ward (1995) indicates conflicting results with some studies supporting JSE efficiency while others do not. However, they submitted that there are more reasons to conclude that JSE is efficient in weak form. According to Vitali and Mollah (2010), subsequent investigations on the JSE have maintained this submission (Magnusson & Wydick, 2002; Smith, Jefferis & Ryoo, 2002; Jefferis & Smith, 2005; Simons & Laryea, 2005) with the exception of Appiah-Kusi and Menyah (2003) and Smith (2008). Conflicting findings, even when similar methodologies are used, may not be unconnected with differences in sample size or data frequencies but one would have expected similar results if markets were to be efficient at all times. Further, while Almudhaf and Alkulaib (2013) employed unit root tests and VR and concluded that the JSE is consistent with RWH, Grater and Struweg (2015), based on unit root test, discovered that JSE is not consistent with RWH. Sub-period analysis was considered by Fusthane and Kapingura (2017) who employed all the popular linear tests except the run test in the pre-, post- and during global financial crisis and showed that JSE, to a greater extent, is weak-form efficient.

In Nigeria, many investigations have been undertaken to test weak-form efficiency. A review of these studies reveals that the problems of efficiency in Nigerian stock market remain inconclusive. In Nigeria, Gimba (2012) applied run, autocorrelation and VR tests; Victor (2010), applied autocorrelation tests and run test; Nwosa and Oseni (2011), Nwidobie (2014) and Obayagbona and Igbinosa (2015) employed autocorrelation and unit root test. All these studies submitted that stock returns do not comply with weak-form efficiency (implying weak-form inefficiency). On the other hand, Ayadi (1984), Olowe (2009), Emeh and Obi (2014), found that Nigerian stock market is weak-form efficient. The finding is supported by Godwin (2010) and Ajao and Osayuwu (2012) using autocorrelation test and runs test; Keyur (2012) using run test; Arewa and Nwakanma (2014) based on portmanteau autocorrelation and LM serial correlation. Apart from the full sample study, some employed sub-sample analyses. For instance, Ezepue and Omar (2012) employed daily and monthly indices and sub-sample analyses (2000-2004; 2005-2010) using financial reform as the basis for breaking the sample and found that the market is inefficient, based on run and autocorrelation test results. Similarly, Ikeora, Nneka and Andabai (2016) showed that three out of the four sub-periods analyses are characterised with dependence and inefficiency using the runs and unit root test. Violation of EMH is also documented by Ogbulu (2016) using the four linear tests and four frequencies of return index from 1999 to 2013.

There are some studies which combine selected African stock markets. For instance, Magnusson and Wydick (2002) studied efficiency in African stock markets from 1989 to 1998 using partial correlation. Botswana, Kenya, Cote d’Ivoire, Mauritius, South Africa and Nigeria markets are found to be weak-form efficient − the exceptions being Ghana and Zimbabwe. Smith *et al.* (2002), using multiple VR and weekly indices from 1990 to

1998, rejected weak-form efficiency of Egypt, Morocco, Kenya, Zimbabwe, Nigeria, Botswana and Mauritius, with South Africa identified as the only efficient market in the sample. Appiah-Kusi and Menya (2003) also employed EGARCH-M to analyse weekly indices and showed that Egypt, Morocco, Kenya, Zimbabwe, Mauritius are efficient while Ghana, Botswana, Ivory Coast, South Africa, Nigeria and Swaziland are not. In Mauritius, Fowdar, Subadar, Lampot, Sannassee and Fawsee (2007) used the traditional linear tests except the VR test and found that returns from 1999 to 2004 are autocorrelated. Mlambo and Biekpe (2007) analysed daily indices from 1997 to 2002 with the aid of run tests and submitted that stock returns in all African markets other than Namibia exhibit serial correlation and do not conform with RWH. They warned, however, that the rejection of the random walk, based on these tests, does not necessarily imply weak-form inefficiency but a presence of serial correlation.

Furthermore, Smith (2008) used samples from 2000 to 2006 and various versions of VR tests and found that Egypt, Botswana, Ghana, Kenya, Ivory Coast, Mauritius, Nigeria, Morocco, South Africa, Zimbabwe and Tunisia are not efficient. Also, by employing (G)ARCH effects tests; GARCH family models, BDS tests and bicovariance test; Alagidede and Panagiotidis (2009) showed that Zimbabwe, South Africa, Morocco, Egypt, Nigeria, Kenya and Tunisia are not efficient but the data are characterised with leverage effect, volatility clustering and leptokurtosis. Nwosu, Orji and Anagwu (2013), also using various linear tests, found that the Egypt, Kenya, Nigeria and South African stock markets behave in a manner that is contradictory to weak efficiency while the US S&P500 comply with the notion of efficiency. Similarly, the combination of autocorrelation, run and unit root test revealed that Kenya stock market is weak-form inefficient (Njuguna, 2016). Gyamfi, Kyei and Kyei (2016) employed non-linear ADF unit root test and the modified Wald and revealed unit root is present in Nigeria, Egypt, Mauritius, Kenya, Mauritius, South Africa, Morocco and Tunisia return except Botswana, hence, non-stationary and weak-form efficient. By and large, findings from stock markets other than developed markets have been mixed with the majority showing that African stock markets are not efficient in weak form.

3.2.3 Non-Linear Empirical Studies from Developed and Emerging Markets

It is noteworthy that the 'traditional' tests of efficiency, as discussed above, have been said to be of little or no use, in the recent literature. It is because such tools may fail to find evidence of linear structure in the data, but this would not necessarily imply that the same observations are independent of one another (Brooks, 2014). In other words, researchers have observed that markets sometimes exhibit non-linear dependence even when there is no linear dependence (Granger & Andersen, 1978; Amini*et al*, 2010). Owing to the presence of non-linear structure in stock returns, which cannot possibly be captured by the study of linear dependence, weak-form efficiency studies have been broadened to cover the examination of non-linear dependence, since the latter portends the possibility of predictability. Thus, where non-linear dependence is observed, absence of linear dependence is not enough to adjudge the market efficient considering the non-normality of return series (Hsieh, 1989; Granger & Anderson, 1978). This leads to the application of myriads of non-linear test to stock returns in the recent time. Non-linear tests[19] include portmanteau tests such as the BDS test (Brock *et al.,* 1996), the bispectrum test (Hinich, 1982), Tsay's test (Tsay, 1989), the neural network test (Lee, White & Granger, 1993) and the bicorrelation test (Hinich, 1996) and Ramsey's RESET test and the specific tests such as SETAR-type non-linearity (Tsay, 1989), smooth transition autoregressive (Luukkonen, Saikkonen &Terasvirta, 1998) and Engle Lagrange multiplier test (Engle, 1982).

The earliest evidence of non-linearity in a stock market was shown by Hinich and Patterson (1985) who applied a bispectrum test to daily returns of stocks on the NYSE. In the same vein, De Gooijer (1989) and Peters (1989) further found significant non-linear dependence in daily returns of 27 stocks and monthly returns of S&P 500 respectively. Similar findings were later documented in the UK market by Abhyankar, Copeland and Wong, (1995), Newell, Peat and Stevenson (1997) and Opong, Mulholland, Fox and Farahmand, (1999). The results of bispectrum and BDS tests

[19] Comprehensive review of these tests is found in Lim and Brooks (2011)

showed that all frequencies of all share indices possess high non-linear dependence that violates RWH. Examination of non-linear dependence is not limited to developed markets alone. Sewell, Stansell, Lee and Pan (1993) found support for the presence of non-linear dependence in a sample of emerging markets. Other recognised studies reporting non-linear dependence in stock return include Afonso and Teixeira (1998) in Portugal, Dorina and Simina (2008) in Turkey, Hungary, Romania, Czech Republic, Slovenia, Poland, Slovakia and Lithuania, among others.

3.2.4 Non-Linear Empirical Studies from African Markets

The developed markets, especially the US, UK, Japan and Germany, have been highly focused when it comes to the examination of non-linear dependence (Brock *et al*., 1996; Abhyankar *et al.,* 1997; Omran, 1997; Serletis & Shintani, 2003) while non-linear tests on African markets are limited. In African stock markets, Kruger (2011) and Kruger, Toerien and MacDonald (2012) examined 109 shares from JSE and showed that there is significant nonlinear dependence for all shares. They also explored sub-period analyses and discovered that the nonlinear dependence is episodic in nature. Similarly, Cheteni (2014) employed LM test, BDS test and VR test in the investigation of chaotic and non-linear tendencies of all bond indices return in JSE. The presence of non-linear dependence was reported; hence, they concluded that the JSE is highly chaotic. In addition, Sarpong (2017) examined chaos on JSE by testing JSEALSI, top 40 and small cap returns with the BDS test. The non-linear model revealed that the three indices negate the notion of RWH with the re-scaled range analysis further showing that JSE small cap index is not as efficient and risky as the rest.

Non-linear tests have also been extended to test the weak-form EMH in other African markets. For instance, the ARCH-LM and McLeod–Li portmanteau tests are combined with linear autocorrelation to investigate efficiency of five indices on the Nigerian stock exchange from 2010 to 2013. The models revealed that all the indices except banking sector are non-linearly dependent and not in support of RWH (Emenike, 2014). In the same vein, Saadi, Gandhi and Dutta (2006) examined the efficiency of Tunisian stock market from the non-linear viewpoint using the BDS test. It was shown through the result of the BDS test that non-linear dependence is inherent in the stock return series and that the weak-form efficiency of the market should be rejected. By examining BDS, Mcleod-Li, Engle LM tests in Egyptian and Tunisian stock markets, Chkir, Chourou and Saadi (2009) found significant non-linear dependence in stock indices return series and advocate for the rejection of RWH in the two African markets. Although this review may not have covered all the available studies, an important observation from the non-linear dependence tests in absolute form is that virtually all the markets (non-African and African) reviewed are culprits of the presence of non-linearity in stock return. While there is limited application of non-linear test in African market studies, JSE seems to have received more attention than others did.

3.3 Empirical Studies on Calendar Anomaly

Although, the reviews of linear and non-linear tests of EMH have been presented above, it has been observed that test of independence of stock returns is incomplete without testing for the presence of anomalies. One of the anomalies that is relevant to the test of weak-form EMH is the calendar anomaly. Much attention has been paid to the examination of calendar anomalies in the literature, making it the most observed or studied of all the types of stock market anomalies. In line with the previous section on the review of empirical studies relating to EMH, empirical review on calendar anomalies is also presented in this section and attention is paid to the markets where the studies are carried out.

3.3.1 Calendar Anomaly from Developed and Emerging Markets

It is not surprising that the earliest empirical studies of calendar anomalies are carried out in developed countries since the theories also emanated from developed economies. In the New York Stock Exchange (NYSE), Rozeff and Kinney (1976) studied the January effect from 1904 to 1974 and found that the January average return is significantly higher than other months. Keim (1983), using the same set between 1963 and 1979, established that just about 50 percent of the average magnitude of risk-adjusted premium of small firms relative to large firms was caused by the January abnormal returns. Over 50 percent of the January excess return was traceable to the first week of January. Likewise, Gultekin and Gultekin (1983) provide international evidence in 17 countries from a 1959 to 1970 sample. January and April effect are identified in all the countries including the UK. Further, Choudhry (2001) evaluated MOY anomalies in three developed countries between 1870 and 1913 using the GARCH (1,1) model. It was concluded that MOY and January effect are found in the US and UK only and not in Germany. GARCH (1,1) was also adopted by Wing-Keung, Aman and Nee-Tat (2006) in the investigation of calendar anomalies in Singapore using a full period over 1993-2005 and sub-periods 1993-1997 and 1998-2005. Results showed that there is the January effect in the post-crisis period, weekend and holiday effects disappear in the post crisis, while turn of the month effect is present in both periods.

Apart from the MOY effects, DOW effect is another prominent calendar anomaly. The earliest academic report on DOW effect was traceable to Cross (1973) who found that Friday return is significantly higher than Monday return based on observation of the US stock market index returns over 1953 to 1970. In addition, Lakonishok and Smidt (1988) investigated the presence of DOW calendar effect in the US from 1897 to 1986 and found high presence of a negative Monday return in the market. Hakan and Halil (2001) also examined the DOW effect on stock market volatility by using the S&P 500 market index during the period of January 1973 and October 1997. The findings showed that the DOW effect is present in both volatility and return equations. While the highest and lowest returns are observed on Wednesday and Monday, the highest and the lowest volatility are observed on Friday and Wednesday, respectively. Further investigation of sub-periods reinforces the findings that the volatility pattern across the days of the week is statistically different. In addition, Shiok, Chong and Brian (2007) used non-parametric test to study stock market calendar anomalies in Malaysia. This study was able to give clear view that Mondays are the only days with negative returns and represent the lowest stock return in a week and there was positive effect in Friday but not as high as the returns on Wednesday. Conversely, some international studies (Rubinstein 2001; Maberly & Waggoner, 2000; Schwert, 2001, Steeley, 2001, Kohers, Kohers, Pandey &

Kohers, 2004; Hui, 2005) have equally argued that both DOW and MOY have grown weaker.

Furthermore, both the MOW and DOW effects are combined in some studies. For instance, Lei and Gerhard (2005) investigated calendar effects in the Chinese stock market, especially monthly and daily effects. Returns of the market index in Shanghai and Shenzhen stock exchanges were used to analyse the monthly and daily effects in stock returns. Results revealed that the highest returns could be achieved after the Chinese year-end in February while Mondays are seen to be weak and Fridays showed significant positive average returns. Yet the daily effect has a minor magnitude and relevance for determining average returns compared to monthly effects. Similarly, Rossi (2007) examined the calendar anomalies in stock returns in South America from 1997 to 2006, focusing on the existence of DOW effects and the monthly patterns in Argentina, Brazil, Chile and Mexico. In full period, it was concluded that there existed the traditional positive Friday effect in Brazil and in Chile; the returns had been lowest on Mondays. In addition, the study documented positive returns on Wednesdays and Fridays. In Mexico highest returns appeared on Wednesdays. For Argentina, there was no record of DOW anomaly. These results change when examined over two sub-periods. Overall, there is absence of monthly anomalies in full period and first sub-period, but January effect is found in Argentina in second sub-period. Additionally, Lukas (2009) studied stock market seasonality with focus on DOW effect and January effect by analysing 30 stocks traded on the German Stock Exchange from 1995 to 2009. By adopting a dummy variable approach to investigate Monday effect and the September effect, it was confirmed that the DOW effect started disappearing in the second half of 1990s. Moreover, Martin (2011) carried out a comprehensive review of the literature on calendar anomalies from 1915 to 2009. It was found that intraday, holiday and intra month effects still exist, the weekend effect seems to have disappeared and the January effect has halved.

With reference to part of the month anomalies, Ariel (1987) discovered that average return in the first half of the month is significantly higher than the remaining half of the month. This finding is supported by Jaffe and Westerfield (1989) in Australia, Arsad and Coutts (1997) in the UK and Bildik, (2004) in Istanbul. Similarly, Kohli and Kohers (1992) found that first week in the month possesses average returns that are higher than other weeks using daily returns of US composite index from 1962 to 1990. In addition, Lukas (2012) investigated seasonality in the US stock exchange across six (6) major industrial sectors using descriptive statistics and GARCH(1,1) model, Wald-chi squared test. The study rejected the DOW and January effects in the US stock market but cannot reject the presence of the part of the month anomaly. In addition, Dragan, Martin and Igor (2012) examined the DOW effect of stock returns in south eastern Europe, namely Bosnia and Herzegovina, Bulgaria, Croatia, Macedonia and Serbia between 2006 and 2011. Results of dummy regression, analysis of variance and Wald test revealed that the mean daily return of all stock indices is negative on Monday in all markets; lesser and significant on Monday than the other days of the week in Croatia and Bulgaria but insignificant in Macedonia. Likewise, Guglielmo, Luis, Alex and Inna (2014) investigated weekend anomalies in the US and Russian stock markets, FOREX market and gold market using the trading-boot approach and fractional integration technique. The study revealed that there is evidence of weekend effect characterised by lowest Monday returns. The evidence is weak in other markets but strong in foreign exchange market as the exploitable profit opportunities based on the weekend anomalies are significant in the FOREX market. Oprea and Ţilică (2014) also examined the DOW anomaly in 18post-communist East European stock markets, namely Bosnia, Bulgaria, Croatia, Czech Republic, Estonia, former Yugoslav Republic of Macedonia, Hungary, Kazakhstan, Latvia, Lithuania, Montenegro, Poland, Romania, Russia, Serbia, Slovakia, Slovenia and Ukraine from January 2005 to March 2014. The results showed that there is presence of DOW effect in Bosnia, Bulgaria, Croatia, Latvia, Serbia and Slovenia while DOW effect is absent in other markets. More recently, Rossi and Gunardi, (2018) studied monthly effect in Spain, France, Italy and Germany from 2001 to 2010. They reported a significant presence of positive April effect in Italy, January effect in Spain and a negative September effect in Germany. In addition, Aziz and Ansari (2018) report the presence of TOM effect in 11 out of the 12 markets examined in Asia from 2000 to 2015. It can be seen that many studies confirmed significant presence of calendar anomalies in developed and emerging markets. On the other hand, some sub-period studies revealed different behaviour in different sub-periods and others who observed weakening and disappearing of calendar anomalies in some quarters. Overall, the evidence is mixed.

3.3.2 Calendar Anomaly from African Markets

The hype of calendar anomaly would mean that other emerging markets and developing African stock markets are not overlooked in the investigation of calendar effects. In the JSE, a negative Monday effect was documented by Bhana (1985) who studied two market-wide JSE indices and Treasury bills from 1978 to 1983, using descriptive statistics and OLS regression. Other days were positive with Wednesday having the highest returns. Similarly, Alagidede and Panagiotidis (2006) analysed the calendar effect of Ghana Stock Exchange using daily closing prices of all equities, dummy regression and asymmetric GARCH models. The study found the presence of April effect as opposed to the usual January effect and the weekend effects with lower Monday and higher Friday returns. On the other hand, Chukwuogor (2007) in another study using Kruskal Wallis and descriptive statistic tests concluded that DOW effect is absent in African countries. The findings could be questioned based on the tests used. Further, Brishan (2012) examined calendar anomalies in nine sectors of the Johannesburg stock market using descriptive statistics, OLS regression and two-sample Kolmogorov-Smirnov test. The study concluded that anomalies are a worldwide phenomenon present in developed and emerging markets; there is presence of daily and monthly effects, reducing pre-holiday effects and absence of weekend or January anomalies. In addition, Umar (2013) used EGARCH model to estimate the DOW anomaly in mean and variance equations for Nigerian and South African equity markets over pre-liberalisation and post-liberalisation periods. After liberalisation, Nigerian stock market exhibits DOW effect on Fridays and Tuesdays/Thursdays in the mean and variance equation respectively. South African market exhibits significant DOW effect on

Mondays and Fridays in the pre-liberalisation and Thursdays and Fridays respectively in mean and variance equation in the post-liberalisation era.

In addition, Julio and Beatriz (2013) evaluated six emerging markets (Colombia Indonesia, Vietmen, Egypt, Turkey and South Africa (CIVETS) stock indices returns from inception to 2012 using GARCH and IGARCH models. There is DOW effect in CIVETS; there is evidence of lags in the effect. Bundoo (2011), in Mauritius, examined stock indices of 10 companies from 2004 to 2006. Dummy regression results found negative Tuesday returns but positive returns for other days of the week especially significant Friday and September effect. Similarly, dummy variables regression and GARCH models were also adopted by Alagidede (2013) in an examination of calendar effect in African countries stock markets using data from inception of the markets to 2006. Holiday effect is reported in South Africa, February effect for Morocco, Kenya, Nigeria and South Africa and January effect in Egypt and Zimbabwe. However, skewness and kurtosis of daily index from 2004 to 2008 were estimated by Shakeel, Douglas and Chimwemwe (2013) and it was submitted that Zambia, Botswana, Nigeria and Morocco displayed significantly different DOW effects in the pre and post financial crisis while South Africa did not exhibit such. Furthermore, Derbali and Hallara (2016) showed through GARCH (1,1) and asymmetry GARCH models that positive Thursdays effect is found in Tunisian market stock returns while negative Tuesday effect are present in both return and volatility. More recently, Du Toit, Hall and Pradhan (2018) studied eight sectors of JSE for DOW effect from 1995 to 2016 using GARCH model. The study found a significant positive Monday/Tuesday and negative Friday effect respectively and argued that the DOW effect is significantly influenced by the estimation techniques.

The review of empirical studies so far revealed that calendar anomalies have been documented in the literature. Although, some studies have observed that weekend/DOW and January/monthly effects are disappearing in recent times (Martin, 2011), especially from developed markets and little has been said regarding this in the emerging African markets. The question is whether these anomalies are disappearing from emerging markets too. It can also be observed from a few sub-periods (pre/post crisis for instance) studies that some calendar anomalies appear in one period (say pre crisis) and disappear in the other period (say post) and *vice versa*. Could calendar anomalies be disappearing and reappearing? It can also be observed that conflicts at times appear in the findings of different studies; for instance, Chukwuogor (2007) rejected presence of calendar anomalies in African markets while others accepted it.

3.4 Empirical Studies on AMH

The majority of the weak-form EMH and calendar anomaly literature largely applies tests and models on the full sample period, assuming that market efficiency is a fixed feature that remains the same, irrespective of stages of market development, or happenings in the market ecology. By so doing, they ended up addressing the issue of market efficiency and anomalies in absolute form and producing conflicting findings. Considering the inconclusiveness of the absolute efficiency tests, Campbell *et al.* (1997) suggest the notion of relative efficiency, a new methodology that permits the level of market efficiency to be tested over time. This is akin to Lo’s (2004) argument in AMH, that market efficiency should be treated as a feature that changes over time and that is relative to market environment conditions. Available studies on the AMH, which considered alternative approaches to fixed state models; that is the possibility of time-varying efficiency/anomaly and market condition are presented in this section. Unlike the previous sections (3.2 and 3.3) where presentation takes market setting into consideration, this section presents a general review because African market studies seem to be limited to time-varying efficiency.

3.4.1 Time Varying Efficiency Studies

The formulation of AMH has ignited the reinvestigation of market efficiency in recent times. The most popular implication of the AMH is that market evolves over time in cyclical version. To examine this assumption, Anatolyev and Gerko (2005) investigated AMH in the US stock market and documented that inefficiencies do alternate efficiencies. Similarly, Todea, Ulici and Silaghi (2009), using daily indices and portmanteau and bi-correlation tests, revealed that there are sub-periods of non-linear and linear dependency in Australia, Hong Kong, Singapore, Japan, India and Malaysia with changes in degrees of dependencies over time. In another study, Ito, Noda and Wada (2012) employed time-varying auto-regressive and moving average models as the estimation tools and concluded that stock market evolves through time and that there are cyclical movements in market efficiency in the US. In Austria and 12 other emerging markets, results of rolling window automatic, wild-bootstrap and joint[20] sign VR tests showed that developed markets are less predictable compared to less developed markets (Dyakova& Smith, 2013). Likewise, Urquhart and Hudson (2013) employed sub-sample methods to examine the evolution of linear and non-linear dependence in the long run US, UK and Japanese markets stock market data. The findings from the linear runs, autocorrelation and VR tests showed that all the markets undergo eras of dependence and independence, while findings from the non-linear tests revealed high dependence in all windows. In addition, Mobarek and Fiorante (2014) tested the same hypothesis in the BRIC, Japan, UK, US using autocorrelation, run and VR tests in five-year fixed length moving windows. It was submitted that the markets are trending towards higher levels of efficiency. In the same period, Dourad and Tabak (2014) examined daily stock index return in Brazil over the 1991 to 2012 period using rolling wild bootstrap VR statistic and generalised spectral to test linear and non-linear dependencies respectively. It was found that RWH is present but varies in line with AMH. Further, rolling automatic VR and generalised spectra tests are adopted by Shi, Jiang and Zhou (2016) in China using daily and weekly data from 1990 to 2015. They found that the return predictability changes through time and high predictability were discovered around 2007 (financial crisis).

It is noteworthy that the study of AMH has been introduced to markets other than stock markets. For instance, Charfeddine, Khediri, Aye and Gupta (2017) employed state-space GARCH-M model, which revealed time-varying efficiency in the developed US and UK and emerging South Africa and India bond markets with the US market being the

[20] The Joint Tests test the joint null hypothesis (H_0) for all periods but the Individual Tests test H_0 for individual periods

most efficient. Similarly, Kumar (2018) validated the AMH in the Indian FOREX market using data from 1999 to 2017. Based on the application of non-overlapping sub-period and rolling automatic VR and Belaire-Franch and Contreras (2004) rank-based tests, they found that though the market is not efficient in full sample, it varies in the level of efficiency over time depending on occasion of fundamental macroeconomic events. In addition, Urquhart (2017) later studied the time-varying behaviour of precious metal returns via the application of rolling window Hurst exponent, VR and BDS tests. They showed that the market is not static but time-varying, with the silver market being less predictable and platinum being most predictable. Moreover, Ahmad, Shahid, Ateeq, Zubair and Nazir (2018) focus on Asia and used four popular linear tests and sub-period approaches. They established that the Indian and Pakistan stock markets are adaptive, fluctuating between inefficiency and efficiency.

It can be seen that most of the above studies concentrate on the developed markets while there are limited empirical studies on time-varying efficiency in African markets. One the first studies in the African stock market was carried out by Jefferis and Smith (2005) who examined evolving efficiency and used daily indices from 1990 to 2001 and GARCH with time-varying factor. They submitted that South Africa is efficient right through the period; Egypt, Morocco and Nigeria are moving towards efficiency while Zimbabwe, Mauritius and Kenya are inefficient all through. Likewise, Smith and Dyakova (2014) applied linear VR tests to daily index between 1998 and 2011. Fixed-length rolling sub-period window analyses disclosed successive periods of inefficiency and efficiency with Egypt, South Africa and Tunisia found to be less predictable while Kenya, Zambia and Nigeria are the most predictable. Seetharam (2016) examined daily, weekly and monthly indices of 44 shares and six local indices of Johannesburg stock exchange from 1997 to 2014 using traditional linear tests, Hurst exponent, non-linear BDS and artificial neural network and sub-sample analysis. The outcome described the JSE as a market with changing levels of efficiency through time. In Egypt, Botswana, Morocco, Kenya, Nigeria, Mauritius, South Africa, Tunisia; Gyamfi, Kyei, Gill (2016) provide support for AMH as markets, which were found to be inefficient in absolute forms revealed periods of unpredictability in rolling window generalised spectra test results. The same finding was reported in a separate study of Ghana stock market using rolling window VR and generalised spectra tests and index return data from 2011 to 2015 (Gyamfi, 2018). In addition, Heymans and Santana (2018) used rolling window of the three versions of VR test to examine AMH in JSE ALSI and other smaller and sectoral indices. They found that the broad market index is ranked more efficient than the others, while the smaller and younger indices from communication, small cap, media and automobiles and parts are found to be most inefficient. However, all the indices exhibit cyclicality in the level of efficiency over time. It can be observed that most of the existing studies on AMH were carried out in markets other than Africa, although there are few studies covering African markets. At this stage, an investigation of an evolving and changing nature of efficiency in African stock markets has not received adequate attention within the framework of AMH. In addition, there is need to compare and exploit linear and non-linear tests because Lim and Hooy (2012), among others, affirmed that non-linear dependence has been revealed in stock returns where linear tests showed absence of dependence. In the presence of non-linear dependence, markets cannot be said to be efficient.

3.4.2 Return Predictability and Market Condition Studies

Another inference of the new AMH is that the fluctuation in efficiency arises from changes in market conditions, although the hypothesis did not itemise the exact makeup of market conditions or its expected relation with return predictability. Researchers, however, have relied on the literature in determining what constitutes market conditions. For instance, where the stock market price or return behaviour or trend is considered, the market conditions may be defined as up or down or bull, bear and normal (Fabozzi & Francis, 1977; Klein & Rosenfeld 1987). Lo (2017) also mentioned external environments such as political, economic, financial, cultural and so on. One of the foremost attempts in the direction of changing efficiency cum market condition is the study by Kim *et al.* (2011), which applied automatic VR and portmanteau tests to generate predictability and OLS regression to examine the effect of market conditions. In consonance with the AMH, they concluded that predictability varies over time and that market conditions such as bubbles, normal, political and economic crises influence return predictability in the US stock market using index return from 1900-2009. In addition, the application of VR and portmanteau test by Zhou and Lee (2013) revealed declining predictability over time. The dummy OLS regression further showed that the US real estate market efficiency is influenced by market development, inflation, volatility and regulatory changes from 1980-2009. In a similar study, Urquhart and McGroarty (2016) used the VR and BDS tests, in 2-year fixed length moving window and dummy regression to analyse daily indices in the US, UK, Japan, and Europe. Changing return predictability is reported in different markets overtime; a behaviour, which can be explained by up, down, bull, bear, normal and volatile conditions. These findings are supported by Soteriou and Svenssion (2017) in the Swedish market using joint rank and sign tests, dummy regression, BDS test, autoregressive-generalised autoregressive conditional heteroscedasticity (AR-GARCH) filter and OLS. It can be seen from the review in this section that studies on the effect of market conditions on market efficiency have largely been a developed market affair**.** Thus, there is a need for further study on other emerging markets such as the African stock markets.

3.4.3 Time-Varying Calendar Anomalies Studies

Owing to its dominance in the determination of weak-form inefficiency, calendar anomalies are now also being evaluated within the time-varying approach of AMH. Although some of the studies (Alagidede & Panagiotidis, 2009; Borges, 2009) have applied the rolling window approach out of curiosity to question the persistence of the calendar anomalies without mentioning of the AMH. Coincidentally, their approach is in line with the AMH. Alagidede and Panagiotidis (2009) seem to be the only recognised African stock market calendar anomaly study where a rolling window analysis was mentioned to examine the persistence of DOW effect in Ghana. The study employed OLS, GARCH, EGARCH and TGARCH and submitted that there is significant Friday effect in the Ghana stock exchange in absolute form, however, they concluded that April and DOW effect evaporates with rolling window estimation. Additionally, Borges (2009) employed GARCH(1,1) to investigate 17 European stock market indices and documented evidence of cross-country rather than across-the-board calendar anomalies, especially in August and September. He submitted that the identified anomalies vary with time and could be more as a result of data mining due to high instability in the behaviours of the anomalies over time. Based on Borges' finding, Ching (2015) states, "the calendar effects may only be a 'chimera' delivered by intensive data mining as they are country-specific results and may not be stable over time" (p. 1). Similarly, Urquhart (2013) employed sub-period analyses to evaluate calendar anomalies within the AMH framework and found that January and Monday effects all change over time while TOM effect remains at all times. Further, Urquhart and McGroarty (2014) also showed in the US that the behaviour of the Monday, January, Halloween and the turn of the month calendar anomalies change over time using rolling window estimation for the S&P 500 index. This study confirmed that AMH provides better descriptions of the behaviour of the studied calendar anomalies.

Additionally, Bampinas, Fountas and Panagiotidis (2015) used daily data and GARCH (1,1), TGARCH and EGARCH to check the DOW effect in global, European and country-specific real estate indices from 1990 to 2010. The full sample analysis indicates the presence of the effect while about 75 percent of the rolling windows reject the presence of the anomaly. Hence, they submit that the effect could be due to data mining and sample selection bias criticism. This conclusion supported Borges' (2009) study in European markets. Similarly, various GARCH family models are analysed in rolling windows by Bampinas, Fountas and Panagiotidis (2016) to establish that the DOW effect, found in two regional and six national indices and Monday effect found in three national indices, all experienced significant reduction in power when rolling window analyses were carried out. Also, eight Dow Jones Islamic indices were studied by Osamah and Ali (2017) using sub-period mean-variance and stochastic dominance analyses and the findings supported varying behaviour of calendar effects in line with the AMH. In addition, Zhang, Yongzen and Jianghong (2017), via the application of GARCH model, established the presence of DOW effect in 25 countries (made up of 13 developed and 15 developing markets), the anomalies, which disappear with rolling windows in all except six countries. Moreover, Evanthia (2017) showed that DOW is present in all the sectors and the general S&P500 indices using non-linear models (EGARCH and TGARCH) in full sample but only one-fifth of the total number of regressions/windows are associated with the anomaly. Hence, the study concluded that the anomalies are weak and time-variant as opposed to being persistent. Overall, the studies of time-varying AMH are not only few, but many of them (apart from Urquhart, 2013; Urquhart and McGroarty, 2014, and Osamah and Ali, 2017, who supported AMH), have not supported the presence of calendar anomaly because only a small proportion of the estimated windows or sub-periods confirms the identified anomaly.

3.4.4 Calendar Anomalies and Market Condition Studies

By inference, AMH also portends that variation in calendar anomaly would emanate from changing market conditions. In line with the reasoning, Agnani and Aray (2011) applied two state MSMs and documented time-changing January effect in the US. The effect is found to be pronounced during the period of high volatility. Similarly, Urquhart and McGroarty (2014) investigated time-varying calendar anomaly in the US market using daily and monthly index from 1900 to 2013. Results of GARCH (1,1) and Kruskal–Wallis test in 19-years equal length sub-samples and 5-year fixed length rolling window disclosed that calendar anomalies vary over time. When market conditions were taken into consideration, the study further showed that calendar anomalies are influenced by conditions such as the up, down bull, bear, normal, expansionary and contractionary, republican and democrats dispensation. These findings were supported by Shahid and Sattar (2017) in Pakistan who documented that the behaviour of calendar anomalies (Monday, January, TOM, Holiday and Ramadan) change through time and under different market conditions, using similar methodology. Evanthia (2017) further examined the presence of DOW effect in relation to recession, uncertainty, liquidity and bearish sentiment. The study submitted that both the positive and negative DOW effect are more likely in the boom than in recession, Monday effect is highly correlated with the uncertainty index, weak relationships exist between DOW effect and liquidity/trading volume and negative DOW effect is associated with an increase in bearish investors. Recently, Rich (2018) in JSE applied MSMs and showed that there is no clear evidence of DOW effect under any market condition, but found a negative January effect in bull, negative July effect in bear and positive august effect in bull regimes. It must be noted that studies reviewed in this subsection are not linked with AMH except the Urquhart and McGroarty (2014) and Shahid and Sattar (2017). In essence, there is a dearth of study of calendar anomalies cum market condition and only a few studies seem to support AMH.

3.4.5 Gap in AMH Empirical Studies

The gaps in the subject under review are depicted in Table 3.1, which shows that while the empirical investigation of market efficiency and calendar anomalies under AMH are limited, they are particularly rare in the African stock markets. It can also be seen that recognised study on the effect of market conditions on market efficiency or return predictability in other markets, other than US, UK, Japan and Germany and Sweden, is almost lacking, thereby creating a need for further studies in developing markets.

Further, the table shows that the consideration of time-changing calendar anomaly is new and the investigation is limited to a few markets. Just as the EMH, which has taken many years of investigation, there are still a lot of markets to cover in the examination of calendar anomalies within the AMH framework. Lastly, calendar anomalies could also be investigated *vis-à-vis* market conditions. Obviously, there is a dearth of empirical study on the explanatory power of market conditions on the behaviour of calendar anomalies globally, especially in the small and so-called inefficient markets like African stock markets. The identified gaps suggest that further investigation of AMH in smaller markets can shed more light on the topic. At this stage, an investigation of changing nature of efficiency and anomalies in response to market condition in African stock markets has not received adequate attention under AMH. An attempt in this direction will make meaningful contribution to the existing body of knowledge on AMH and bridge the empirical literature gaps between developed markets and African Markets.

Table 3.1: Research gap

Hypotheses	Developed	Emerging	Africa
Time-varying efficiency	Urquhart (2013): + Noda et al (2012) + Almail&Almudhaf (2017) + Todea, et al (2009) + Dyakova& Smith (2013) + Niemczak& Smith (2013) +	Lim, *et a.l* (2006): + Hiremat & Kumari (2014)+ - Smith (2012) + Maghyereh (2007) +	Smith &Dyakova (2014) +, Seetharam (2016) +
Return predictability &market condition	Zhou & Lee (2013) + Andreas & Louise (2017) + Soteriou&Svenssion (2017) Kim *et al.* (2011) + Urquhart & McGroarty (2016)+	?	?
Time-varying calendar anomalies	Borges (2009) Urquhart&McGroarty (2014) + Evanthia (2017)	Shahid & Sattar (2017)	?
CA &market condition	Agnani&Aray (2011)+ Urquhart&McGroarty (2014) + Evanthia (2017)	Shahid and Sattar (2017)	?

Source: Author’s compilation (2019)

3.5 Summary and Concluding Remarks

This chapter presents the review of empirical studies on weak-form EMH and calendar anomalies, both in absolute form and under AMH. It can be seen from the review that evaluation of market efficiency is a controversial subject in the literature. While there is preponderance of linear dependency tests in the early periods (believed to be unable to capture non-linear dependency), there has also been an upsurge in the adoption of non-linear testing tools later. In the same manner, investigation of calendar anomalies has evolved from the linear OLS test to the non-linear types of GARCH family models. The rationale for the influx of non-linear tests and models is due to the realisation of the fact that many aspects of economic behaviour may not be linear. Since the existence of non-linearity also disagrees with the EMH and gives market participants an occasion to earn surplus profits, reliance on linear testing tools alone, to determine predictability, may lead to wrong inferences. Thus, (i) combining both the linear and non-linear testing tools or one that is able to pick both non-linear and linear dependence will ensure the avoidance of possible wrong inferences. Generally, the linear tests of EMH have produced conflicting findings, although developed markets have been found to be more efficient than other markets. On the other hand, non-linear tests, in most cases found non-linear dependence, whether the market is developed or developing. Hence, (ii) the issue of weak-form efficiency has remained inconclusive and its problem has been traced to the approach of evaluating EMH and calendar anomalies in absolute form. Thus, a market when investigated for dependency and predictability can be found to be either efficient or inefficient. This assumption can be described as viewing efficiency as absolute or all-or-nothing. In other words, the EMH can be described as a fixed or final state model (Seetharam, 2016).

Due to the defect of the absolute efficiency and calendar anomaly studies, Campbell *et al.* (1997) and Lo (2004) have advocated evolving efficiency and time-varying efficiency respectively as the alternatives to the traditional EMH methods. Consequently, there are a gradually increasing number of investigations of time-varying efficiency and calendar anomaly in recent times. Some efficiencies/anomalies found in one sub-period sometimes change/disappear in another sub-period; seasonal effects such as weekend/DOW and January/monthly effects are said to be disappearing or weaker in some markets**.** This observation suggests that AMH approach could be more appropriate but this will require investigation of several sub-samples. Rolling analyses has so far been pointed out as the best-developed class of alternative tests to the absolute approach, while researchers are still facing the task of identifying models best suited to capture cycles or dynamics inherent in the new AMH. While the investigation started from developed markets like the US, other emerging markets are now receiving a fair share of interest from researchers. Obviously, there is now a shift from absolute framework to time-varying frameworks. Recent evidences are suggesting that AMH could be a more appropriate approach and efficiencies/anomalies are now being linked to market conditions, yet there have been very few studies on them. Thus, there is need for further studies.

CHAPTER 4: DATA AND METHODOLOGY

4.1 Introduction

The significance of appropriate methodology cannot be overemphasised because it is *sine qua non* for the successful attainment of the study objectives. This research is empirical and quantitative in nature, involving examination of behaviour of stock market returns and the effect of market conditions on return behaviour. It employs secondary time-series data collected over a long period of time and analysed them using different estimation techniques. Results of the analyses are succinctly reported, objectively interpreted and discussed in the latter chapter, with reference to the research problems, objectives and questions. This chapter describes the type of data and sources of data collection, the procedure for sample selection and statistical methods for analytical purposes. Thus, there exist three main sections of data and methodology, which are the population and data, econometric and estimation techniques and the concluding remarks.

4.2 Markets, Sample and Data Property

This section provides a brief overview of African stock markets and describes the sample selection procedure. Each of the selected markets is further described along with the data source, calculation and properties.

4.2.1 Population and Sampling

African stock markets have undergone significant evolution over the years. For instance, African stock markets overall MCAP has grown from $113 billion to around $2 trillion, between 1992 and 2013. As of 2013, there are 29 bourses in Africa (African Securities Exchanges Associations, 2013), representing 38 countries' capital markets; however, the number has grown to 35 bourses at various levels of maturity (WFE, 2018). African stock markets are usually classified into four[21], namely (i) largest, (ii) medium, (iii) small and (iv) very small. The largest stock market is found in South Africa while the medium size group covers Egypt, Kenya, Nigeria, Morocco, Tunisia and Zimbabwe (Smith *et al.,* 2002; Ntim, 2012, Boako, 2016). The markets in the first two groups account for the buck of stock market activities in the continents. For instance, it was noted that South Africa, Egypt, Nigeria, Morocco and Kenya account for 96 percent of average daily trade as of 2013, with South Africa accounting for about 75 percent (ATLFH, 2016).

Satisfactorily large sample size is essential for the model estimation task at hand. Hence, the availability of averagely long sample size forms the basis for market selection because the nature of the study requires fairly long sample size to examine changing behaviour of equity market returns over time. Consequently, relatively new markets[22] are automatically omitted. In addition, most markets (including Egypt and Kenya) are dropped for lack of long and consistent data. Thus, the final sample selected for the study comprises five African stock markets, namely the South African, Nigerian, Moroccan, Mauritian and Tunisian stock markets. Incidentally, the selected markets based on the MCAP and listing, account for over 70 percent of the total indices in the continent (ATLFH, 2016). As at September 2017, the selected markets have US$ 1,230,977, US$ 37,218, US$ 67,048, US$ 9,743 and US$ 8,923 in millions in terms of MCAP and 294, 166, 73, 74 and 81 listed companies respectively according to the World Development Indicators[23]. South Africa, Nigeria and Morocco are amongst the largest markets in the continent while the presence of Mauritius and Tunisia ensures that the smaller markets are also represented. In addition, the selected markets are opened to foreign participation and they have all gone online and adopted electronic systems with respect to their trading mechanism (Boako, 2016). The choice of the

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[21] Small (iii) include Botswana, Coted'Ivoire, Ghana, Namibia and Mauritius; very small (iv) include Libya, Malawi, Mozambique, Sudan, Swaziland, Tanzania, Uganda and Zambia others struggling to take off

[22] Such as Angola, Cameroon, Lesotho, Libya, Rwanda, Seychelles, Somalia,

[23] http://wdi.worldbank.org/table/5.4

sample is thus based on the availability of consistent data and the exclusion of the countries with insufficient data is well accepted in the literature (Auret & Cline, 2006; Basiewicz & Auret, 2010).

4.2.2 Data Description and Sources

Daily returns of the stock indices are used in this study. Daily data are employed because it provides observations, long enough to track changes in efficiency over time. The data covers a period of 20 years (1998:1-2018:2), selected based on data availability except for Tunisian market, which covers 1999:4-2018:2. The period, however, is sufficient to generate robust analyses. The data are sourced from Bloomberg, a major global provider of real-time and historic price and financial data. Simple return for the Nigerian Stock Exchange All Share Index (NGSEINDX), the JSE All Share Index (JALSH), the Stock Exchange of Mauritians All Share Index (SEMDEX), the Casablancan/Morocco Stock Exchange All Share Index (MOSENEW) and the Tunisian Stock Exchange All Share Index (TUSISE) are obtained directly from Bloomberg and are calculated using the following formula.

$$\mathrm{IR_t} = \left(\frac{\mathrm{P_t} - \mathrm{P_{t-1}}}{\mathrm{P_{t-1}}}\right) \mathrm{x}\ 100 \qquad (1)$$

Where $\mathrm{IR_t}$ is the time t return of stock index and $\mathrm{P_t}$ and $\mathrm{P_{t-1}}$ are the time t and $\mathrm{t} - 1$ price index of each stock. Each index return represents total return gross dividend (inclusive of dividends). Brooks (2014) observed that ignoring dividend would lead to underestimation of total return and cause distortion between cross section return data. It is noteworthy that additional data frequency (monthly) is generated from the daily returns for the purpose of objective two. However, the procedures for the generation of such data are clearly described in section 4.3.2.1 and 4.3.2.2.

NGSEINDX is the Nigerian Stock Exchange All Share Index formulated in 1984 with a base value of 100. Only ordinary shares are included in the computation of the index. The index is value related and computed daily. Bloomberg displays it as per NSE disseminated. The JALSH, otherwise known as FTSE JSE All Share Index, is a MCAP-weighted index. Companies included in the index make up the top 99 percent of the total free-float MCAP of all companies listed in the Johannesburg stock exchange. The MOSENEW is a broad based free float index comprising all shares listed on the Casablanca stock exchange.

The SEMDEX is a capitalisation weighted index, including all shares traded on the stock exchange of Mauritius. The index is obtained as market value of all listed shares over base market value of all listed shares multiplied by 100 (where the market value of any share is equal to the number of shares outstanding multiplied by the market value). The base value is adjusted to reflect the new listings and right issue. The TUSISE/TUNIDEX is a capitalisation-weighted index containing all equities from Tunisia stock exchange (TSE). The index is open to listed companies admitted in the capital market with a minimum period of quotation of one month. The index was launched in December 31, 1997 with an initial base level of 10000. As of January 2, 2009, the index has become a free float weighted index.

4.2.3 Data Property

This section covers the tests of the data generating and distributional properties of stock return. The tests cover the common features of stock returns and are usually carried out for robustness purposes. Figure 4.1 plots the time series of the indices returns of the five African markets, which clearly showed the feature of volatility clustering. Volatility clustering describes the tendency of big changes in stock prices (of either sign) to trail big changes and little changes (of either sign) to trail little changes (Brooks, 2014 p. 386). It suggests that stock return has some features of non-linearity. The distributional properties of returns are further examined using Jarque-Bera normality tests.

- **Normality Tests**

Jarque-Bera is a test statistic for checking whether return series conform to normal distribution. The JB statistic measures the variance of the skewness and kurtosis of the series with those from the normal distribution. Under the null hypothesis of a normal distribution, the statistic is distributed as X^2 with two degrees of freedom under the null hypothesis of normal distribution. The reported probability is the probability that the absolute value of JB statistic is greater than the observed value under the null hypothesis in which the hypothesis that return series follows a normal distribution is rejected by very small probability value. The statistic is obtained as:

$$S = \frac{N}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \qquad (2)$$

Where S and K are the skewness and the kurtosis respectively. S is given by:

$$S = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i - \check{y}}{\check{\sigma}}\right)^3 \qquad (3)$$

Where $\check{\sigma}$ is a variance-based standard deviation estimator. The skewedness takes the value zero if the series is normally distributed or symmetric. Long right tail is indicated by positive skewedness of the distribution while long left tail is indicated by negative skewedness. The kurtosis is calculated by:

$$K = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i - \check{y}}{\check{\sigma}}\right)^4 \qquad (4)$$

Where $\check{\sigma}$ is also based on the biased estimator for the variance. The kurtosis value is three if the series follows a normal distribution. If the kurtosis is above or below three, the distributions are said to be peaked (leptokurtic) or flat (platykurtic) respectively, relative to the normal.

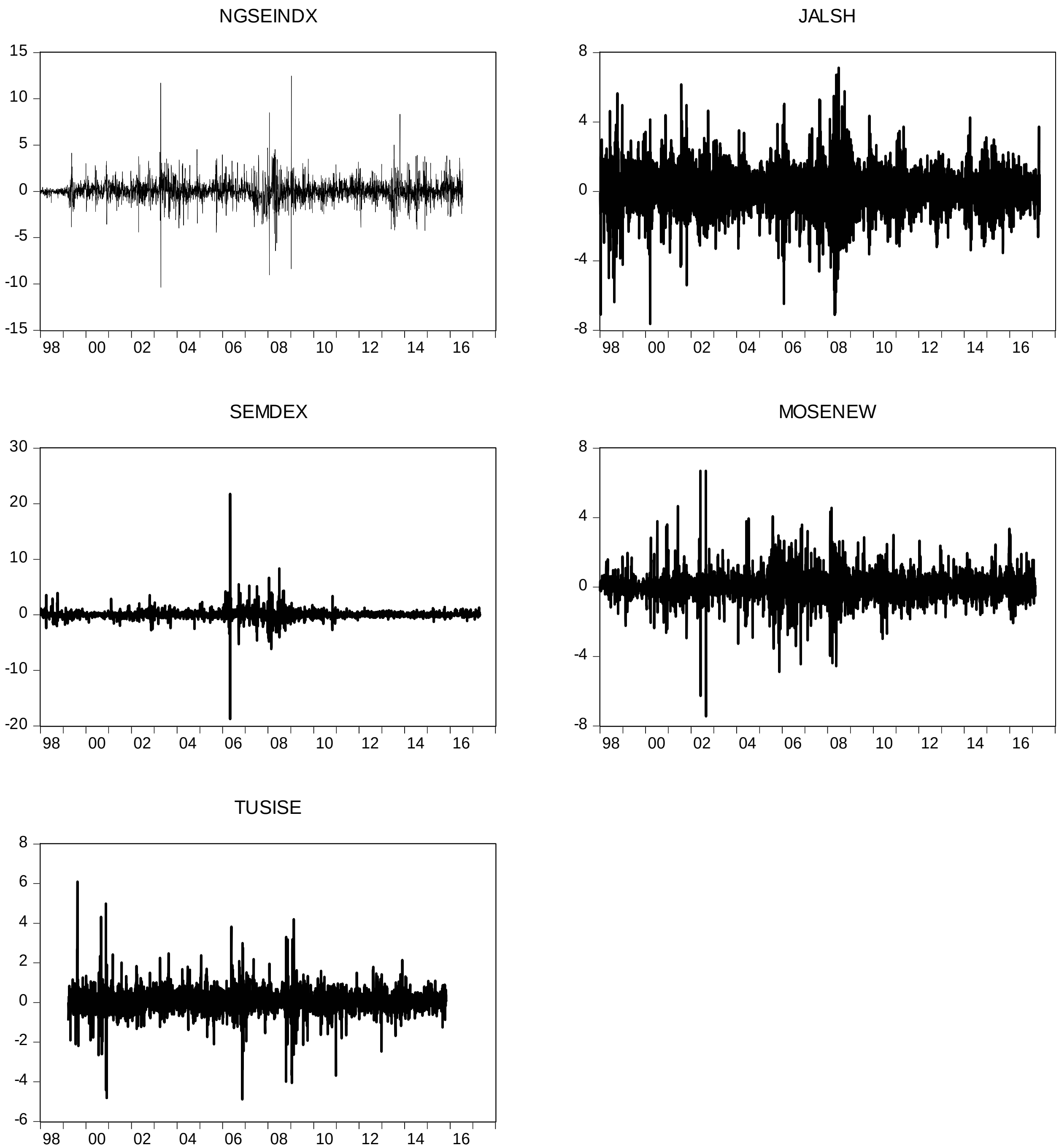

Figure 4.1: Time Plot of NGSEINDX, JALSH, SEMDEX, MOSENEW and TUSISE Returns

4.3 Model Specifications

This part discusses the models employed for the analyses of each objective. There are four segments, one for each of the objectives. The first segment entails testing for the independence and identical distribution of the indices return series using linear and nonlinear approaches; the second captures the models employed in examining the effect of market conditions on the dependence of stock returns; the third part explains the models and framework for analysing the time-changing calendar anomalies, while the last section specifies how changing market conditions or regimes could be incorporated in the analyses of calendar anomalies. Each of the segments thus provides detailed explanations of the models used in achieving each of the objectives and how the hypotheses are tested.

4.3.1 Modelling Time-varying Market Efficiency

The empirical method for the evaluation of weak-form EMH has undergone considerable evolution over the years and the methodology employed seems to impart on the results. The techniques range from linear dependency tests to nonlinear dependency tests. There are four major linear tests employed in testing weak-form efficiency in literature, namely the autocorrelation/partial autocorrelation tests, VR, run and unit root tests (Urquhart, 2013) and they constitute the earliest testing tools. However, it has been observed that markets/returns sometimes exhibit nonlinear dependence, which is tantamount to predictability, even when there is no linear dependence (Granger & Andersen, 1978; Amini *et al*, 2010; Lim & Hooy, 2012). Since nonlinear dependence cannot be picked by linear testing tools, combining both the linear and non-linear testing tools[24] or one that is able to pick both nonlinear and linear dependence will ensure the avoidance of possible wrong inferences. Therefore, this study considers linear and non-linear tests.

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[24]Nonlinear tests include Engle LM test (1982), McLeod and Li test (1983) and BDS (1987, 1996) test

4.3.1.1 Methodological Note on Weak-Form Efficiency

The majority of the weak-form EMH and calendar anomaly literature largely applies above tests or models on the full sample period, assuming that market efficiency is a fixed feature that remains the same irrespective of stages of market development. By so doing, they ended up addressing the issue of market efficiency and anomalies in absolute form. However, the researchers have now come up with new alternatives in order to evaluate cyclical efficiency. The first set is the equal-length non-overlapping sub-samples estimation in which the entire sample period is broken into two or more subsamples and one or more of the various tests/methods of efficiency is applied to each subperiods. This practice enabled the researcher to assess the effect of major events (e.g. pre & post liberalisation, financial crisis, adoption of electronic trading system, change in regulatory system, etc.) on the efficiency of the market (Lim & Brooks, 2011). This may have been accompanied by conflicting result too; nevertheless, the research framework adopted shows that these investigators are aware of the non-static characteristic of market efficiency. Non-overlapping sub-period analyses suppose that the road toward market efficiency follows a distinct switch in the underlying parameter at a known breakpoint. However, it is ideal to allow market efficiency to vary over time, a dynamic feature, which non-overlapping sub-period analyses failed to capture (Lim & Brooks, 2011). As a result, few recent literatures on weak-form efficiency use state space model to capture the time-varying weak-form efficiency, which permits standard regression parameters to change over time (Lim & Brooks, 2011). The merit of this method lies in permitting the application of regression models to a more dynamic conception like time-varying efficiency. This model, however, is said to require more methodological innovations for it to be a more appropriate measure of weak-form market efficiency (Verheyden *et. al.*, 2013).

Furthermore, rolling window estimation constitutes another alternative to absolute method. A rolling analysis assesses the stability of a model over time. A time series model assumed parameter constancy. If so, then the estimates over rolling windows should not be too different (Springer, 2006). This method involves breaking the full sample (N) into a number of consecutive observations (m-known as window size), pushed by a certain number of observations (k-step size) ahead at each repetition (Evanthia, 2017). Different windows overlap as they are rolled (k step) forward, dropping the farthest K observation, until the entire sample is exhausted. This rolling method enables one to look at the underlying changes in efficiency on a shorter time scale, compared to non-overlapping sub-period analysis and to measure varying and relative levels of efficiencies over time. This method is relatively new and has only been employed by a few researchers. Rather than applying the traditional tests in full sample, researchers are now using rolling window analyses, hence the terms rolling VR tests; rolling ADF unit root tests; rolling bicorrelation tests; rolling parameters of ARCH models; rolling Hurst exponents (Verheyden, *et al.,* 2013). The superiority of rolling window analyses lies in the fact that, apart from capturing sub-period analyses, it also captures dynamics that otherwise would have been omitted in non-overlapping sub-period analyses. In fact, the procedure of rolling estimation was employed by Lo (2005) in the maiden test of the AMH in the US. Verheyden *et al.* (2013 p. 38) state that "[r]olling estimation windows are more suited for broad market efficiency research……that take into account the possible time-variant character of weak-form market efficiency". Hence, the approach is more suited for the investigation of time-varying behaviour inherent in the new AMH and is now being applied to test EMH.

4.3.1.2 Rolling Windows Approach

Consequent to the preference for rolling methodology in the investigation of varying behaviour, this study uses the rolling linear and nonlinear tests to investigate whether market efficiency changes in cyclical version over time in African stock markets according to AMH. This study uses two-year rolling windows (window size), rolled forward by one-year (step size) and dropping the farthest year to detect the behaviour of stock returns through time. There are a total of 20 years, 2 month daily data points in the study sample. The study uses the first 2 years to estimate the tests and then rolls the sample forward by one year at a time, constructing a new one-step (year) ahead *p*-value at each stage. A two-year window (window size) generates about 500 observations of daily data, which is enough to produce robust results. This is consistent with previous studies (Smith. 2012, Lim *et al.*, 2013; Smith &Dyakova, 2014). The adequacy of one-year step size in evaluating changing efficiency has been established in literature (Urquhart & McGroarty, 2014).

4.3.1.3 Linear Dependence Tests

The linear dependence tools constitute the earliest methods of testing weak-form EMH. It has been established that the unit root test is not enough to establish the randomness of price changes, except when it is complemented with serial correlation tests (Rahman & Saadi, 2008). This study places emphasis on the VR test being the primary and the most influential test (Verheyden, *et al.,* 2013), although autocorrelation and unit root tests, which are common linear dependence tests, are also estimated for robustness and confirmation purposes. Urquhart (2013) noted that none of the linear tests is without its own weakness but the accuracy of the results can be confirmed if different tests point to the same conclusion. These linear dependence tests are explained below.

4.3.1.3.1 Unit Root Tests

Unit root is a necessary but insufficient condition for RWH (Gilmore & McManus, 2003, p. 44; Rahman & Saadi 2008). Stationary stochastic process has received great attention from researchers. Gujarati (2013, p. 752) states, that "a stochastic process is said to be stationary if its mean and variance are constant over time and the value of the covariance between the two time periods depends only on the distance or gap or lag between the two time periods and not the actual time at which the covariance is computed"

To explain weak stationarity, let P_t be a stochastic time series with these properties:

Mean is constant: $E(P_t) = \mu$

Variant is constant: $Var\ (P_t) = E(P_t)^2 = \sigma^2$

Covariance depends on distance not time $\gamma_k = E[(P_t - \mu)(P_{t+k} - \mu)]$

Where γ_k, is the covariance (or autocovariance) at lag k, between the values of P_t and P_{t+k}, that is, between two *Y* values *k* periods apart. If k=0, we obtain γ_0, which is simply the variance of P(=σ^2); if $k = 1$, γ_1 is the covariance between two adjacent values of$R$. Summarily, a stationary time series has $E(P_t)$, $Var\ (P_t)$ and γ_k unchanged at various lags, which means that they are time invariant.

The RWM provides a classic instance of nonstationary process. The terms nonstationarity, random walk and unit root are synonymous (Gujarati, 2013). RWM could be without drift, with drift or with drift and intercept. Assume a white noise error term u_t with mean 0 and variance σ^2, then the series P_t is said to be a random walk if

$$P_t = P_{t-1} + u_t \qquad (5)$$

The RWM as P_t shows the value of Pat time$t$amounts to its lagged $t-1$ plus a stochastic error term. While P_t is a unit root, its first order derivative is stationary. Thus, the first order derivative of a random walk time series are stationary, such that:

$$\Delta P_t = (P_t - P_{t-1}) = u_t \qquad (6)$$

By introducing drift term δ in equation, it becomes RWM with drift, which is nonstationary as shown below.

$$P_t = \delta + P_{t-1} + u_t \qquad (7)$$

Again, the first order derivative of P_t is stationary. Thus, the first order derivative of a random walk time series are stationary, such that:

$$\Delta P_t = (P_t - P_{t-1}) = \delta + u_t \qquad (8)$$

It implies that P_t drifts up or down, subject to whether the sign associated with δ is positive or negative. By adding a deterministic trend βt to equation (7), the last form of non stationary RWM is obtained as:

$$P_t = \beta t + \delta + P_{t-1} + u_t \tag{9}$$

If the mean of P_t is removed from P_t, the ensuing series will be stationary, thus the name trend stationary. Again, the first order derivative of a random walk time series is stationary, such that

$$\Delta P_t = \beta t + \delta + u_t \tag{10}$$

Brooks (2014) noted that RWH with drift and trend stationary processes are the two main commonly tested features of nonstationarity. The Dickey-Fuller (1979) tests have been employed in the literature to establish nonstationarity or whether series of return is efficient in weak form from the above equations. The test is based on the assumption that error terms (u_t) are not autocorrelated. Augmented Dickey-Fuller (ADF) has, however, been designed to take care of autocorrelation in the error term, basically by incorporating adequate amounts of lagged terms ΔP_t. The ADF equation, according to Brooks (2014), is given thus:

$$\Delta P_t = \beta_1 + \beta_2 t + \delta P_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta P_{t-1} + \varepsilon_t \tag{11}$$

Where ε_t is a pure white noise error term and $P_{t-1} = (P_{t-1} - P_{t-2})$, $P_{t-2} = (P_{t-2} - P_{t-3})$ and so on. The test belongs to asymptotic distribution and examines whether the series contain unit root (δ = 0) against the alternative of stationarity (δ ∠ 0). The statistical significance of the results is discussed using *p*-values that are drawn from the test statistic (*t*-statistic).

The ADF has been criticised on certain grounds. For example, its power is low if the process is stationary and hence, it is biased toward accepting null hypothesis of unit root (Brooks, 2014, Gujarati 2013). The test is also exposed to size distortion, leading to high probability of committing a Type I error (i.e. rejecting the null hypothesis when in fact, it is true (Gujarati, 2013). Brooks (2014) suggested the joint use of the stationarity and the unit root tests, the approach which is known as confirmatory data analysis as a way around the weaknesses of ADF test. Thus, the result of the ADF test is compared to one alternative test, namely the KPSS.

The Kwiatkowski, Phillips, Schmidt and Shin (KPSS) (1992) test differs from the ADF explained above because it tests the null hypothesis that series P_t is (trend-) stationary. The KPSS statistic is based on the residuals from the OLS regression of P_t on the exogenous variables Q_t :

$$P_t = Q_t{'}\delta + u_t \tag{12}$$

$$u_t = u_{t-1} + \ e_t e_t \sim (0, \delta^2)$$

Where $Q_t{'}\delta$ contains deterministic components, u_t is I(0) and is a pure random walk with variance. The hypothesis of stationarity is stated as $H_0 : \delta^2 = 0$, which implies that u_t is constant.

The LM statistic is defined as:

$$LM = \sum_t \frac{S(t)^2}{(T^2 fo)} \tag{13}$$

Where fo, represents estimator of the residual spectrum at frequency zero and $S(t)$ stands for cumulative residual function:

$$S(t) = \sum_{r=1}^{t} \hat{u}_r \tag{14}$$

based on the residuals $\hat{u}_t$=$P_t - Q_t^{'}\delta(0)$. The reported critical values for the LM test statistic are based upon the asymptotic results presented in KPSS (1992, p. 166). Where the ADF results conflict with KPSS, the latter should be trusted (Pfaff, 2008, p.103). Using stock prices, the unit root is accepted when ADF statistic is greater than critical value at 5 percent or when the KPSS statistic is less than critical values at 5 percent at level, which implies that the return follows a RWH. The tests as also carried out in rolling windows and successive windows of unit roots and stationarity would mean that market efficiency varies over time.

4.3.1.3.2 Autocorrelation Test

The autocorrelation test is one of the earliest tests for the examination of independence of stochastic variable in return series. The presence of autocorrelation is tantamount to dependency in stock returns. Absence of autocorrelation, however, does not necessarily amount to independence but an absence of linear autocorrelation. Of course, such return series could possess nonlinear dependence, which cannot be observed by autocorrelation test (Amini *et al.*, 2010).

The autocorrelation of a series Y at lag K is estimated by:

$$\rho_k = \frac{\sum_{t=k+1}^{T}\left(\left(Y_t - \check{Y}\right)\left(Y_{t-k} - \check{Y}_{t-K}\right)\right)/(T-K)}{\sum_{t=1}^{T}\left(Y_t - \check{Y}\right)^2/T} \qquad (15)$$

Where $\check{Y}_{t-k}$=$\sum Y_{t-k}/(T-k)$. ρ_k is the correlation coefficient for return series, k periods apart, which is a consistent estimator. T stands for the total number of observations. First order serial correlation occurs if ρ_1 is non-zero. The null hypothesis is that $\rho = 0$. If $\rho < 0$, it is a case of negative autocorrelation. If $\rho > 0$, it is a case of positive autocorrelation. The denominator is the covariance at lag *k* and numerator is the variance. $\check{Y}$ is the overall sample mean, which is the mean of both Y_t and Y_{t-k}. The dotted lines in the plots of the autocorrelations are the approximate two standard error bounds computed as $\pm 1.96/(\sqrt{T})$. If the autocorrelation is within these bounds, it is not significantly different from zero at (approximately) the 5 percent level of significance. A non-zero value of ρ_1 denotes market inefficiency. The hypothesis is tested across rolling windows to determine how the market efficiency varies over time. If windows of zero value of ρ_1 interchange with windows of nonzero value of ρ_1, over time, market efficiency is said to vary over time, in line with the AMH.

4.3.1.3.3 Variance-Ratio Test

Among the linear estimation tools, namely the runs test, the autocorrelation test, the unit root test and the VR test, the latter (VR test) is the standard and most popular test for determining whether price changes are not serially correlated because it is efficient and has good power (Lo & MacKinlay, 1988; Urquhart, 2013). Its advantage also lies in its ability to correct the heteroscedasticity property inherent in stock returns. The test assumes that if changes in asset price are consistent with RWH, the variance of the *p*-period change must be *p* multiplied by the variance of *1*-period change (Lo &MacKinlay, 1988). VR for Γ_t, with holding period P is given as:

$$VR(P) = \frac{\delta^2 \mathrm{p}}{(1)\delta^2} \tag{16}$$

where $VR(P)$ is variance ratio; $\delta^2\mathrm{p}$ is variance $\left(\Gamma_t + \Gamma_{t-1} + \Gamma_{t-2} + \cdots + \Gamma_{t+p-1}\right)$of return at *p*-period; $(1)\delta^2$ is the variance of the first difference. Γ_t is time t stock return, with t taking the value from $1, 2, 3, \ldots, M$. Alternatively, equation (16) can be expressed as follows:

$$VR(P) = 1 + 2 \sum_{j=1}^{p-1} \left(1 - \frac{\mathrm{j}}{\mathrm{p}}\right) \varphi(j) \tag{17}$$

where $\varphi(j)$ is the autocorrelation of Γ_t of lag j. That is, $VR(P)$ is 1 plus *t* a weighted sum of autocorrelation coefficients for the stock returns with positive and declining weights. Since stock return series are prone to heteroscedasticity, Lo and MacKinlay (1988) derived the heteroscedasticity consistent VR with test statistics $M_2(P)$:

$$M_2(P) = \frac{VAR(X;P) - 1}{\psi(\mathrm{P})^{-\frac{1}{2}}} \tag{18}$$

Where:

$$\psi(P) = \sum_{j=1}^{p-1} \left[\frac{2(p-j)}{P}\right]^2 \beta(j)$$

$$\beta(j) = \frac{\left\{\sum_{t=j+1}^{M} (X_t - \mu)^2 (X_t - \mu)^2\right\}}{\{[\sum_{t-1}^{M} (X_t - \mu)^2]^2\}}$$

VR sets the null hypothesis (H_0) as: $VR(P) = 1$ for all P as long as price changes are uncorrelated. This hypothesis is rejected when probability of VR statistic is significant (<0.05). The rejection of this hypothesis implies that returns are not uncorrelated or unpredictable or the market is not efficient. The hypothesis is tested across rolling windows to determine how the market efficiency varies over time. Where windows of significant dependence (predictability) alternate independence (unpredictability), over time, market efficiency is said to vary over time, in line with the AMH. The VR *p*-values are generated for all windows and they can be referred to as annual[25] measures of linear predictability. A graphical plot of the windows' VR *p*-values result can show how linear dependence behaves over time.

VR has undergone significant developments over the years as contained in Charles and Darné (2009). It was been observed that statistical inference of VR test could be misleading in small sample because the VR statistics follow asymptotic theory (Richardson & Stock, 1989). To deal with this shortcoming, a wild bootstrap VR statistics of Kim (2006) is implemented. The approach requires estimating the individual VR with joint VR test statistics on samples of observations formed by weighting the original data by mean 0 and variance 1 random variables, and using the results to form bootstrap distributions of the test statistics. The bootstrap *p*-values are computed directly from the fraction of replications falling outside the bounds defined by the estimated statistic. Another alternative to the popular Lo and MacKinlay VR test was offered by Wright (2000) who modified the tests using standardised ranks of the increments, ΔX_t. If $r(\Delta X_t)$ is the rank of ΔX_t, the standardised rank (r_{it}) is

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[25] Since the step size is one year (every window is rolled forward by one year).

$$r_{it} = \frac{\left\{r(\Delta X_t) - \frac{M+1}{2}\right\}}{\sqrt{\frac{(M-1)(M+1)}{12}}} \tag{19}$$

Wright (2000) equally replaced ΔX_t by its sign to derive the sign-based VR test, s_{it}:

$$s_{it} = \frac{\left\{s(\Delta X_t) - \frac{M+1}{2}\right\}}{\sqrt{\frac{(M-1)(M+1)}{12}}} \tag{20}$$

The Wright VR test statistics are derived by computing the Lo and MacKinlay homoscedastic *t* statistic using the ranks and signs as opposed to the original data. By assuming that X_t is generated from martingale difference sequence with no drift, s_t is an *i.i.d*. The original heteroscedasticity consistent VR of Lo and MacKinlay (1988) and subsequent innovations (using wild bootstrap, ranks and signs) are performed in this study for comparison. However, the former is reported, being the most influential in the past.

4.3.1.4 Nonlinear Dependence Test

The linear dependence tests considered in this study are highlighted in the previous section. However, Alagidede (2009) quoted Campbell *et al.* (1997, p. 467) that:

> Many aspects of economic behaviour may not be linear. Experimental evidence and casual introspection suggest that investor's attitudes towards risk and expected return are non-linear. And the strategic interactions among market participants, the process by which information is incorporated into security prices, and the dynamics of economy wide fluctuations are all inherently non-linear. Therefore, a natural frontier for financial econometrics is the modelling of non-linear phenomena.

Arising from the above, consideration is given to nonlinear dependence, in addition to linear tests, in order to avoid the possibility of wrong inference. In the family of non-linear dependency tests, namely Engle LM test (1982), McLeod and Li test (1983) and BDS (1987, 1996) test, BDS is relatively better under different situations (Patterson & Ashley, 2000). Named after the three authors, BDS by Brock, Dechert and Scheinkman (1987; 1996) is a common test of nonlinear predictability in time series and its one of the most widely employed tests (Brock *et al*., 1996). BDS is a pure hypothesis test. That is, it has the null hypothesis that the series are totally random or pure noise. Further, it is proven to possess power to spot a range of departures from randomness -- linear or non-linear stochastic processes, deterministic chaos etcetera (Brock *et al*., 1991; Brooks, 2014) and it does not need returns to be normally distributed.

4.3.1.4.1 AR (p) Filter

A common principle of nonlinear test is that after the removal of linear serial autocorrelation any residual dependence must be caused by nonlinearity in the series-generating mechanism (Alagidede & Panagiotidis, 2009). Hence, linear dependence must be removed before the estimation of the nonlinear test (Urquhart, 2013). This involves fitting an AR (p) model with *p* determined when Ljung-Box (LB) *Q*-statistic is not significant at the 10 percent level of significance. The *Q*-statistic at lag n tests the null hypothesis that there is no autocorrelation up to order n and it is given as:

$$\mathrm{Q_{LB}} = T(T+2)\sum_{i=1}^{n}\left[\frac{\phi_i^2}{T-i}\right] \tag{21}$$

Where, ϕ_{i} is the $i\mathrm{th}$ autocorrelation and T is the number of observations. Residual of the selected $AR(p)$ model is subjected to BDS test for nonlinear dependence. However, it has been established in the literature that nonlinear dependence in return series usually results from conditional heteroscedasticity, which cannot be filtered by ordinary $AR(p)$ model (Lim & Hooy, 2013). In addition, if nonlinear dependence were caused by conditional heteroscedasticity, it would not amount to violation of the EMH (Hsieh 1989, 1991; Opong *et al*., 1999; Poshakwale 2002; Saadi *et al.,* 2006). Urquhart and

McGroarty (2016) noted that nonlinear dependence caused by conditional heteroscedasticity can only be filtered by ARCH-type model. Hence, the return data are also filtered to remove heteroscedasticity by obtaining standardised residual series $[\frac{\epsilon_t}{\delta_t}]$ of $AR(p) - GARCH$, which is then used for the BDS test. Thus, $AR(p) - GARCH\ (q, p)$ model is fitted to filter the original returns such that:

$$r_t = \beta_0 + \sum_{t=1}^{p} \beta_i r_{t-i} + \varepsilon_t \qquad (22)$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \qquad (23)$$

Any remaining dependence shown by the results of BDS test on the standardised residuals of $AR(p) - GARCH\ (q, p)$ most likely entered the series through the mean of the return-generating process, hence, contradicts the efficient market hypothesis. $GARCH(1{,}1)$ is used because hardly ever is any higher order model estimated or even entertained in the academic finance literature (Brooks, 2014).

4.3.1.4.2 BDS Test

Standardised residuals (whitened/filtered returns) obtained from the AR (*p*) and $AR(p) - GARCH\ (q, p)$ described in the previous section are subjected to BDS test. The BDS test follows a standard normal distribution under the null hypothesis (Brooks, 2014, P. 382). The test employs the correlation dimension of Grassberger and Procaccia (1983). The correlation integral is the probability that any pair of points are within a given distance 'ε' apart in phase space. Consider a return series x_t, t taking the value from $1, 2, 3, \dots, T$ and having *m*-history $x_t m$ = $(x_t, x_{t-1}, \dots \dots, x_{t-1+m})$, the correlation integral at consecutive point *m* can be estimated as:

$$C_{m,\varepsilon} = \frac{2}{T_m(T_m - 1)} \sum_{m \le s} \sum_{\angle t \angle \le T} I(\,x_t^m, x_s^m; \varepsilon) \qquad (24)$$

With $T_m = T - m + 1$ and $I(x_t^m, x_s^m; \varepsilon)$ being an indicator function takes1 if $|x_t$ - $x_{t-1}| \leq \varepsilon$ or 0 otherwise. The estimation of joint probability of independence of x_t is:

$$\mathrm{PR}(|\ x_t - x_s\ | \angle \varepsilon, |\ x_t - x_{t-1}\ | \angle \varepsilon, \ldots\ldots, |\ x_{t-1+m} \angle x_{s-1+m}\ | \angle \varepsilon)$$

Brock *et al.* (1996) show that:

$$W_{m,\varepsilon} = \sqrt{\mathrm{T}} \frac{\mathrm{C}_{\mathrm{m},\varepsilon} - C_{1,\varepsilon^m}}{\mathrm{S}_{\mathrm{m},\varepsilon}} \tag{25}$$

Where C_{1,ε^m} is the probability equaling $\mathrm{PR}(|\ x_t - x_s\ | \angle\ \varepsilon)^m$ while $\mathrm{S}_{\mathrm{m},\varepsilon}$ stands for standard deviation of $\sqrt{T}(\mathrm{C}_{\mathrm{m},\varepsilon} - C_{1,\varepsilon^m})$. $\mathrm{W}_{\mathrm{m},\varepsilon}$ is the BDS, which tests the null hypothesis that return series are independent. This hypothesis is rejected when p-value of BDS is significant at 5 percent, implying non-linear dependence or market inefficiency. The hypothesis testing was carried out on a rolling window basis to determine how the market efficiency varies over time. The BDS *p*-values are generated for all windows and they can be referred to as annual[26] measures of nonlinear predictability. A time plot of the windows' *p*-values is presented to show how nonlinear dependence behaves over time.

4.3.2 Modelling Return Predictability and Market Conditions

In addition to modelling of time-varying efficiency, AMH further requires determining the market condition that favours efficiency and inefficiency. Thus, this study investigates whether return predictability or market efficiency relation varies under different market conditions as postulated by Lo (2004). Therefore, it was hypothesised that market efficiency and investors' decision on stock investment is influenced by general stock market conditions. To evaluate how the market conditions affect return predictability in

[26] Since the step size is one year (every window is rolled forward by one year).

the selected African stock markets as propounded by AMH, the monthly[27] measures of return predictabilities are regressed on dummies of market conditions as explained below.

4.3.2.1 Measures of Return Predictability

Test statistics of linear and nonlinear dependence tests or the associated *p*-values are natural measures of return predictabilities (Kim *et al.,* 2011 and Urquhart, 2016). Following Urquhart and McGroarty (2016)*, p*-value of VR and BDS tests are used as proxies for the linear and nonlinear return predictability. This measure is similar to the absolute value of VR and portmanteau tests *t*-statistics used by Kim *et al.,* (2011) and Zhou and Lee (2013); however, the *P*-values are easier to understand and interpret. High or large *P*-values indicate low predictability and *vice versa*. The *p*-values of joint VR test and BDS test, generated by implementing the tests in two-year rolling window, rolled forward by one-month, are adopted as monthly measures of linear and non-linear predictability. When the window is rolled forward by one month, the first window covers first trading day of January 1998 to last trading day of December 1999 while the second window covers February 1998 to January 2000 and the last window starts from March 2016 to February 2018.

4.3.2.2 Measures of Market Condition

AMH links fluctuation in efficiency to changes in market conditions, although it did not itemise the exact makeup of market conditions or its expected relation with return predictability. From the literature, where the stock market price or return behaviour or trend is considered, the market conditions may be defined as bullish or bearish. The terms bull and bear conditions are the primary ways of describing market situation in the investing world. These conditions are adopted because they described the path of the market which is a major force influencing investment portfolio. Fabozzi and Francis

[27] Step size is 1-month (windows roll forward by 1-month) (Kim *et al*. 2011 and Urquhart & McGroarty, 2014, 2016), unlike annual measures (with 1-year step size). Different sizes serve a robustness purpose.

(1977) identified various definitions of bull and bear market conditions. To identify these market conditions, the first definition separates returns data into up and down months when returns are positive and negative, respectively (Fabozzi & Francis 1977; Urquhart & McGroarty, 2016). This categorisation accordingly does not take trend into consideration; hence, the definitions of the bull, bear and normal market conditions by Klein and Rosenfeld (1987) are also considered. A window is deemed bullish or bearish when its mean return is greater or less than 50 percent of the market standard deviation obtained over entire windows. Any window that does not fall into the bull or bear category is categorised as normal month. Note that for a month to qualify as bullish, there must be two or more consecutive substantial movements (Klein & Rosenfeld, 1987). Since the monthly measures of return predictabilities are calculated on two-year window basis, the steps in determining the market conditions are also on window basis and are as stated as follows:

> i. Calculate μ (mean return) for each of the windows as monthly average return; ii. Define as Up market when a window's μ is positive and Down market when window's μ is negative; iii. Calculate δ (standard deviation) of the entire (windows') monthly average returns in (i); iv. Define as Bull market when μ in step (i) is > 0.5 of the δ in step (iii) for 2 or more consecutive windows; v. Define as Bear market when μ in step (i) is < 0.5 of δ in step (iii) for 2 or more consecutive windows; and vi. Define as Normal market any month (window) that does not fall into Bull or Bear market (Urquhart & McGroarty, 2016).

Further, Kim *et al.* (2011) identify subprime mortgage global financial[28] crisis, which covered 2008 to 2009 as one of the fundamental conditions influencing return predictability. Financial crisis tends to impart on the behaviour and psychology of market

[28]External environment (financial, political and economic) can also affect market efficiency (Lo, 2017).

operators and affect the movement in stock returns (Kim & Shamsuddin, 2008; Lim, Brooks & Kim, 2008). The incidence of a market crash or financial crisis is one more probable cause of market inefficiency. The reason is that market participants are usually swamped by panic during that chaotic financial atmosphere and this would adversely influence their ability to price assets efficiently (Lim & Brooks, 2011). Hence, this condition, which produced a uniform of 19 months of financial crisis for each of the five markets (2007:12–2009:6) is also incorporated in this study. The crisis periods are guided by Kim *et al.* (2011).

The study also implements Anderson, Bollerslev, Diebold and Labys's (2003) realised volatility as a surrogate for market risk and a control variable (Kim *et al.,* 2011). Realised volatility is obtained in this study as the square root of squares of the two-year's window returns. This is done by squaring daily returns over a window, adding them up and obtaining the square root of the sum (Urquhart & McGroarty, 2016) and repeating the same for all windows. The value is regressed against predictability without necessarily categorising the value into high or low. Brailsford and Faff, (1996, p. 419) and Brooks (2014, p. 424) note that "the conclusion arising from this growing body of research is that forecasting volatility is a notoriously difficult task". Therefore, this study employs the realised volatility. Realised volatility has become popular in recent times because it is less noisy than, for example, the daily squared or absolute returns and it is an unbiased and highly efficient estimator of return volatility (Andersen, Bollerslev, Diebold & Labys, 2001; Barndorff-Nielsen & Shephard, 2001, 2002).

4.3.2.3 Dummy Regression Model for Predictability and Market Condition Relation

Moreover, after the generation of return predictabilities and dummies of market conditions as dependent and independent variables respectively, the regression models are estimated. For comparative[29] purpose, the dummy regression models for return

[29] Since the two definitions are deferent ways of defining bull and bear markets

predictability and different definitions of market conditions (up and down & bull, bear and normal) are specified respectively and the best model is selected using information criteria. Such that:

$$RP_t = \beta_1 UP + \beta_2 DW + \beta_3 FC + \beta_4 VOL + \varepsilon_t \tag{26}$$

$$RP_t = \beta_1 BU + \beta_2 BE + \beta_3 NO + \beta_4 FC + \beta_5 VOL + \varepsilon_t \tag{27}$$

$$H_0 : \beta_i = 0 \ldots \ldots H_1 : \beta_i \neq 0$$

RP_t is time t return predictability (*P*-values of VR and BDS tests). UP_1 is the dummy, which is equal to 1 if t is UP and 0 if nut; DW is the dummy, which takes the value of 1 if t is Down and 0 if not; BU is the dummy, which is equal to 1 if t is Bull and 0 if not and so on. FC_3 is the dummy for global financial crisis which takes the value of 1 when t is any month between 2007:12 to 2009:6. $\beta_i (i = 1, \ldots, 5)$ are the coefficient estimates of market conditions and ε_t is stochastic error term. AR term (lagged dependent variable) is included as a regressor to ensure the residuals mimic white noise. Significant negative (positive) β_i is used to determine the market condition that is associated with high (low) predictability or inefficiency.

4.3.3 Modelling Time-varying Calendar Anomaly

One of the objectives of this study is to examine also time-varying calendar anomalies, as with time-varying efficiency, since anomaly and efficiency are viewed as two sides of the same coin. Various methods have been deployed to investigate calendar anomalies, ranging from descriptive statistics based method, through the OLS and to different GARCH family models or combinations of two or more techniques. Alagidede (2013) and Evanthia (2017) categorised studies on calendar anomalies with reference to the method of analyses or estimation techniques. So, Evanthia (2017) observed that the first set of studies employed descriptive statistics, ANOVA and Kruskal-Wallis tests. Another group combines descriptive statistics with dummy OLS regression but they do not consider the time series properties of the sample data (Alagidede, 2013). The reliability of their results could be questioned on the grounds of data generation process and misspecification. This popular dummy OLS regression method was also challenged on the ground of autocorrelated error term and possibly misleading inferences. Consequently, researchers resort to introducing lagged return to the regressors and using heteroscedasticity-consistent standard errors. However, this set does not consider the distributional properties of the data employed.

The last set of studies commences by reporting descriptive statistics of the distributional properties of the return series and estimating GARCH models to detect anomalies upon establishing that the series are leptokurtic (Alagidede, 2013). Most of the studies of stock market anomalies have applied an OLS regression (Urquhart & McGroarty, 2014); however, more recent studies have favoured the use of several versions of GARCH (p, q) models. Evanthia (2017) noted that OLS is not favoured because it assumes that variance of error term is constant while there is substantial proof that variance is time-dependent. Therefore, this study applies GARCH family models as the main estimation techniques, although ANOVA tests are carried out as preliminary tests of difference in mean and variances. GARCH models permit modelling and forecasting of conditional variances, capture the possibility for volatility clustering and are able to incorporate heteroscedasticity into the estimation procedure (Brooks, 2014). These features cannot be captured by the linear model. The argument has been that a GARCH model, being a nonlinear model, is better able to handle nonlinearity and non-normal distribution features of the stock return data.

4.3.3.1 Methodological Note[30] on Calendar Anomalies

Most of the calendar anomaly studies used static models, just like the fixed state EMH models. Applying models (OLS, GARCH) on the full sample period data implies that calendar anomaly is a fixed feature and the findings have been conflicting too. Thus,

[30]This is similar to methodological note on time varying efficiency in Section 4.3.1.1

sub-period and rolling window analyses[31] are the alternatives to fixed state models. Rolling analyses are adopted in the investigation of changing behaviour of calendar anomalies in this study.

4.3.3.2 Rolling Regression Analyses

The use of rolling window in estimating model coefficients is recent in the study of calendar anomaly (Evanthia, 2017). The procedure challenged the ability of identified anomaly to remain unchanged over time. In general, rolling analysis can evaluate the constancy of a model over time (Springer, 2006). Rolling regression has two main features, namely the window size and step. The former represents the amount of successive observations used for each regression while the latter represents the amount of increments between consecutive rolling windows. Therefore, to analyse if patterns in calendar anomalies vary over time or conform to AMH in African stock markets, DOW, MOY and HOM regression models are estimated in five-year fixed length rolling window[32], rolled forward by one year. It is such that the first window covers 1998-2002, followed by 1999-2003, 2000-2004 until the end of 2017. Hence, the tests of equality of means and variance are carried out as preliminary analysis, followed by rolling GARCH models.

4.3.3.3 ANOVA Test

The mean equality tests can provide some insight as to whether the returns are significantly different across the days of the week, months of the year, and halves of the month. There are three different ANOVA tests implemented in this study, namely the Kruskal-Wallis (KW) and *F*-test for equality of mean and Levene test for the equality of variance. The three tests are carried out for robustness purposes; otherwise, KW is sufficient to achieve the purpose.

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[31] Arguments for rolling window analyses is the same as found in Section 4.3.1.1

[32] 5-year window size and 1-year step size is consistent with literature (Urquhart & McGroarty, 2016)

4.3.3.3.1 Kruskal-Wallis

The Kruskal-Wallis one-way ANOVA by ranks, being a non-parametric test, is applied to test differences between two or more groups (in this case, days of the week, months of the year and halves of the month returns) (Lim, Ho & Dollery, 2007). EViews shows that the test utilises ranks of series from smallest to biggest and compares the sum of the ranks from one group to another. Evidence from financial research has revealed that stock price returns are not normally distributed and exhibit leptokurtic features (Fama, 1965; Hui, 2005). However, KW test makes no distributional assumptions about stock index returns (Urquhart & McGroarty, 2014). The test equation is given as:

$$\mathrm{KW} = \left(\frac{12}{\mathrm{N}(\mathrm{N}+1)}\sum_{\mathrm{j}=1}^{\mathrm{k}}\frac{R_j^2}{n_j}\right) - 3(\mathrm{N}+1) \qquad (28)$$

Where N represents the whole number of observations, R_j^2 is the average rank of observations in the jth group, n_j is the total number of observations in the jth group, k is the number of trading day, month or periods (groups). EViews reports the X^2 approximation to the KW test statistic (with tie correction). Under the null hypothesis, this statistic is approximately distributed as a X^2 with $G-1$ degrees of freedom (Sheskin, 1997). This study uses KW to test the H_0 of no difference in returns across days of the week, Months of the year and halves of the months. The H_0 is rejected at 10 percent level of significance. The test is carried out in rolling windows to see whether there are windows of significant and insignificant differences over time.

4.3.3.3.2 *F*-test

In addition, the second mean equality test, which is *F*-test is based on the assumption that if the mean of subgroups is the same, then the dispersion amid the sample means (between groups) and dispersion in any subgroup (within group) should be the same. Denote the ith observation in subgroup g as $x_{g,i}$, where $i = 1,..,n_g$ for groups $g = 1, 2, \dots, G$. The between and within sums of squares are defined as:

$$SS_B = \sum_{g=1}^{G} n_g(\breve{x}_g - \breve{x})^2 \tag{29}$$

$$SS_W = \sum_{g=1}^{G}\sum_{i=1}^{n_g}(x_{ig} - \breve{x}_g)^2 \tag{30}$$

Where $\breve{x}_g$ is the sample mean within group g and $\breve{x}$ is the overall sample mean. The *F*-statistic for the equality of group means is computed as:

$$F = \frac{SS_B/(G-1)}{SS_W/(N-G)} \tag{31}$$

Where N is the total number of observations, the F-statistic has an *F*-distribution with $G-1$ numerator degrees of freedom (DOF) and $N-G$ denominator degrees of freedom under the null hypothesis of independent and identical normal distributed data, with equal means and variances in each subgroup (Welch, 1947). Where there are more than two subgroups (in case of DOW, MOY), Welch (1951) proposed modified *F*-statistic using the weight function of Cochran (1937):

$$w_g = \frac{n_g}{s_g^2} \tag{32}$$

s_g^2 is subgroup g sample variance and the modified F-statistic is given thus:

$$F^* = \frac{\sum_{g=1}^{G} w_g(\breve{x}_g - \breve{x}^*)^2 / G - 1}{1 + \frac{2(G-2)}{G^2-1}\sum_{g=1}^{G}\frac{(1-h_g)^2}{n_g-1}} \tag{33}$$

Normalised weight is given as $h_g$and weighted grand mean as $\breve{x}^*$. The null hypothesis of equality of means (no significance difference) is rejected if the *p*-value of *F*-test is significant at 5 percent level of significance. The test is conducted in rolling windows to see whether there are windows of significant and insignificant differences over time.

4.3.3.3.3 Levene test

Unlike the KW and *F*-tests, which are mean equality tests, the Levene test is a test of absolute difference from the mean (that is equality of variance). The statistic for the test has an approximate *F*-distribution with $G = 1$ numerator DOF and $N - G$ denominator DOF under the null hypothesis of equal variances in each subgroup (Levene, 1960).

$$F = \frac{(N-k)}{(k-1)} \cdot \frac{\sum_{i=1}^{k} N_i \, (\check{Z}_{i.} - \check{Z}_{..})^2}{\sum_{i=1}^{k} \sum_{j=1}^{N_i} (Z_{ij} - \check{Z}_{i.})^2} \qquad (34)$$

Where $Z_{ij} =| R_{ij} - \check{R}_{i.} |$ is the return for day 1and weekday j $(j = 1,2,.,,J)$. $J = 5$ for DOW and 12 for MOY and $\check{R}_{i.}$ is the means of $i\text{-}th$ subgroup. $\check{Z}_{i.}$ are the group means of the Z_{ij}. Unlike Bartlett's test, the Levene test does not require data to be normally distributed. This test is also executed in rolling windows.

4.3.3.4 GARCH Models

The standard model in the investigation of calendar anomalies is the OLS regression model (Alagidede, 2013). This model is linear and found to be unable to capture the desirable characteristics of stock return data. These characteristics include the volatility clustering, leptokurtosis and leverage effect (Brooks, 2014). A set of models, which can capture these important features is the nonlinear (GARCH family) models, applied in this study. The models include the ARCH, GARCH, EGARCH and TGARCH, all of which are expounded below.

4.3.3.4.1 ARCH (q) Model

ARCH (q) is the simplest model in the ARCH family of models. ARCH (q) is written as the autoregressive conditional heteroscedasticity of order (q); it was introduced by Engle (1982). It takes the form:

$$Y_t = X_t'\theta + \varepsilon_t \varepsilon_t \sim N(0, \delta_t^2) \qquad (35)$$

$$\delta_t^2 = w + \sum_{i=1}^{q} \pi_i \, \varepsilon_{t-i}^2 \qquad (36)$$

Where mean equation is Y_t written as a function of exogenous variable X_t and error term. δ_t^2 (otherwise called h_t in the literature) is called the conditional variance of error term, which is a function of lag q squared residual. The value of δ_t^2 must be strictly nonzero as negative value is inconsequential. Hence, the condition sufficiently (but not necessarily) requires that $\pi_i \leq 0$. The problem with the determination of q and the possibility of violating nonnegative assumption leads to the extension of ARCH (p) to generalised ARCH model (Brooks, 2014).

4.3.3.4.2 Generalised ARCH (GARCH q, p) Models

The GARCH model emerged from independent works of Bollerslev (1986) and Taylor (1986) in which current conditional variance is dependent on q lags of the squared residual and p lags of the conditional variance so that:

$$\delta_t^2 = w + \sum_{i=1}^{q} \pi_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \Lambda_j \delta_{t-j}^2 \qquad (37)$$

π_i indicates short-run persistence of shock and Λ_j long-run. Consider the conditional variance in its simplest case, GARCH (1,1), which is a one-period-ahead estimate for the variance depending on any relevant previous information:

$$\delta_t^2 = w + \pi_1 \varepsilon_{t-1}^2 + \Lambda_1 \delta_{t-1}^2 \qquad (38)$$

Brooks (2014) noted that GARCH(1,1) model adequately captures the volatility clustering in the data and it is uncommon to have higher order model estimated or considered as far as the academic finance literature is concerned. Again, non-negativity assumption remains sacrosanct. While the conditional variance is changing, the unconditional variance ε_t is constant and it is given as:

$$Var\ (\varepsilon_t) = \frac{\pi_0}{1 - (\pi_1 + \Lambda)} \tag{39}$$

so long as $\pi_1 + \Lambda < 1$. If $\pi_1 + \Lambda \geq 1$, the unconditional variance of ε_t *is* meaningless and this would be termed 'non-stationarity in variance' as the conditional variance forecast will tend to infinity as the forecast horizon increases. $\pi_1 + \Lambda = 1$ is termed 'unit root in variance', or 'integrated GARCH' or IGARCH. There are various extensions (Bollerslev, Chou & Kroner, 1992) of GARCH model because of the shortcoming of the GARCH (*q, p*) such as possible violation of the non-negativity conditions, inability to explain leverage effects and failure to provide feedback between the conditional variance and the conditional mean.

4.3.3.4.3 Asymmetric GARCH Models

The general GARCH model presumes that the effects of positive and negative shocks on volatility are the same, since it depends on the square of the previous shocks. However, it has been argued that equity returns respond differently to positive and negative shocks (Brooks, 2014). Hence, there is high tendency of a negative shock causing volatility to increase by more than a positive shock of the same magnitude. In the case of equity returns, such asymmetries are typically attributed to leverage effects (Brooks, 2014). Hence, the duo of the most popular asymmetric models, namely the Glosten, Jagannathan and Runkle (GJR) (1993) threshold GARCH (TGARCH) and exponential GARCH (EGARCH), which are widely used and able to overcome the identified shortcomings of GARCH are also estimated in this study.

- **GJR (1993) TGARCH**

The Glosten, Jagannathan and Runkle (GJR) (1993) TGARCH added an additional term to the GARCH model to provide explanation for likely asymmetries. The specification for the conditional variance is given by:

$$\delta_t^2 = w + \sum_{i=1}^{q} \pi_i\, \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \Lambda_j \delta_{t-j}^2 + \sum_{k=1}^{r} \gamma_k\, \varepsilon_{t-k}^2 I_{t-k} \tag{40}$$

where $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$ and = 0 otherwise

For a leverage effect of ith order, $\gamma_i > 0$ hence, bad news increases volatility. The impact is asymmetric if $\gamma_k \neq 0$. The condition for non-negativity will be $w > 0,\ \pi_1 > 0, \Lambda_1 \geq 0$ and $\Lambda_1 + \gamma_1 \geq 0$ i.e. the model is still admissible, even if $\gamma_1 < 0$, provided that $\pi_i + \gamma_i \geq 0$. In this model, good news, $\varepsilon_{t-1} > 0$ and bad news, $\varepsilon_{t-1} < 0$, have differential effects on δ_t^2 the conditional variance; good news has an impact of π_i, while bad news has an impact of $\pi_i + \gamma_i$.

- **EGARCH**

The exponential GARCH (EGARCH) model was credited to Nelson (1991). The conditional variance specification is:

$$ln(\delta_t^2) = w + \sum_{j=1}^{q} \Lambda_j \ln(\delta_{t-j}^2) + \sum_{i=1}^{p} \pi_i \left|\frac{\varepsilon_{t-i}}{\delta_{t-i}}\right| + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-i}}{\delta_{t-i}} \qquad (41)$$

The log ln attached *to* the conditional variance shows that the leverage effect is not quadratic but exponential and that forecasts of the conditional variance are certainly positive. Hence, it is not necessary to impose artificially non-negativity constraints on the model parameters. Further, asymmetries are allowed for under the EGARCH formulation, since if the relationship between volatility and returns is negative, γ_k, will be negative. The presence of leverage effects can be tested by the hypothesis that $\gamma_k < 0$. The impact is asymmetric if $\gamma_k \neq 0$. Equation 39 is estimated by Eviews 10, which allows choice of normal, student's *t*-distribution, or GED as opposed to the Nelson version, which is restricted to GED for the errors.

As noted earlier, GARCH(q, p), TGARCH(q, p) and EGARCH(q, p) models specified in equations 35, 38 and 39 are estimated in rolling window for each market. The three models are estimated with the intention of selecting the best. It is necessary to check different GARCH models because different markets may possess different features. For instance, some data may be asymmetric while others may be not. The appropriate lags and models are selected using information criteria and diagnostic tests. Maximum value of likelihood and minimum values of AIC and BIC are compared. Equality of the variance equation parameters to approximately unity (1) is also considered. GARCH models of the three calendar anomalies, namely the DOW, MOY and HOM or intra-month effects are estimated in rolling windows with the actual mean equations specified below.

4.3.3.5 Calendar Effect Models

Calendar anomalies are usually estimated using regression models with dummy variables. There are two ways of introducing dummies in regression models (Gujarati, 2013). One is to introduce a dummy for each category (in this case, each day of the week and each month of the year and each half of the month) and omit constant (C) or intercept. Inclusion of C in this case would result in dummy variable trap. The other way is to include C and introduce only (*m-1*) dummies. The first approach of omitting intercept is used in this study as it produces exactly the mean values of the various categories (DOW, MOY and HOM). Alagidede (2013), among other, followed the same approach. Therefore, intercept (C) is omitted from equations 42, 43 and 44 to avoid perfect multicollinearity (Gujarati, 2013).

The actual mean equation estimated for the (DOW) effect in this study is given as:

$$DR_t = \sum_{i=1}^{5} \beta_i D_i + \sum_{i=1}^{k} \alpha_i DR_{t-i} + \varepsilon_t \qquad (42)$$

$H_0\colon \beta_i = 0 \ldots \ldots H_1\colon \beta_i$

Where DR_t is the index returns on day t, D_1 the dummy variable, which takes value of 1 if t is Monday and 0 if not, D_2 the dummy variable, which takes the value of 1 if t is Tuesday and 0 if not and so on and so forth. β_i $(i = 1, 2, .., 5)$ are coefficient estimates. The hypothesis is tested for each day using t-statistics. The presence of seasonal effect in a given day is indicated by a statistically significant p-value of the dummy coefficient for that day. Note that β_1 must be negative (low) and β_5 must be positive (high) for weekend effect to exist.

Similarly, MOY effect mean regression equation is given thus:

$$MR_t = \sum_{i=1}^{12} \theta_i D_{it} + \sum_{i=1}^{k} \alpha_i MR_{t-i} + \varepsilon_t \tag{43}$$

$H_0: \theta_i = 0 \ldots \ldots H_1: \theta_i \neq 0$

Where MR_t is the index return of month t, D_{it} are monthly dummies such that, D_{1t} is equal to1 if month t is January and 0 otherwise, D_{2t} is equal to1 if month t is February and 0 otherwise and so forth, $\theta_i(\text{ where } i = 1, 2, .., 12)$ are the parameters to be estimated. The hypothesis is tested for each month using t-statistic. θ_1 must be positive and greater than other θs for January effect to hold.

The presence of intra-month anomaly is examined with the use of regression model specified as follows:

$$IMR_t = \alpha_1 D_1 + \alpha_2 D_2 + IMR_{t-i} + \varepsilon_t \tag{44}$$

$H_0: \alpha = 0 \ldots \ldots H_1: \alpha \neq 0$

Where IMR_t represents index return, D_1 is a dummy, which is equal to 1 for the first half[33] of the month and 0 if otherwise, D_2 is a dummy, which equal to 1 for the second half of the month and 0 if otherwise. α_1 is the coefficient representing the mean returns of first half of the month, α_2 the coefficient representing the mean returns of second half of the month, ε_t is a stochastic error term. Intra-month effect is indicated by greater and significant positive value of α_1 relative to α_2.

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[33]First half covers all trading days between 1st & 15th; second half between 16th & last day of every month

To determine if patterns in calendar anomalies vary over time or conform to AMH in African stock markets, the hypotheses associated with the DOW, MOY and HOM regression models in equations 42, 43 and 44 are tested on rolling window basis. If windows of statistical significance and insignificance of $\beta_i,\ \alpha_1\ and\ \theta_i$ occur in turn repeatedly, patterns in calendar anomalies are said to vary over time in conformity with AMH.

4.3.4 Modelling Calendar Anomalies and Market Conditions

The last objective is a follow-up of the time-varying calendar anomaly. In the wake of the AMH, which supports the disappearance and reappearance of market efficiency due to changing market conditions, researchers are now faced with the task of determining a framework or model that accommodates efficiency and anomaly with a view to bringing out effect of changes in episode. While there is a dearth of empirical investigation of market condition and anomalies under AMH as shown in Table 3.1 (Chapter 3), the few available studies (Urquart & McGroarty, 2014; Shahid & Sattar, 2017) determine the behaviour of calendar anomalies under different market conditions, by separating the return data into up and down periods. Estimating anomalies on the separated returns, as also the case with sub-period analyses is valid but prone to be wasteful of information and result in loss of model efficiency (Brooks, 2014). For instance, there may be too few observations in each subsample to analyse individual (linear) models.

An alternative method of analysing calendar anomalies under different market conditions (bull, bear and normal) is to subject stock market returns to the regime switching model. This is because the regime switching model is able to capture market conditions or cycles (here defined as bull and bear) by producing distinct regression results for each condition. Various economic and financial time series usually go through periods in which the movement (e.g. in mean or volatility or both) of the series varies quite significantly relative to what was obtained in the past (Brooks, 2014). A one-off change in the behaviour is often referred to as a structural break. Where the behaviour changes for a period of time and returns to its previous behaviour or shift to yet a new way of behaviour, it is known as a regime shift or switch (Brooks, 2014); which is typical of the behaviour described by the recently developed AMH. Brooks (2014) notes that regime shift could take place on a regular basis and result in significant variation in equity return behaviour. Obviously, in the presence of such 'regime changes' a linear model estimated over the entire sample covering the change would be unsuitable. This study examines the three calendar anomalies in stock returns (DOW, MOW, HOM effects) by applying MSM, which, while permitting the estimation of the entire observations on a series, are also adequately flexible to permit different types of behaviour at different regimes or cycles (Brooks, 2014). The MSM has been widely used in academic finance literature but its application to calendar anomaly and for testing AMH is rare. Further, the usual non-normality nature of return and nonlinearity property of the data provides added justification for MSM.

4.3.4.1 Markov Switching Model

Switching models, which permit the behaviour of return series to follow various processes at various points in time, are the most accepted non-linear financial models apart from the ARCH and GARCH models (Brooks, 2014). Suppose that the stock return R_t follows a process that depends on the value of an unobserved discrete state variable s_t. It is assumed that there are M possible regimes and that the process is said to be in state or regime m in period t when $s_t = m$, for $m = 1, 2, .., M$. The switching model associates different regression models with each regime.

A DOW, MOY and HOM model with regime switching intercept and regressors is defined as follows:

$$DR_t = \mu_{s_t} + \sum_{i=1}^{5} \alpha_{is_t} D_i + \varepsilon_{s_{t,t}} \qquad (45)$$

$$MR_t = \mu_{s_t} + \sum_{i=1}^{12} \alpha_{s_t} D_{it} + \varepsilon_{s_{t,t}} \qquad (46)$$

$$MR_t = \mu_{s_t} + \alpha_{1s_t} D_1 + \alpha_{2s_t} D_2 + \varepsilon_t \quad (47)$$

$H_0: \alpha = 0 \dots \dots H_1: \alpha \neq 0$

Where R_t is index returns, μ_{s_t} state dependent intercept, s_t are states of the market; D_i ($i = 1, 2, 3, 4, 5$ for DOW; $1, 2, \dots, 12$ for MOY and $1, 2$ for HOM) are calendar dummy variables with state dependent coefficients α_{s_t} and $\varepsilon_{s_{t,t}}$ is error term. Markov switching regression is capable of generating M regression models, associating different models with each regime (bull or bear or normal) and showing under which regime are calendar anomalies significant. Since the models contain as many dummy variables as the number of categories of the variables (calendar days and months), one must drop the intercept from equations 45, 46 and 47 to avoid dummy variable trap (Gujarati, 2013). Doing so, the models become:

$$DR_t = \sum_{i=1}^{5} \alpha_{is_t} D_i + \varepsilon_t \quad (48)$$

$$MR_t = \sum_{i=1}^{12} \alpha_{s_t} D_{it} + \varepsilon_{s_{t,t}} \quad (49)$$

$$MR_t = \alpha_{1s_t} D_1 + \alpha_{2s_t} D_2 + \varepsilon_t \quad (50)$$

The Markov switching regression model is an extension of a simple exogenous probability, which could be obtained by specifying a first-order Markov process for the regime probabilities. This technique involves the specification of regime probability, likelihood computation, filtering and smoothing. For the purpose of this study, regime probability and likelihood computation are specified below.

4.3.4.2 Regime Probabilities

The persistence of each regime follows a first-order Markov process given by the transition probability matrix. The first-order Markov assumed that the probability of being in a state depends on the most recent state (Hamilton, 1989), so that:

$$P(\, s_t = j \mid s_{t-1} = i\,) = p_{ij}(t) \tag{51}$$

Where the ij-th element is the probability of moving from regime i in period $t-1$ to regime j in period t. The probabilities are assumed to be constant so that $p_{ij}(t)$= p_{ij} for all $t,$ however, this restriction is not required. These probabilities may be presented in a transition matrix such that:

$$p(t) = \begin{bmatrix} p_{11}(t) & \dots & p_{1M}(t) \\ . & \dots & . \\ p_{1M}(t) & \dots & p_{MM}(t) \end{bmatrix} \tag{52}$$

Although a two-regimes MSM is common in the literature following the maiden work of Hamilton (1989), this study ascertains appropriate number of regimes by running a number of Markov-switching models and regimes and selecting one that minimises the information criterion (BIC) (Chu *et al.*, 2004). For a two regime model, however, the matrix takes the following form:

$$P = \begin{bmatrix} P(s_t = 0\,/s_{t-1} = 0) & P(s_t = 1\,/s_{t-1} = 0) \\ P(s_t = 0\,/s_{t-1} = 1) & P(s_t = 1\,/s_{t-1} = 1) \end{bmatrix} = \begin{bmatrix} P00 & P01 \\ P10 & P11 \end{bmatrix} \tag{53}$$

where $P00$ is the probability that the return is at state 0 (low) at time $t-1$ and remains there at time t; $P01$ is the probability that the return is at state 0 at time $t-1$ and move to 1 (high) at time t; $P10$ is that the return is at state 1 at time $t-1$ and move to state 0 at time t; and $P11$ is the probability that the return is at state 1 at time $t-1$ and remains there at time t (Brooks, 2014).

The probability of a change from regime i to j follows a logistic model. Since, each row of the transition matrix specified contains a full set of conditional probabilities; a separate multinomial logit model is specified for each row of the transition matrix as given in equation:

$$P_m(G_{t-1}, d_i) = \frac{\exp(G'_{t-1},\ \ d_{ij})}{\sum_{s=1}^{M} \exp(G'_{t-1},\ \ d_{is})} \tag{54}$$

for j = 1, …, M and i = 1, …, M with the normalisations d_{iM} = 0. MSMs are normally and generally specified with constant probabilities so that G_{t-1} contains only a constant. Hamilton's (1989) model of GDP, which is a popular case of a constant transition probability specification, is adopted for this study. The Markov switching specification of Hamilton (1989) is naturally a benchmark in this class of models (Perlin, 2015).

4.3.4.3 Likelihood Evaluation

The likelihood contribution for a given observation is formed by weighted density function in each of the regimes by one-step ahead probability of being in that regime:

$$L_t(\mathrm{B}, \mathrm{A}, \mathrm{v}, \mathrm{d}) = \sum_{m=1}^{M} \frac{1}{v_m} \phi\left(\frac{y_t + U_t(m)}{v_m}\right). P(s_t = m|\lambda_{t-1}, d) \tag{55}$$

B = (B_1,…. B_M) and v = (v_1 …., v_M), d are parameters that determine the regime probabilities, $\phi(.)$ and λ_{t-1} are the standard normal density function and information set in period t-1 respectively, while the d simply represents the regime probabilities. The full log-likelihood is a normal mixture:

$$\mathrm{L}(\mathrm{B}, \mathrm{A}, \mathrm{v}, \mathrm{d}) = \sum_{t=1}^{T} \{log \sum_{m=1}^{M} \frac{1}{v_m} \phi\left(\frac{y_t + U_t(m)}{v_m}\right). P(s_t = m|\lambda_{t-1}, d)\} \tag{56}$$

The equation (56) above can be maximised with respect to $\mathrm{L}(\mathrm{B}, \mathrm{A}, \mathrm{v}, \mathrm{d})$

4.4 Summary of the Chapter

This study presents quantitative analyses of the market efficiency and calendar anomalies in stock returns from the point of view of AMH in selected African stock markets. The chapter elucidates on the source of data and how the data are calculated.

The sample period for the study is 20 years from January 1998 to February 2018. The study analyses returns of five stock market indices for return predictability and calendar anomalies and how they are influenced by market conditions. The selected markets are the NGSE, the JSE, the SEM, the MOSE and the TSE. A brief description of the makeup of each of the market indices is given. Furthermore, the various return dependence tests employed to determine market efficiency, ranging from linear and nonlinear testing tools are discussed in this chapter. The traditional linear testing tools such as the VR test, the autocorrelation tests and the unit root tests are applied for the first objective. However, it is established that the linearity tests are not adequate as they are unable to detect nonlinear movements that are inherent in stock returns. Therefore, Urquhart (2013) argues that at least one nonlinear test should be performed.

Consequently, the specification of nonlinear test, namely the BDS test, is discussed although the test is not without its own shortcoming being a general test of nonlinearity. However, the BDS test has been recognised as the best in the family of nonlinear tests of efficiency. It is explained how time variation is incorporated in those tests with the aid of rolling window approach. In addition, the chapter discusses the dummy regression for return predictability and market condition relation and explains how the variables such as predictability, bull and bear conditions are derived. Moreover, the various GARCH models used to evaluate the calendar anomalies are elucidated and the procedure for the selection of the best model and hypothesis testing are described. GARCH family model is favoured for its ability to capture the features of stock returns that cannot be explained by linear OLS regression model. Lastly, the chapter explains how MSM can be applied in the investigation of calendar anomalies cum market conditions and its applicability in testing the AMH. Like the GARCH models, MSM is a nonlinear model, capable of accounting for the desirable feature of stock returns and revealing the behaviour of calendar anomalies under different conditions. Suffice to state that the specified models are adequate to investigate AMH. The following chapter (Chapter 5) contains the results and interpretations of the various model estimation techniques described in this chapter.

CHAPTER 5: DATA ANALYSES AND INTERPRETATION

5.1 Introduction

The controversies between the proponents of EMH and the supporters of BF informed the seemingly unending debates on the behaviour of stock market returns over several decades. There are signs that the recently introduced AMH might go a long way in harmonising the position of the earlier schools of thought. The focus of this study is to determine whether AMH provides better explanations for stock return and calendar anomaly behaviours in selected African stock markets and the analyses so presented in this chapter are tailored in that direction. In other words, the analyses cover the time-varying efficiencies, return predictability and market condition relations, time-varying calendar anomalies and calendar anomalies cum market condition relations.

It must be noted that the analytical results and their interpretations are contained in this chapter while the full discussion of findings is given in the subsequent chapter. This chapter is presented in five main segments, with the first segment presenting the results on the distributional properties of the indices return series of the selected stock markets. The second segment consists of the rolling window linear and nonlinear dependence analyses. The third segment contains the results of the regression analyses for return predictability and market conditions. The fourth segment contains the rolling window GARCH regression results for the analyses of time varying calendar anomalies. The fifth section presents the results from the application of MSM to the three calendar anomalies in the selected African stock markets. The last section provides a brief summary of the contents and findings of the whole chapter.

5.2 Descriptive Statistics

Descriptive statistics of return indices for the full sample period and rolling window analyses are found in Table 5.1. It shows that JALSH, followed by NGSEINDX have the highest mean return and volatility, which may not be surprising since they are the most liquid African stock markets. MOSENEW has the lowest mean return, while the remaining two markets are similar. The least volatile return is found in TUSISE while SEMDEX and MOSENEW are identical in terms of volatility. The same behaviour holds for the volatility both for full periods and rolling window analyses. However, NGSEINDX, SEMDEX and MOSENEW respectively in 2006-2007 windows, have mean returns, which are far greater than what can be found in the two other markets. All the markets have at least three sub-periods when mean returns are negative, however, the only period when JALSH has a negative return is 2007-2008, which could be as a result of the global financial crisis. Overall, returns and standard deviations fluctuate over time in a manner described by the AMH.

Descriptive statistics of daily returns are found in Table 5.1 A, B, C, D and E for NGSEINDX, JALSH, SEMDEX, MOSENEW and TUSISE respectively. For the examination of the normality assumption, considerations are given to the Jarque-Bera (JB) test, skewness (S) and kurtosis (K). Under the null hypothesis of normal distribution, the JB, S and K are 0, 0 and 3 respectively. The presence of negative or a positive S distribution in a series implies the presence of asymmetry in returns data, while the smaller than or larger than three coefficient value of K implies flatness and peakedness respectively. It can be seen that four of the five markets are positively skewed in full sample period, which is an indication of longer right tails. Most of the windows also have positive S except for two windows in NGSEINDX, five windows in SEMDEX, seven windows each in MOSENEW and TUSISE. Only the JALSH has longer left tail compared to the mean values with negative S in full period and 13 of the 19 windows; suggesting that the market may belong to high risk asset class. The values of K are positive and greater than the three expected of normal distribution, for all the markets except for JALSH, which has at least two windows in conformity with normal distribution. It means that indices returns are peaked relative to normal distribution and hence, leptokurtic. SEMDEX has the highest leptokurtic distribution while the JALSH has the lowest.

Table 5.1: Descriptive statistics

Table 5.1A: Descriptive statistics NGSEINDX									
Period	**Obs**	**Mean**	**Median**	**Max**	**Min**	**SD**	**Skewness**	**Kurtosis**	**JB**
Full sample	**4840**	**0.051419**	**0.00000**	**12.47760**	**-10.36450**	**1.066686**	**0.446663**	**17.15621**	**40574.62*** **
1998 -1999	497	-0.03894	-0.0276	4.138200	-3.85010	0.556620	0.315659	16.89265	4005.079***
1999-2000	496	0.074918	0.001000	4.138200	-3.85010	0.750854	0.244382	7.462390	416.4709***
2000-2001	496	0.151021	0.097750	3.258400	-3.55540	0.788200	0.063437	5.954660	180.7530***
2001-2002	486	0.086580	0.037750	3.776800	-4.38570	0.850257	-0.00181	6.491673	246.8838***
2002-2003	446	0.143337	0.070250	11.70570	-10.3645	1.218923	0.595851	32.86432	16600.45***
2003-2004	426	0.162773	0.049100	11.70570	-10.3645	1.392081	0.268643	21.06684	5798.911***
2004-2005	427	0.046602	-0.00020	4.534700	-3.97710	1.075865	0.026768	5.592966	119.6728***
2005-2006	443	0.084074	-0.00020	4.534700	-4.43850	0.908904	0.306844	8.665294	599.3822***
2006-2007	470	0.192710	0.000000	3.95400	-4.43850	0.911120	0.223189	7.132580	338.3505***
2007-2008	480	-0.004993	-0.00030	3.902400	-3.84170	1.118160	-0.03130	4.434546	41.23684***
2008-2009	484	-0.198333	-0.32580	8.507700	-9.04020	1.596092	0.201126	7.240044	365.8188***
2009-2010	486	-0.028852	-0.01915	12.47760	-9.040200	1.644651	0.680984	14.20210	2578.677***
2010-2011	492	0.018701	-0.01285	12.47760	-8.36970	1.118100	2.069052	39.60876	27825.17***
2011-2012	494	0.041373	0.02995	3.500200	-2.42770	0.729779	0.218648	4.718755	64.74174***
2012-2013	497	0.154472	0.12990	3.175200	-3.87710	0.767804	0.017912	5.692914	150.1989***
2013-2014	497	0.061328	0.02020	5.010700	-4.06980	0.963840	0.157103	7.457034	413.4187***
2014-2015	495	-0.051087	-0.07730	8.331900	-4.18630	1.160600	0.912126	10.84017	1336.421***
2015-2016	494	-0.026022	-0.06290	8.331900	-4.23120	1.205590	0.624681	9.353910	863.1226***
2016-2017	494	0.083808	0.05590	3.912900	-4.23120	1.075133	0.083033	5.767612	158.2293***

Table 5.1B: Descriptive statistics JALSH									
Period	**Obs**	**Mean**	**Median**	**Max**	**Min**	**SD**	**Skewness**	**Kurtosis**	**JB**
Full sample	**5038**	**0.066408**	**0.084450**	**7.119500**	**-7.638400**	**1.227568**	**-0.153936**	**6.586793**	**2720.492*** **
1998 -1999	499	0.10742	0.129500	5.63900	-7.09010	1.450235	-0.61023	6.211609	245.4238***
1999-2000	497	0.114463	0.074600	4.96090	-7.63840	1.176741	-0.48002	7.636931	464.3394***
2000-2001	498	0.064440	0.056350	6.161000	-7.63840	1.348313	-0.195348	6.772657	298.5009***
2001-2002	500	0.046408	-0.00135	6.161000	-5.40480	1.294550	0.233616	5.212290	106.5111***
2002-2003	500	0.019401	-0.02070	4.646700	-3.30130	1.154720	0.163169	3.263143	3.661254***
2003-2004	501	0.080967	0.065100	515100	-3.30130	1.018611	0.179014	3.490206	7.692144**
2004-2005	502	0.126874	0.156450	3.515100	-3.29570	0.872737	-0.002044	3.970786	3.970786***
2005-2006	499	0.153959	0.224300	5.040200	-6.48070	1.143477	-0.449938	7.133756	372.1233***
2006-2007	498	0.113541	0.237400	5.040200	-6.48070	1.299116	-0.442361	5.450060	140.7997***
2007-2008	501	-0.000496	0.078700	7.119500	-7.10240	1.827668	0.013726	5.183125	99.50675***
2008-2009	501	0.022209	0.035900	7.119500	-7.10240	1.949430	0.111380	4.393618	41.57868***
2009-2010	501	0.099352	0.113000	5.761300	-3.626500	1.322831	0.157272	4.034767	24.41709***
2010-2011	500	0.046339	0.056300	4.355800	-3.626500	1.123401	-0.001703	3.908568	17.19807***
2011-2012	499	0.057327	0.106600	3.718100	-3.155800	0.974640	-0.076121	4.209412	30.89343***
2012-2013	500	0.089655	0.098250	2.447000	-3.207300	0.827819	-0.441118	4.152439	43.88447***
2013-2014	499	0.063552	0.050000	4.247000	-3.207300	0.871298	-0.068746	4.913392	76.51275***
2014-2015	500	0.035446	0.031450	4.247000	-3.387300	0.943736	-0.058131	4.730932	62.70087***
2015-2016	500	0.021332	0.061000	3.106700	-3.556700	1.062111	-0.264436	3.578784	12.80616***
2016-2017	498	0.047690	0.058950	2.981400	-3.556700	0.878976	-0.227987	4.099666	29.40641***

Table 5.1C: Descriptive statistics SEMDEX									
Period	**Obs**	**Mean**	**Median**	**Max**	**Min**	**SD**	**Skewness**	**Kurtosis**	**JB**
Full sample	**5036**	**0.045077**	**0.017850**	**21.75500**	**-18.74110**	**0.752092**	**2.089486**	**229.2859**	**10748247*** **
1998 -1999	487	0.02335	0.015300	3.909700	-2.38880	0.579145	1.08611	13.17963	2198.471***
1999-2000	500	-0.034806	-0.011100	1.257600	-1.778500	0.338144	-0.628898	7.463011	447.9275***
2000-2001	505	-0.048028	-0.017300	2.864600	-1.997700	0.325923	0.390482	19.34384	5633.505***
2001-2002	488	0.005670	0.000000	2.864600	-1.997700	0.428677	0.612103	9.609390	918.7154***
2002-2003	468	0.103574	0.052500	3.520200	-2.781900	0.547456	0.449898	10.22223	1032.919***
2003-2004	454	0.127684	0.098000	3.520200	-2.781900	0.532497	0.170245	12.13818	1581.856***
2004-2005	468	0.082200	0.061450	2.298300	-2.534000	0.416755	-0.253393	11.73313	1492.227***
2005-2006	491	0.120769	0.068200	21.75500	-18.74110	1.448615	2.352067	161.0664	511604.1***
2006-2007	494	0.189832	0.108700	21.75500	-18.74110	1.564205	1.852783	118.3844	274320.1***
2007-2008	496	0.018434	0.000000	6.650200	-6.183200	1.249915	-0.046956	10.51142	1166.225***
2008-2009	509	0.002728	0.000000	8.333800	-6.183200	1.351186	0.344994	9.874655	1012.422***
2009-2010	517	0.116009	0.082500	8.333800	-4.069500	0.930240	1.499038	17.74917	4879.758***
2010-2011	512	0.038042	0.026900	3.367200	-2.762500	0.514261	-0.036485	9.475054	894.5417***
2011-2012	513	-0.012293	-0.011100	3.367200	-2.762500	0.417097	-0.109998	17.96580	4788.504***
2012-2013	517	0.031982	0.024200	1.264900	-0.999400	0.278163	0.200590	4.170475	32.97934***
2013-2014	517	0.045968	0.031700	1.264900	-0.849200	0.265154	0.256507	3.899311	23.09144***
2014-2015	515	-0.017127	-0.020000	0.861600	-0.849200	0.250613	0.258803	3.663020	15.18202***
2015-2016	518	-0.013574	-0.021900	1.366400	-1.259800	0.280817	0.549133	5.819383	197.5978***
2016-2017	521	0.050780	0.020800	1.366400	-1.259800	0.295708	0.479882	6.291066	255.1221***

Table 5.1D: Descriptive statistics MOSENEW									
Period	**Obs**	**Mean**	**Median**	**Max**	**Min**	**SD**	**Skewness**	**Kurtosis**	**JB**
Full sample	**4989**	**0.03244**	**0.019300**	**6.689500**	**-7.448400**	**0.752995**	**0.017988**	**13.32256**	**22150.46*** **
1998 -1999	497	0.023924	-0.006900	1.957800	-2.233500	0.439181	0.071913	6.751236	291.8313***
1999-2000	498	-0.049941	-0.075650	3.788900	-2.363800	0.555675	1.349907	13.79968	2571.381***
2000-2001	494	-0.059903	-0.112700	4.660000	-2.641500	0.752999	1.658575	11.69583	1782.946***
2001-2002	498	-0.054331	-0.053150	6.689500	-7.448400	0.949883	0.464728	25.09850	10151.06***
2002-2003	500	0.023414	0.030250	6.689500	-7.448400	0.829014	-0.233348	38.30064	25965.69***
2003-2004	472	0.088497	0.078000	3.940100	-3.268500	0.651032	0.356361	10.46263	1105.245***
2004-2005	468	0.075157	0.081300	3.940100	-3.268500	0.656084	-0.027534	10.81116	1189.836***
2005-2006	493	0.156697	0.158700	4.064400	-4.893000	0.954549	-0.382611	6.357992	243.6586***
2006-2007	501	0.171799	0.203900	4.064400	-4.893000	1.137963	-0.496653	5.361988	137.0579***
2007-2008	497	0.035432	0.040100	4.564700	-4.445900	1.075224	-0.339761	6.603774	278.5051***
2008-2009	493	-0.027489	0.025600	4.564700	-4.558400	0.991257	-0.341668	7.217720	375.0109***
2009-2010	501	0.044971	0.051600	2.859000	-4.558400	0.743652	-0.555221	8.400411	634.5483***
2010-2011	505	0.027142	0.023800	3.001400	-2.988300	0.710575	0.131536	5.584016	141.9543***
2011-2012	503	-0.042506	-0.051100	3.001400	-2.988300	0.716392	0.052734	5.050547	88.35757***
2012-2013	496	-0.019828	-0.028450	2.657500	-1.846900	0.587985	0.327002	4.443748	51.91733***
2013-2014	493	0.025367	0.023300	2.364300	-1.740300	0.502296	0.203332	5.010055	86.39201***
2014-2015	494	0.015134	0.028750	1.946300	-1.740300	0.487115	0.108664	4.831316	70.00286***
2015-2016	496	0.059204	0.046650	3.350300	-1.610300	0.568669	0.896452	7.089735	412.1025***
2016-2017	500	0.085713	0.067400	3.350300	-2.069000	0.63864	0.76056	6.95986	374.8821***

Table 5.1E: Descriptive statistics TUSISE									
Period	**Obs**	**Mean**	**Median**	**Max**	**Min**	**SD**	**Skewness**	**Kurtosis**	**JB**
Full sample	**4232**	**0.047619**	**0.025500**	**6.092900**	**-4.880500**	**0.571153**	**0.056720**	**17.90639**	**39183.60*** **
1998-1999	NA	NA	NA	NA	NA	NA	NA	NA	NA
1999-2000	NA	NA	NA	NA	NA	NA	NA	NA	NA
2000-2001	399	0.023408	-0.004600	6.092900	-4.812000	0.822791	0.862468	19.88302	4788.194***
2001-2002	403	-0.061367	-0.092900	4.991700	-4.812000	0.731538	0.204257	19.08709	4348.391***
2002-2003	423	-0.002285	-0.011500	2.418800	-1.330400	0.499323	0.631377	5.086124	104.8064***
2003-2004	398	0.046304	0.008300	2.254500	-1.330400	0.458817	0.608401	5.459936	124.9039***
2004-2005	403	0.064463	0.000000	2.478200	-1.229800	0.423077	1.339581	7.985752	537.9316***
2005-2006	451	0.124812	0.101500	2.478200	-1.376500	0.454149	0.867726	6.440860	279.0808***
2006-2007	482	0.101292	0.102850	2.376200	-2.102200	0.485068	0.017173	5.477444	123.2897***
2007-2008	490	0.050622	0.029850	3.821900	-4.880500	0.694980	-0.432317	12.28813	1776.597***
2008-2009	496	0.111163	0.077600	3.821900	-4.880500	0.688401	-0.482153	12.63090	1936.140***
2009-2010	501	0.123409	0.108900	3.302700	-3.98900	0.550945	-0.23177	13.55179	2328.715***
2010-2011	489	0.030673	0.070200	4.194100	-4.059200	0.790603	-0.448487	11.68079	1551.774***
2011-2012	489	-0.012510	0.015600	4.194100	-4.059200	0.728011	-0.399763	12.38557	1807.835***
2012-2013	498	-0.006841	0.000800	1.593200	-3.687500	0.449962	-1.283758	12.88752	2165.369***
2013-2014	495	0.030551	0.009400	1.796700	-3.687500	0.432567	-0.905715	15.70534	3397.080***
2014-2015	497	0.036947	0.005700	1.796700	-2.474900	0.433617	0.168504	7.087440	348.3295***
2015-2016	500	0.024094	0.006450	2.137900	-2.474900	0.438054	0.038664	6.678864	282.0837***
2016-2017	503	0.053243	0.021700	2.137900	-1.172700	0.374275	0.703518	5.463371	168.6715***

For further confirmation of the non-normality of the return series, as shown by S and K, the JB test of normality is carried out and presented in the last column of Table 5.1 A, B, C, D and E. Significance tests are applied to the Jarque-Bera statistics. ***, **, * indicate significance at 1 percent, 5 percent and 10 percent respectively. *P*-values of JB statistic are less than 1 percent, which implies a rejection of the null hypothesis of normal distribution of the return series.

From the foregoing, the return series of the five markets are not normally distributed and thus seem to violate the basic RWM assumption, which requires return to be normally distributed. It must be noted that the non-normal distribution and leptokurtic nature of stock index returns has long been established in the financial literature as mentioned in Chapter 4.

5.3 Time-varying Efficiency Results

When examining market efficiency from the absolute point of view, data over the entire sample period are often tested for predictability. AMH requires that market should not be evaluated in absolute form, rather efficiency tests should be carried out by analysing data bit by bit to establish whether a feature (efficiency in this case) persists or varies over time. Consequently, the results of the linear and nonlinear dependence tests (both tests are required to avoid wrong inference as explained in Section 4.3.1 of Chapter 4) in both the full sample and rolling windows are presented in this section. The interpretation of results in this section sheds light on the time varying behaviour of market efficiency in the selected African stock markets.

5.3.1 Linear Empirical Result

The results of the various linear testing tools (unit root, ACF, VR) explained in Section 4.3.1.3 of the previous chapter are presented and interpreted below.

5.3.1.1 Rolling Unit Root and Stationarity Results

Unit root is a necessary but insufficient condition for RWH; hence, the two unit root tests estimated in this study are interpreted. Reported in Table 5.2 are the ADF unit root tests statistics and critical values for NGSEINDX, JALSH, SEMDEX, MOSENEW and TUSISE. The ADF test of the random walk with drift reported in Table 5.1 tests the null hypothesis of unit root against alternative hypothesis of stationarity. For the ADF test at levels, the test statistic for NGSEINDX in full sample is greater than the critical values in absolute term and, therefore, the null hypothesis that the return series contains a unit root is rejected. For rolling window analysis, the results show that test statistics are also more negative than the critical values, suggesting that the return series is stationary at level. This is confirmed by the very small *p*-value of less than 1 percent as depicted by ***. The presence of unit root in price series is a necessary condition for random walk, however, the first difference of a nonstationary series is most likely to be stationary (Urquhart, 2013). Thus, it is not surprising that the hypothesis of unit root is rejected at level since the return series employed in the test is ideally a first difference of the actual price indices.

The ADF results for JALSH, SEMDEX, MOSENEW and TUSISE also rejected the null hypothesis of unit root in favour of the alternative of stationarity both in the full sample periods and in rolling window analyses because the test statistics are more negative than the critical values at virtually all (1,5,10) levels of significance. The result is also confirmed by the very small *p*-value of less than 1 percent. Since the stationarity at first difference of a nonstationary series does not violate its randomness, the results suggest that the five series follows a random walk and hence, the market may be efficient. However, the significance of *p*-value does not vary over time in the manner described by the AMH.

The alternative to ADF unit root test is the KPSS test. As opposed to the ADF test, KPSS tested the null hypothesis of stationarity against alternative hypothesis of unit root. The test results of the KPSS at level are reported in Table 5.3for the five return series. The NGSEINDX full sample result shows that the test statistics are much smaller than the critical value; therefore, the null hypothesis that the series is stationary cannot be rejected in favour of the alternative that the series contains a unit root hence, the KPSS test at levels confirms the conclusion of ADF in full sample. This connotes that the NGSEINDX return is integrated of order zero. Considering the rolling window analyses, the KPSS results for the NGSEINDX show that the return series is stationary in all the windows except 2003-2004, 2007-2008, 2011-2012, 2011-2012 when the test statistics are larger than the critical values as indicated by ***. Unlike the ADF rolling window results, the NGSEINDX KPSS results appear to pass through periods of stationarity in many windows and nonstationary in four windows in line with the AMH.

The full sample KPSS result for JALSH in Table 5.3 also reveals that the test statistic is smaller than the critical values. Hence, the non-rejection of the null hypothesis that the return series is stationary against the alternative of a unit root as would be expected for return series at level, which is ordinarily a first difference of a supposedly nonstationary price series. Just as the ADF rolling window analyses JALSH, KPSS results reveal that the return series remains stationary over the 19 windows, which do not reflect in any way the time varying behavioural pattern embedded in the AMH. Column 6 and 7 of Table 5.3 show the KPSS results for SEMDEX in the full sample and rolling windows. The full sample results reveal that the return series are stationary at level since the critical values are larger than the LM test statistic, hence the null hypothesis of stationarity cannot be rejected. However, the KPSS results for the SEMDEX in rolling window shows that the return series is nonstationary in 2005-2006, 2007-2008 and 2012-2013 when the critical values are smaller than the LM test statistics as indicated by **. This suggests that SEMDEX returns undergo periods of stationarity and nonstationary as propounded by the AMH.

The results of KPSS test for MOSENEW in full and rolling windows are presented in column 8 and 9 of Table 5.3. The results point to non-rejection of the null hypothesis of stationarity at level for full sample, demonstrating the stationary property of the MOSENEW return series. As stated earlier, the stationarity of return series does not necessarily violate the RWH since return is ideally a first difference of price series. Considering the rolling window results, it can be seen that the MOSENEW return series has windows when it is stationary and at least four windows when returns are nonstationary. Nonstationarity of return occurs in 1998 -1999, 2003-2004, 2007-2008, 2015-2016 windows. Suffice to state that the stationarity of stock return follows the time-varying pattern of an adaptive market. TUSISE KPSS results for full sample and rolling window are given in the last two columns of Table 5.3. It can be seen from the full sample result that the return is stationary at level just like the ADF test results. Unlike the ADF test, however, the TUSISE return provides evidence of stationarity and nonstationarity from rolling window analyses. The stationarity of returns were intercepted by two windows of non-stationarity in 2006-2007 and 2009-2010. This is in consonance with the proposition of the AMH.

Table 5.2: ADF results for NGSE, JALSH, SEMDEX, MOSENEW and TUSISE

SAMPLE	Test Stat	Critical Value @ 5%	Test Stat	Critical Value @ 5%	Test Stat	Critical Value @ 5%	Test Stat	Critical Value @ 5%	Test Stat	Critical Value @ 5%
	NGSEINDX		**JALSH**		**SEMDEX**		**MOSENEW**		**TUSISE**	
Full sample	**-48.13665*****	**-2.861942**	**-66.6355*****	**-2.861918**	**-46.6778*****	**-2.861919**	**-55.8836*****	**-2.861924**	**-52.7026*****	**-2.862011**
1998 -1999	-7.15698***	-2.867183	-17.9671***	-2.86712	-9.80388***	-2.867279	-14.0049***	-2.867147	NA	NA
1999-2000	-13.25964***	-2.867159	-18.8579***	-2.86715	-10.2997***	-2.867124	-14.9171***	-2.867136	NA	NA
2000-2001	-12.6185***	-2.867159	-19.8321***	-2.86714	-22.6600***	-2.867055	-16.4865***	-2.867183	-17.9776***	-2.868583
2001-2002	-15.0623***	-2.867279	-20.2566***	-2.86711	-19.2930***	-2.867255	-23.2887***	-2.867136	-18.5585***	-2.868511
2002-2003	-12.2924***	-2.867830	-19.6931***	-2.86711	-16.5712***	-2.867509	-15.1530***	-2.867124	-14.5278***	-2.868169
2003-2004	-11.3501***	-2.868137	-14.0080***	-2.86712	-16.8571***	-2.867700	-11.3137***	-2.867470	-15.2809***	-2.868601
2004-2005	-12.4731***	-2.868105	-22.3307***	-2.86709	-17.7206***	-2.867509	-17.5400***	-2.867509	-18.4597***	-2.868511
2005-2006	-11.7658***	-2.867889	-23.3246***	-2.86712	-7.58079***	-2.867342	-14.8547***	-2.867195	-11.2238***	-2.867757
2006-2007	-13.5273***	-2.867483	-22.7792***	-2.86714	-28.5095***	-2.867183	-14.2333***	-2.867112	-15.2932***	-2.867329
2007-2008	-9.47639***	-2.867379	-21.6433***	-2.86710	-15.8044***	-2.867171	-16.6885***	-2.867147	-18.7690***	-2.867231
2008-2009	-10.2935***	-2.867317	-21.1964***	-2.86710	-18.1627***	-2.867010	-16.4522***	-2.867195	-19.1250***	-2.867159
2009-2010	-16.7303***	-2.867279	-21.4073***	-2.86710	-18.1338***	-2.866922	-16.7980***	-2.867101	-19.2798***	-2.867101
2010-2011	-17.1364***	-2.867219	-22.0833***	-2.86711	-17.3662***	-2.866976	-18.7975***	-2.867055	-15.8039***	-2.867243
2011-2012	-17.2882***	-2.867183	-22.0268***	-2.86712	-19.1839***	-2.866965	-19.0146***	-2.867078	-14.9707***	-2.867243
2012-2013	-19.5517***	-2.867147	-23.6281***	-2.86711	-11.9439***	-2.866933	-18.9968***	-2.867159	-18.5479***	-2.867136
2013-2014	-15.3060***	-2.867147	-23.2812***	-2.86712	-12.1325***	-2.866933	-21.8929***	-2.867195	-16.3501***	-2.867171
2014-2015	-12.7622***	-2.867183	-24.0050***	-2.86711	-12.1746***	-2.866954	-22.0213***	-2.867183	-17.2846***	-2.867147
2015-2016	-14.3703***	-2.867195	-22.4266***	-2.86711	-11.864***	-2.866922	-19.1010***	-2.867159	-18.7774***	-2.867112
2016-2017	-9.41139***	-2.867219	-21.3768***	-2.86714	-17.9234***	-2.866879	-17.1770***	-2.867112	-18.1798***	-2.867078
Decision	**Efficient**		**Efficient**		**Efficient**		**Efficient**		**Efficient**	

The first row reports the test statistics and critical values. *** and ** indicate rejection of H_0 at 1% and 5%

Table 5.3: KPSS Results for NGSEINDX, JALSH, SEMDEX, MOSENEW and TUSISE

KPSS	Test Stat	Critical Value @ 5%	Test Stat	Critical Value @ 5%	Test Stat	Critical Value @ 5%	Test Stat	Critical Value @ 5%	Test Stat	Critical Value @ 5%
	NGSEINDX		JALSH		SEMDEX		MOSENEW		TUSISE	
Full sample	**0.150909**	**0.463000**	**0.071135**	**0.463000**	**0.187151**	**0.463000**	**0.225407**	**0.463000**	**0.168278**	**0.463000**
1998 -1999	0.072948	0.463000	0.187561	0.463000	0.294721	0.463000	0.52112**	0.463000	NA	NA
1999-2000	0.375736	0.463000	0.210158	0.463000	0.198046	0.463000	0.093668	0.463000	NA	NA
2000-2001	0.127367	0.463000	0.175908	0.463000	0.186956	0.463000	0.035149	0.463000	0.452326	0.463000
2001-2002	0.165387	0.463000	0.166510	0.463000	0.344737	0.463000	0.046050	0.463000	0.023650	0.463000
2002-2003	0.275552	0.463000	0.278621	0.463000	0.156004	0.463000	0.60990**	0.463000	0.360966	0.463000
2003-2004	0.508234**	0.463000	0.200051	0.463000	0.131572	0.463000	0.135401	0.463000	0.087898	0.463000
2004-2005	0.237097	0.463000	0.215984	0.463000	0.214685	0.463000	0.111436	0.463000	0.096664	0.463000
2005-2006	0.250512	0.463000	0.024920	0.463000	0.480452**	0.463000	0.119541	0.463000	0.071489	0.463000
2006-2007	0.101722	0.463000	0.111887	0.463000	0.141008	0.463000	0.192825	0.463000	0.531410**	0.463000
2007-2008	1.183196**	0.463000	0.266753	0.463000	0.943638**	0.463000	0.80074**	0.463000	0.160156	0.463000
2008-2009	0.136701	0.463000	0.248252	0.463000	0.425901	0.463000	0.143100	0.463000	0.148172	0.463000
2009-2010	0.193109	0.463000	0.041622	0.463000	0.101723	0.463000	0.081950	0.463000	0.511564**	0.463000
2010-2011	0.425600	0.463000	0.040229	0.463000	0.287498	0.463000	0.442816	0.463000	0.354688	0.463000
2011-2012	0.582637**	0.463000	0.178391	0.463000	0.135500	0.463000	0.027325	0.463000	0.208107	0.463000
2012-2013	0.085069	0.463000	0.038469	0.463000	0.845080**	0.463000	0.196125	0.463000	0.177099	0.463000
2013-2014	0.452075	0.463000	0.071817	0.463000	0.432656	0.463000	0.167775	0.463000	0.199203	0.463000
2014-2015	0.052732	0.463000	0.068982	0.463000	0.248751	0.463000	0.369718	0.463000	0.415685	0.463000
2015-2016	0.082229	0.463000	0.050937	0.463000	0.297994	0.463000	0.52116**	0.463000	0.144572	0.463000
2016-2017	0.247897	0.463000	0.084620	0.463000	0.378311	0.463000	0.118194	0.463000	0.079929	0.463000
2017-2017	0.110784	0.463000	0.064866	0.463000	0.408917	0.463000	0.058314	0.463000	0.121863	0.463000
Remarks	**Adaptive**		**Efficient**		**Adaptive**		**Adaptive**		**Adaptive**	

The first row reports the test statistics and critical values. *** and ** indicate rejection of H_0 at 1% and 5%

Now that the two unit root tests produce conflicting results, it must be noted that the tests are usually combined for confirmatory purposes. As stated in the methodology section, the latter is more acceptable. It has also been documented in the literature that the unit root tests as a whole are not sufficient to establish randomness of return series but are usually carried out for robustness purposes, except when it is complemented with serial correlation tests (Rahman & Saadi, 2008).

5.3.1.2 Rolling ACF Results

Results of autocorrelation (ACF) tests are given in Table 5.4 with the ACF coefficients for the five markets in Tables 5.4 A, B, C, D and E respectively. The test is carried out setting a 95 percent non-rejection region given by $\pm 1.96 \text{ x} \sqrt{\frac{1}{T}}$. The spikes (***) attached to the ACF coefficients are indications of autocorrelation in return series. In full sample, the ACFs particularly, at lags 1, fall outside of the confidence interval; therefore, the null hypothesis that they are equal to zero is rejected. In other words, ACF at this lag 1 is significantly different from zero, therefore, null hypothesis that there is no evidence of autocorrelation is rejected for the five markets in full sample. The implication is that the return indices are dependent and predictable based on previous price information.

The rolling window results are contained in the same Table 5.4A, B, C, D and E. Evidences of first-order autocorrelation are found in all windows for all indices except JALSH, although NGSEINDX (2002-2003) and SEMDEX (2000-2001) have one window each and MOSENEW three windows (2001-2002, 2013-2014 and 2014-2015) without significant first order autocorrelations. The autocorrelation behaviour of TUSISE is not consistent with the time varying efficiency as suggested by AMH as the spikes observed for the entire windows imply that the returns are predictable over the entire sample period.

It can be seen that JALSH in Table 5.4B is characterised by small nonsignificant autocorrelation in all windows apart from the first five and the last windows, which have significant autocorrelation at virtually all lags. Hence, JALSH only has significant autocorrelation in 1998-1999, 1999-2000, 2000-2001, 2001-2002, 2002-2003 and 2016-2017. The results show that the JALSH indices have undergone an era of significant and insignificant autocorrelation in line with the AMH.

Table 5.4: ACF results for NGSEINDX, JALSH, SEMDEX, MOSENEW and TUSISE

Table 5.4A NGSEINDX	**Lag-length**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
					NGSEINDX					
Full sample	**0.351*** **	**0.151***	**0.021**	**0.017**	**-0.009**	**-0.036**	**-0.008**	**0.017**	**0.025**	**0.029**
1998 -1999	0.393***	0.183*	0.163*	0.251**	0.201*	0.086*	0.074	0.012	0.014	0.005
1999-2000	0.47***	0.235**	0.175*	0.137*	0.042	-0.006	-0.003	-0.009	0.021	0.038
2000-2001	0.512***	0.26**	0.067	-0.104*	-0.198*	-0.146*	-0.029	-0.013	0.05	0.069
2001-2002	0.36***	0.19*	-0.016	-0.071*	-0.141*	-0.095*	-0.015	0.018	0.039	-0.018
2002-2003	0.068	0.155*	-0.051	0.018	-0.087*	-0.095*	-0.022	0.039	0.01	0.056
2003-2004	0.208*	0.165*	-0.043	-0.027	-0.063	-0.084*	0.02*	0.086	0.019	0.052
2004-2005	0.464***	0.166*	-0.02	-0.082*	-0.056	-0.027	0.027	0.119*	0.058	0.023
2005-2006	0.45***	0.172*	-0.065	-0.13*	-0.129*	0.004	0.005	0.055	0.051	0.023
2006-2007	0.43***	0.195*	-0.042	-0.125*	-0.092*	-0.028	0.059	0.056	0.036	0.001
2007-2008	0.622***	0.426***	0.198*	0.028	-0.04	-0.065	-0.038	-0.061	-0.051	-0.022
2008-2009	0.426***	0.288**	0.071	0.011	-0.051	-0.046	-0.046	-0.039	-0.018	0.002
2009-2010	0.266**	0.059	-0.003	0.041	0.003	-0.028	0.013	0.054	0.069	0.074*
2010-2011	0.24**	-0.156*	-0.048	0.038	0.033	-0.058	0.009	0.074*	0.061	0.051
2011-2012	0.245**	0.104*	-0.000	-0.005	0.097*	0.069	0.057	0.069	0.073	0.101*
2012-2013	0.119*	0.09*	0.122*	0.000	0.105*	0.01	0.051	0.006	0.055	0.027
2013-2014	0.359***	0.165*	0.108*	-0.017	-0.045	-0.098*	0.017	0.003	0.031	-0.018
2014-2015	0.446***	0.106*	-0.01	0.001	-0.036	-0.141*	-0.13*	-0.141*	-0.088*	-0.003
2015-2016	0.38***	0.031	-0.087*	0.064	0.107*	0.029	-0.073*	-0.062	-0.012	-0.04
2016-2017	0.321**	0.055	-0.046	0.08*	0.111*	0.079*	0.002	0.054	0.072	0.008
Decision					**Adaptive**					

Spike(s) ***, **, * symbolise significant autocorrelation.

Table 5.4B JALSH	**Lag-length**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
					JALSH					
Full sample	**0.063**	**0.003**	**-0.043**	**-0.026**	**-0.030**	**-0.014**	**0.035**	**0.001**	**0.006**	**0.003**
1998 -1999	0.212*	0.096*	-0.009	0.006	0.028	0.033	0.069	0.007	0.066	0.051
1999-2000	0.162*	0.09*	-0.063	-0.013	-0.04	-0.024	-0.046	0.081*	-0.027	-0.031
2000-2001	0.114*	0.052	-0.011	0.009	-0.05	-0.04	0.03	0.006	-0.017	0.032
2001-2002	0.095*	0.016	0.002	-0.066*	-0.07*	-0.013	0.141*	0.031	0.028	0.026
2002-2003	0.126*	0.011	-0.095*	-0.07*	-0.047	-0.014	0.027	0.052	0.058	-0.009
2003-2004	0.105*	0.057	-0.144*	0.039	-0.025	0.036	-0.051	0.015	0.018	0.011
2004-2005	0.002	0.047	-0.115*	0.056	-0.007	0.075*	-0.001	0.006	-0.106*	0.113*
2005-2006	-0.046	-0.019	0.055	0.007	-0.042	-0.048	-0.057	-0.043	-0.068*	0.006
2006-2007	-0.026	0.001	0.011	-0.05	-0.082*	-0.008	-0.047	-0.017	-0.007	-0.045
2007-2008	0.031	-0.01	-0.106*	-0.074*	-0.058	-0.028	0.078*	0.013	0.014	-0.032
2008-2009	0.052	-0.021	-0.119*	-0.053	-0.027	-0.023	0.056	0.014	0.005	-0.052
2009-2010	0.042	-0.028	-0.078*	-0.012	-0.008	-0.005	0.022	-0.015	0.016	-0.029
2010-2011	0.01	-0.042	-0.014	-0.009	-0.04	-0.092	0.014	-0.075	-0.001	0.02
2011-2012	0.011	-0.09	-0.037	0.005	-0.049	-0.089*	-0.025	0.002*	0.03	-0.058
2012-2013	-0.05	-0.102*	0.016	-0.069*	-0.07*	0.009	0.097*	0.014	0.045	-0.007
2013-2014	-0.039	-0.071*	0.04	-0.105*	-0.021	0.024	0.068	-0.009	-0.01	0.029
2014-2015	-0.073*	-0.047	0.025	-0.01	0.048	-0.059	0.023	-0.076*	-0.11*	0.113*
2015-2016	-0.006	-0.099*	-0.012	-0.025	-0.031	-0.061	0.05	-0.038	0.004	-0.004
2016-2017	0.049	-0.11*	0.006	-0.082*	-0.074*	-0.015	0.072	0.051	0.05	-0.033
Decision					**Adaptive**					

Spike(s) ***, **, * symbolise significant autocorrelation.

Table 5.4C SEMDEX	Lag-length									
	1	2	3	4	5	6	7	8	9	10
	SEMDEX									
Full sample	**0.029**	**0.058**	**0.012**	**0.059**	**0.016**	**0.005**	**0.066**	**0.057**	**-0.022**	**0.006**
1998 -1999	0.32**	0.336**	0.116*	0.07	-0.042	-0.025	-0.055	0.001	0.00	0.047
1999-2000	0.341**	0.304**	0.223**	0.109*	0.087*	0.044	0.039	0.057	-0.058	0.006
2000-2001	-0.013	-0.002	0.042	-0.013	0.06	0.038	0.052	0.041	-0.028	0.06
2001-2002	0.129*	0.106*	0.103*	0.071	0.094*	0.037	0.057	0.01	0.022	0.013
2002-2003	0.257**	0.083*	0.069	0.006	0.012	0.01	0.088*	-0.004	-0.03	-0.034
2003-2004	0.227**	0.061	0.044	-0.029	-0.007	0.013	0.093*	-0.035	-0.06	-0.055
2004-2005	0.195*	0.164*	0.136*	0.077*	0.07	0.028	0.017	-0.02	-0.026	-0.011
2005-2006	-0.32**	0.04	-0.039	0.005	0.004	0.031	0.034	0.07	0.003	-0.024
2006-2007	-0.247**	0.013	-0.051	0.017	-0.01	0.021	0.063	0.076*	-0.047	-0.052
2007-2008	0.212*	-0.075*	-0.019	0.05	0.00	-0.062	0.055	0.033	-0.05	0.00
2008-2009	0.211*	0.021	0.025	0.112*	0.031	-0.043	0.079*	0.048	-0.028	0.056*
2009-2010	0.219**	0.152*	0.073	0.136*	0.074*	0.014	0.103*	0.048	0.002	0.092*
2010-2011	0.255**	0.064	-0.019	0.002	-0.032	-0.027	0.023	0.014	0.034	0.011
2011-2012	0.164*	0.047	-0.031	-0.02	-0.062	0.012	0.048	0.02	0.082*	0.053
2012-2013	0.205*	0.208*	0.16*	0.064	0.122*	0.084*	0.118*	0.056	0.109*	0.127*
2013-2014	0.237**	0.188*	0.093*	0.105*	0.093*	0.000	0.053	0.088*	0.029	0.00
2014-2015	0.272**	0.173*	0.064	0.082	0.029	-0.02	-0.04	-0.047	-0.073*	-0.114*
2015-2016	0.272**	0.207*	0.113*	-0.062	0.002	0.052	-0.025	-0.065	-0.072	-0.075*
2016-2017	0.233**	0.149*	0.105*	-0.057	0.016	0.113*	0.031	0.035	-0.009	-0.025
Remark	**Adaptive**									

Spike(s) ***, **, * symbolise significant autocorrelation.

Table 5.4D MOSENEW	Lag-length									
	1	2	3	4	5	6	7	8	9	10
	MOSENEW									
Full sample	**0.230****	**0.074**	**-0.008**	**0.006**	**0.012**	**-0.017**	**-0.013**	**0.010**	**0.017**	**0.028**
1998 -1999	0.432***	0.187*	0.121*	0.126*	0.126*	0.089*	0.029	0.031	0.044	0.04
1999-2000	0.379***	0.089*	-0.006	-0.013	0.028	-0.031	-0.063	-0.078*	-0.008	0.02
2000-2001	0.284**	0.1*	-0.009	-0.067*	0.052	-0.051	0.007	0.037	0.024	0.005
2001-2002	-0.047	0.097*	-0.009	0.004	0.015	-0.029	-0.001	0.02	0.024	0.003
2002-2003	-0.121*	0.137*	0.022	0.062	0.012	0.006	-0.026	-0.039	0.006	0.024
2003-2004	0.273**	0.205*	0.046	0.138*	0.139*	0.076*	-0.016	0.05	0.06	0.053
2004-2005	0.204*	0.151*	0.015	0.099*	0.076*	0.052	-0.051	0.08*	0.081*	0.05*
2005-2006	0.379***	0.065	0.065	0.06	-0.016	-0.057	-0.014	0.054	0.013	0.041
2006-2007	0.366***	0.025	0.01	-0.002	-0.055	-0.066*	-0.003	0.037	0.019	0.038
2007-2008	0.278**	-0.009	-0.099*	-0.055	-0.052	-0.081*	-0.062	-0.008	-0.013	0.013
2008-2009	0.293**	0.047	-0.053	-0.016	0.012	-0.029	-0.052	-0.051	-0.08*	-0.054
2009-2010	0.303**	0.108*	-0.02	-0.046	-0.019	0.025	0.012	-0.038	-0.049	-0.028
2010-2011	0.177*	0.016	-0.122*	-0.083*	-0.078*	-0.002	-0.024	0.003	0.021	0.027
2011-2012	0.161*	0.03	-0.093*	-0.12*	-0.088*	-0.047	-0.042	0.01	0.024	0.055
2012-2013	0.153*	0.073	-0.027	-0.093*	0.014	-0.021	-0.01	-0.012	-0.005	0.085*
2013-2014	0.011	0.07	-0.05	-0.029	0.089*	0.043	0.005	0.009	0.029	0.048
2014-2015	0.005	0.073	-0.014	0.068	0.112*	0.063	-0.032	-0.001	0.038	0.02
2015-2016	0.148*	-0.044	0.048	0.109*	0.111*	-0.011	-0.005	-0.024	0.04	0.034
2016-2017	0.255**	0.013	0.012	0.01	-0.016	-0.101*	-0.034	-0.02	0.083*	0.077*
Remark	**Adaptive**									

Spike(s) ***, **, * symbolise significant autocorrelation.

Table 5.4E TUSISE	Lag-length									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
TUSISE										
Full sample	**0.219*** **	**0.071**	**0.018**	**0.021**	**0.009**	**-0.005**	**-0.028**	**0.026**	**0.006**	**0.021**
1998 -1999	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
1999-2000	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
2000-2001	0.114*	-0.085*	-0.078*	0.037	0.042	0.018	0.032	0.045	-0.137*	-0.028
2001-2002	0.075*	-0.06	-0.127*	0.000	0.063	0.058	0.049	-0.043	-0.236**	0.007
2002-2003	0.332**	0.162*	0.008	0.05	0.029	0.116*	0.147*	0.005	0.011	0.074*
2003-2004	0.257**	0.113*	0.056	0.024	0.025	0.063	0.11*	0.02	0.024	0.059
2004-2005	0.077*	0.106*	0.102*	0.003	-0.025	0.015	0.004	-0.016	0.065	0.022
2005-2006	0.282**	0.189*	0.079*	0.098*	0.03	0.046	-0.03	0.013	0.027	-0.005
206-2007	0.343**	0.2*	0.027	0.046	-0.028	-0.02*	-0.027	0.032	0.084*	0.102*
2007-2008	0.161*	0.118*	-0.009	-0.02	-0.004	-0.083*	-0.111*	0.083*	0.116*	0.096*
2008-2009	0.148*	0.077*	0.01	0.015	0.033	-0.042	-0.105*	0.08*	0.072	0.052
2009-2010	0.148*	-0.014	0.017	0.125*	0.013	0.05	0.034	-0.009	0.014	0.079*
2010-2011	0.321**	0.084*	0.01	-0.018	-0.084*	-0.072*	-0.141*	-0.049	-0.002	0.016
2011-2012	0.368***	0.105*	0.037	-0.053	-0.058	-0.071*	-0.153*	-0.033	0.005	-0.046
2012-2013	0.181*	0.024	0.051	0.034	0.096*	0.027	0.016	0.05	0.012	-0.044
2013-2014	0.299**	0.076*	0.055	0.048	-0.025	-0.056	-0.024	0.038	-0.055	-0.039
2014-2015	0.24**	0.122*	0.132*	0.004	-0.034	0.017	-0.037	0.073	0.067	0.045
2015-2016	0.17*	0.117*	0.051	-0.079*	0.007	0.066	-0.024	0.051	0.124*	0.005
2016-2017	0.209*	0.131*	0.026	-0.027	0.067	0.059	-0.013	-0.018	0.048	-0.009
Remark	**Inefficient**									

Spike(s) ***, **, * symbolise significant autocorrelation.

Table 5.4C reveals that SEMDEX is predictable for the first two windows (1998-1999, 1999-2000). The series, however, become unpredictable in the 2000-2001 window. Significant return predictability continues thereafter until the last window. Hence, there is a swing in return autocorrelation as advocated by the AMH but the persistence of its occurrence is not pronounced.

MOSENEW rolling window autocorrelation analysis displays that most of the windows have significant predictive power, except for 2001-2002, 2013-2014 and 2014-2015 windows, which provide evidence of unpredictability. MOSENEW has three windows (2001-2002, 2013-2014 and 2014-2015) without significant first order autocorrelations. The results support time varying behaviour put forth by AMH.

Thus, while TUSISE did not display fluctuation in predictability, NGSEINDX, SEMDEX, MOSENEW and JALSH returns, to an extent, change with time in agreement with the proponent of AMH. The autocorrelation result is followed by the interpretation of the Lo and MacKinlay (1988) VR tests estimated in this study.

5.3.1.3 Rolling VR Results

The results of the Lo and MacKinlay (1988) VR test for the full sample and rolling windows are presented in Table 5.5. The columns show variance ratios for number k (lag). A p-value less than 0.05 means that the H_0 of a random walk can be rejected at the 5 percent level of significance, in favour of the H_1 that the returns are serially correlated. ***, **, * indicate significance at 1 percent, 5 percent and 10 percent. In absolute form (full sample), the results of the VR show that the markets are inefficient or are predictable in linear form since the probability values of the test at individual levels (lags) are significant at 5 percent for the five markets. According to AMH, these findings do not present the true behaviour of return or markets, suggesting that absolute test of efficiency cannot reveal the changing magnitude of efficiency over time.

The VR tests in rolling window show that there are windows or sub-periods of efficiency in some markets. NGSEINDX for instance, in 2002-2003, 2003-2004 and 2010-2011, SEMDEX in 2005-2006 and 2006-2007 and MOSENEW in 2000-2001 and 2001-2002 windows have large and insignificant *p*-values. These windows of efficiency are tantamount to periods of significant return unpredictability while other windows represent periods of significant return predictability as indicated by ***.

On the results of further innovations (not reported) to original Lo and MacKinlay (1988) VR test, It must be noted that the wild bootstrap VR p-values for the five stock indices return, are mostly consistent with the Lo and MacKinlay VR results, although with p-values that are somewhat lower. On the other hand, p-values of ranks-based and signs-based VR are generally lower than 5 percents for all markets, meaning that the markets are inefficient and predictable throughout. Comparing different versions of VR tests, Lo and MacKinlay (1988) VR test shows the most adaptive behaviour. For better understanding of the time-varying behaviour, the *p*-values of two-year rolling window joint VR tests for NGSEINDX, JALSH, SEMDEX, MOSENEW and TUSISE respectively are presented in Figure 5.1. It can be seen that there are cycles when the *p*-value is less than 0.05 (demarcated by red horizontal line) and there are periods when it is greater than 0.05. They represent cycles of inefficiency and efficiency respectively.

Table 5.5: VR results for NGSEINDX, JALSH, SEMDEX, MOSENEW and TUSISE

	TABLE 5.5A: NGSEINDX			
Period	**K=2**	**K=4**	**K=8**	**K=16**
Full sample	**0.65434*** **	**0.38185*** **	**0.18995*** **	**0.09484*** **
1998 -1999	0.311524*	0.208326**	0.108479**	0.675124*
1999-2000	0.723606**	0.409971***	0.241163***	0.120030***
2000-2001	0.761181***	0.570455***	0.265120***	0.134249***
2001-2002	0.632475***	0.420910***	0.193068***	0.094742***
2002-2003	0.455715*	0.267084*	0.132517*	0.069839
2003-2004	0.529374*	0.328491*	0.147750*	0.082199*
2004-2005	0.780383***	0.511355***	0.207319***	0.12360***
2005-2006	0.759762***	0.524301***	0.222357***	0.117060***
2006-2007	0.71133***	0.497918***	0.210595***	0.117560***
2007-2008	0.759230***	0.647550***	0.355824***	0.176235***
2008-2009	0.622249**	0.435668**	0.327214*	0.120020**
2009-2010	0.643263**	0.328561***	0.164350***	0.084831**
2010-2011	0.762677	0.318675*	0.153258*	0.076726*
2011-2012	0.611609***	0.359411***	0.179344***	0.099691**
2012-2013	0.518176***	0.286948***	0.144490***	0.077279**
2013-2014	0.654175***	0.390426***	0.183870***	0.087481***
2014-2015	0.804648***	0.453903***	0.263389***	0.109369***
2015-2016	0.775727***	0.370566***	0.212107***	0.102616***
2016-2017	0.702169***	0.349765***	0.173446***	0.089352***
REMARK	**ADAPTIVE**			

	TABLE 5.5B: JALSH			
Period	**K=2**	**K=4**	**K=8**	**K=16**
Full sample	**0.53197*** **	**0.27422*** **	**0.13281*** **	**0.06681*** **
1998 -1999	0.57489***	0.3183***	0.15632***	0.08250***
1999-2000	0.54482***	0.29963***	0.13496***	0.075268***
2000-2001	0.53680***	0.28173***	0.13919***	0.070323***
2001-2002	0.54443***	0.29406***	0.13526***	0.071182***
2002-2003	0.56808***	0.30984***	0.13848***	0.075787***
2003-2004	0.52835***	0.27116***	0.14050***	0.07169***
2004-2005	0.47835***	0.23755***	0.12625***	0.069420***
2005-2006	0.48886***	0.23982***	0.12757***	0.066863***
2006-2007	0.48894***	0.25876***	0.12631***	0.061520***
2007-2008	0.52238***	0.27963***	0.12985***	0.062011***
2008-2009	0.54049***	0.28057***	0.13317***	0.06661***
2009-2010	0.53714***	0.26532***	0.13404***	0.067327***
2010-2011	0.52805***	0.25778***	0.13916***	0.072733***
2011-2012	0.55314***	0.25396***	0.12888***	0.071861***
2012-2013	0.52686***	0.25600***	0.11956***	0.06245***
2013-2014	0.51671***	0.26796***	0.12141***	0.06326***
2014-2015	0.48924***	0.23774***	0.12750***	0.064226***
2015-2016	0.54328***	0.25354***	0.12944***	0.06236***
2016-2017	0.59259***	0.28736***	0.12711***	0.06631***
REMARK	**INEFFICIENT**			

	TABLE 5.5C: SEMDEX			
Period	**K=2**	**K=4**	**K=8**	**K=16**
Full sample	**0.48525****	**0.24241****	**0.1216****	**0.06328****
1998 -1999	0.4904***	0.3446***	0.1877**	0.0869**
1999-2000	0.5302***	0.3416***	0.1834***	0.0955***
2000-2001	0.4936***	0.2512***	0.1204***	0.05766***
2001-2002	0.5152***	0.2697***	0.1456***	0.0691***
2002-2003	0.6178***	0.3339***	0.1715***	0.0860***
2003-2004	0.6097***	0.3355***	0.1714***	0.0822***
2004-2005	0.5215***	0.2895***	0.1618***	0.0715***
2005-2006	0.365068	0.147015	0.051158	0.027919
2006-2007	0.397432	0.199415	0.095224	0.054056
2007-2008	0.6848***	0.3036***	0.1561***	0.0820***
2008-2009	0.62208***	0.2837***	0.1540***	0.07990***
2009-2010	0.5449***	0.2794***	0.1560***	0.0791**
2010-2011	0.6312***	0.3381***	0.1687***	0.0882***
2011-2012	0.5714**	0.30787**	0.1495**	0.0809**
2012-2013	0.4992***	0.2973***	0.1512***	0.0757***
2013-2014	0.5334***	0.2961***	0.1525***	0.0763***
2014-2015	0.5665***	0.3128***	0.1804***	0.0918***
2015-2016	0.5455***	0.3679***	0.1868***	0.0905***
2016-2017	0.5482***	0.3413***	0.1593***	0.0829***
REMARK	**ADAPTIVE**			

	TABLE 5.5D: MOSENEW			
Period	**K=2**	**K=4**	**K=8**	**K=16**
Full sample	**0.716937*****	**0.387875*****	**0.218167*****	**0.110733*****
1998 -1999	0.735139***	0.411064***	0.221409***	0.107072***
1999-2000	0.629770***	0.376426***	0.172432***	0.093691***
2000-2001	0.432632***	0.239700**	0.119500**	0.062793**
2001-2002	0.103337	0.209943	0.118432	0.061871
2002-2003	0.053466	0.216076*	0.116640	0.062398
2003-2004	0.534719***	0.286104***	0.148287***	0.081245***
2004-2005	0.755910***	0.382276***	0.194335***	0.107298***
2005-2006	0.772275***	0.398612***	0.193372***	0.104174***
2006-2007	0.700128***	0.366826***	0.175185***	0.081367***
2007-2008	0.677211***	0.363168***	0.190429***	0.090498***
2008-2009	0.616778***	0.357913***	0.177769***	0.092378***
2009-2010	0.600336***	0.325466***	0.150476***	0.086625***
2010-2011	0.577429***	0.335126***	0.148326***	0.089079***
2011-2012	0.549168***	0.324671***	0.151976***	0.080394***
2012-2013	0.549168***	0.324671***	0.151976***	0.080394***
2013-2014	0.471891***	0.261968***	0.127435***	0.063366***
2014-2015	0.467364***	0.235908***	0.126756***	0.063661***
2015-2016	0.614115***	0.262033***	0.141269***	0.066484***
2016-2017	0.664530***	0.336129***	0.175436***	0.089809***
REMARK	**ADAPTIVE**			

	TABLE 5.5E: TUSISE			
Period	**K=2**	**K=4**	**K=8**	**K=16**
Full sample	**0.594519*** **	**0.313483*** **	**0.156216*** **	**0.078291*** **
1998 -1999	NA	NA	NA	NA
1999-2000	NA	NA	NA	NA
2000-2001	0.616271***	0.273853***	0.127375***	0.070389***
2001-2002	0.575267***	0.273898***	0.145423***	0.076209**
2002-2003	0.630388***	0.360776***	0.192610***	0.099773***
2003-2004	0.598544***	0.332364***	0.168433***	0.089632***
2004-2005	0.486275***	0.273713***	0.141386***	0.072040***
2005-2006	0.566916***	0.315806***	0.175617***	0.089456***
2006-2007	0.611167***	0.367508***	0.189093***	0.094708***
2007-2008	0.527606***	0.306653***	0.139297***	0.083569**
2008-2009	0.543986***	0.292505***	0.138100***	0.083021**
2009-2010	0.596001***	0.256462***	0.149433***	0.073068***
2010-2011	0.673655***	0.375680***	0.196796***	0.083823***
2011-2012	0.710019***	0.420724***	0.197010***	0.069899***
2012-2013	0.598761***	0.298191***	0.148449***	0.073998***
2013-2014	0.661512***	0.343534***	0.174492***	0.083641***
2014-2015	0.579425***	0.330255***	0.155363***	0.080757***
2015-2016	0.534038***	0.328449***	0.144984***	0.081120***
2016-2017	0.546894***	0.325195***	0.160779***	0.082768***
REMARK	**INEFFICIENT**			

Specifically, NGSEINDX *p*-value is less than 0.05 over the first four windows from 1998-2002 during which returns are predictable and the market is inefficient. This was followed by two windows (2002-2004) when *p*-values are insignificant and the market is deemed efficient or unpredictable. The remaining windows from 2004 to 2017 represent sessions of return predictability, intercepted/alternated by unpredictability in 2010-2011 window. The result of JALSH VR test in two-year rolling windows given in Figure 5.1 shows that *p*-value is less than 0.05 over the 19 years rolling windows, indicating serial correlation in returns throughout.

JALSH results imply that the series has linear dependence both in full sample and in rolling windows and this does not align with the types of return behaviour described by the new AMH. Additionally, Figure 5.1 also shows that for SEMDEX, *p*-values are significant during the first eight windows (1998-2006), indicating significant return predictability. SEMDEX becomes unpredictable during the subsequent two windows (2005-2007) as the *p*-values are not significant at 5 percent level of significance. The remaining periods from 2007 to 2017 are characterised by linear correlation as revealed by significant VR *p*-values.

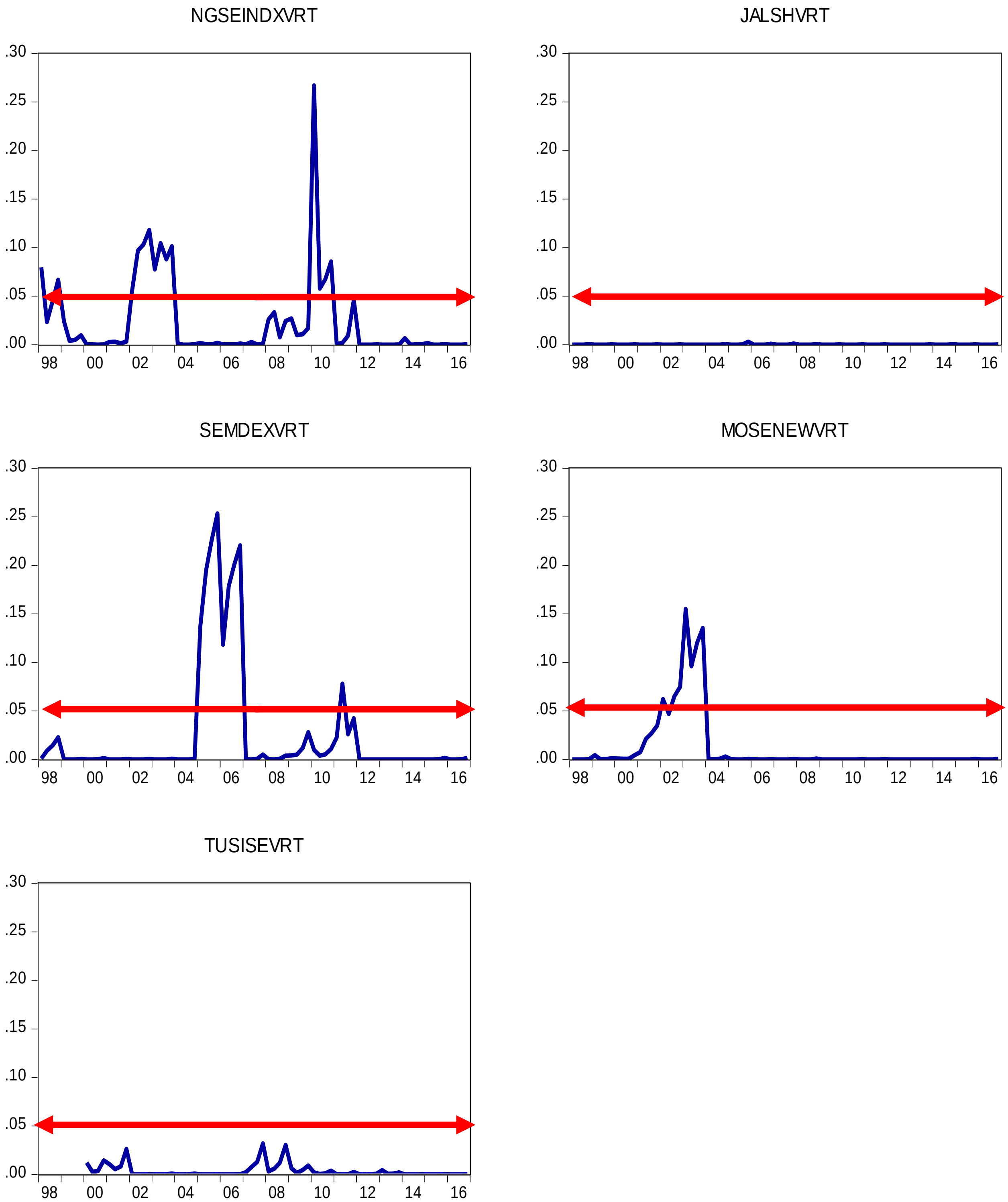

Figure 5.1: VRT P-VALUES (two-year window; rolled forward by 1 YEAR)

Red line implies 5% significant level.

MOSENEW *p*-values are smaller than 0.05 for the first three windows from 1998-2001, hence there are linear returns predictability and the market is inefficient. The inefficiency was intercepted by two windows (2001-2003) when *p*-values are not significant at the 5 percent level of significance, representing a cycle of efficiency or unpredictability. The rest of the windows from 2003 to 2017 signify sessions of significant linear correlation or return predictability. For TUSISE, each of the 17 windows has *p*-value of VR below 5 percent; hence, the market is linearly predictable at all time for the period under consideration. This is similar to the behaviour displayed by JALSH VRT. In essence, VR reveals that all the markets apart from the JALSH and TUSISE have undergone periods of linear dependency and independency as propounded by AMH.

5.3.2 Nonlinear Predictability Results

Linear dependence tests examined in the previous section are not enough to establish whether a market is weak-form efficient since there can be nonlinear dependence, which also implies a degree of predictability. The results of the nonlinear BDS test are presented and interpreted in this subsection. For the test to perform better, linear autocorrelation must firstly be removed before the estimation of the nonlinear BDS test because the presence of linear autocorrelation makes it difficult to detect nonlinear dependence (Alagidede, 2009; Urquhart, 2013). Hence, the Ljung-Box (LB) *Q*-statistic is fitted to returns up to lag order 20 to determine the lags at which returns become uncorrelated.

The results of the rolling window LB *Q*-statistic test are presented in Table 5.6. The results reveal that NGSEINDX and TUSISE for all the windows possess high autocorrelation beyond lag order 10 as indicated by significant *p*-value of LB *Q*-statistic. SEMDEX has autocorrelation in all the windows except 2000-2001. For MOSENEW, autocorrelations are found in all the periods except 2001-2002 and 2013-2014. JALSH, however, has 11 windows when returns are uncorrelated. Since virtually all the markets possess linear dependence as revealed by the LB *Q*-statistic test, it is necessary to filter the returns so that the BDS can capture nonlinear dependence. An AR (p)[34] model is fitted to the returns and its residuals are subjected to BDS test.

Results of BDS test on AR (p) whitened returns are reported in Table 5.7. BDS statistics at 2, 4 and 6 dimensions show that there exists a significant nonlinear dependence in return series for all markets and in all windows since the smallness of p-values leads to the rejection of null hypothesis of independent and identical distribution (*i.i.d.*). However, it has been established in the literature (Lim & Hooy, 2013; Urquhart, 2013) that nonlinear dependence in return series usually results from conditional heteroscedasticity, which cannot be filtered by ordinary AR(p) model. In addition, if nonlinear dependence were caused by conditional heteroscedasticity, it would not amount to violation of the EMH. Therefore, it is necessary to remove possible heteroscedasticity in the return index. Urquhart and McGroarty (2016) noted that nonlinear dependence caused by conditional heteroscedasticity could only be filtered by ARCH-type model; thus, AR-GARCH (1, 1) is also fitted to the returns. The standardised residuals of the AR-GARCH (1,1) are subjected to BDS test.

The results of the BDS test on the standardised residual of AR-GARCH (1, 1) are presented in Table 5.8 for the full sample period and rolling windows. BDS results in Table 5.8 reveal that nonlinear dependence in return series have diminished markedly compared to ordinary AR (p) filtered returns. It can be seen that while all markets except TUSISE possess nonlinear predictability in full sample period, the magnitude of dependent varies over time in rolling windows. In NGSEINDX nonlinear dependence is present in 1998 -1999, 2000-2001, 2002-2003, 2004-2005, 2007-2008, 2009-2010, 2013-2014, 2016-2017 and absent in the remaining six windows. JALSH has nonlinear dependence in 2003-2004 and 2008-2009, while the remaining windows are free of nonlinear dependence. SEMDEX also has nonlinear predictability in 1998 -1999, 2003 -2004, 2005-2006, 2007-2008, 2010-2011 and 2014-2015 while, other windows are free of nonlinear dependence. MOSENEW has linear dependence in 1998 -1999, 2000 -2001, 2002 -2003, 2007-2008, 2011-2012 and 2016-2017, while other windows are unpredictable as revealed in Table 5.8.

[34] The model required to filter the returns is AR (1).

Table 5.6: Ljung-Box statistics for the NGSEINDX, JALSH, SEMDEX, MOSENEW and TUSISE

Ljung-Box statistics								
	NGSEINDX				**JALSH**			
Lag	**5**	**10**	**15**	**20**	**5**	**10**	**15**	**20**
Full sample	**712.17*** **	**727.27*** **	**736.61*** **	**744.94*** **	**37.554*** **	**45.133*** **	**57.700*** **	**67.570*** **
1998 -1999	159.47***	166.16***	173.15***	183.44***	27.569***	34.106***	42.504***	47.672***
999-2000	163.25***	164.25***	181.38***	186.09***	20.007***	25.574***	31.332***	32.433**
2000-2001	191.85***	206.76***	215.04***	220.25***	9.2523*	11.213	15.868	20.152
2001-2002	93.519***	99.185***	103.47***	104.33***	9.3657*	20.808**	27.983**	34.302**
2002-2003	17.619***	24.133***	27.667**	28.081	16.326***	19.953**	22.281	26.008
2003-2004	33.005***	40.785***	42.287***	46.679***	18.717***	21.055**	25.389**	26.659
2004-2005	108.87***	117.44***	119.35***	127.76***	9.4427*	24.589***	27.82**	34.048**
2005-2006	120.59***	123.41***	124.75***	126.62***	3.6696	9.7703	16.014	27.156
2006-2007	117.66***	121.84***	127.21***	133.04***	5.0759	7.406	18.184	22.318
2007-2008	295.09***	301.23***	304.9***	313.81***	10.685*	14.928	17.295	32.083**
2008-2009	132.39***	135.36***	143***	145.42***	10.544*	13.956	18.937	27.2
2009-2010	37.194***	44.217***	51.01***	59.038***	4.5167	5.4473	9.3068	24.957
2010-2011	42.897***	50.543***	53.685***	64.315***	1.8774	9.389	11.514	20.337
2011-2012	39.906***	54.211***	59.795***	63.031***	6.037	12.56	16.303	24.934
2012-2013	24.234***	27.561***	35.283***	41.594***	11.55**	17.509*	22.803*	29.623*
2013-2014	85.044***	90.736***	92.983***	96.83***	9.8476*	13.03	16.015	23.431
2014-2015	105.48***	137.87***	143.76***	157.68***	5.3436	23.014**	37.673***	41.541***
2015-2016	83.658***	89.571***	107.62***	109.09***	5.8369	9.8132	14.718	15.303
2016-2017	63.05***	70.286***	72.343***	73.219***	13.45**	19.397**	22.281	23.083
	SEMDEX				**MOSENEW**			
Full sample	**40.695*** **	**81.420*** **	**91.617*** **	**107.27*** **	**291.83*** **	**300.12*** **	**309.82*** **	**314.58*** **
1998 -1999	115.43***	118.33***	147.08***	155.08***	134.02***	140.71***	146.7***	160.17***
1999-2000	139.97***	145.15***	146.21***	151.27***	76.374***	82.231***	83.367***	92.02***
2000-2001	2.8896	8.0867	11.038	20.128	48.783***	51.087***	53.789***	58.045***
2001-2002	25.762***	28.401***	34.85***	39.684***	5.9857	6.9124	7.5135	10.03
2002-2003	36.772***	41.511***	58.189***	72.032***	19.097***	20.542**	23.565*	30.023
2003-2004	26.48***	34.216***	41.512***	57.148***	74.838***	82.062***	87.405***	91.412***
2004-2005	44.401***	45.487***	47.359***	54.238***	37.906***	47.818***	55.336***	65.315***
2005-2006	52.05***	55.854***	64.013***	66.765***	77.582***	81.732***	89.865***	91.019***
2006-2007	31.86***	39.483***	45.543***	50.311***	69.5***	73.351***	81.403***	82.773***
2007-2008	26.702***	31.995***	40.92***	51.291***	46.594***	52.083***	62.918***	68.738***
2008-2009	30.236***	37.607***	45.495***	48.885***	45.201***	52.99***	55.648***	57.305***
2009-2010	52.279***	63.639***	70.271***	74.836***	53.603***	56.342***	58.143***	60.279***
2010-2011	36.398***	37.832***	40.896***	45.139***	30.222***	31.149***	34.941***	47.164***
2011-2012	17.762***	24.232***	25.986**	27.659	29.309***	33.254***	41.534***	65.883***
2012-2013	67.607***	95.055***	112.32***	123.03***	19.148***	23.184**	30.016**	34.835**
2013-2014	62.382***	68.36***	69.99***	76.139***	8.1064	10.681	13.657	26.728
2014-2015	59.917***	71.718***	76.016***	79.439***	11.363**	14.795	16.714	17.7
2015-2016	69.381***	79.08***	82.673***	88.152***	25.089***	26.856***	30.707**	33.078**
2016-2017	47.771***	56.098***	58.65***	61.663***	33.103***	45.617***	49.809***	52.018***
	TUSISE							
Full sample	**233.06*** **	**241.57*** **	**265.87*** **	**273.41*** **				
1998-1999	NA	NA	NA	NA				
1999-2000	NA	NA	NA	NA				
2000-2001	11.831**	21.182**	29.602**	33.149**				
2001-2002	11.985**	38.146***	44.718***	49.456***				
2002-2003	59.692***	59.692***	59.692***	59.692***				
2003-2004	33.407***	41.778***	49.174***	54.978***				
2004-2005	11.438**	13.613	15	19.945	NA			
2005-2006	60.036***	61.826***	63.834***	65.034***				
2006-2007	78.364***	88.056***	91.408***	99.27***				
2007-2008	19.857***	44.262***	59.427***	65.769***				
2008-2009	14.64**	28.334***	45.251***	49.835***				
2009-2010	19.296***	24.531***	26.495**	43.839***				
2010-2011	57.924***	71.72***	84.697***	111.68***				
2011-2012	75.909***	91.6***	99.686***	133.78***				
2012-2013	23.361***	26.172***	35.909***	39.218***				
2013-2014	50.4***	55.294***	57.118***	64.765***				
2014-2015	45.648***	52.525***	60.449***	66.45***				
2015-2016	25.794***	37.463***	45.16***	46.307***				
2016-2017	33.843***	37.135***	38.771***	50.475***				

***, **, *indicate *p*-values at 1%, 5% and 10% respectively.

Table 5.7: BDS statistics from BDS tests on the AR(*p*) filtered stock returns

Dimension	**2**	**4**	**6**	**2**	**4**	**6**	**2**	**4**	**6**
	NGSEINDX			**JALSH**			**SEMDEX**		
Full sample	**0.03672*****	**0.08972*****	**0.10458*****	**0.01750*****	**0.05588*****	**0.06898*****	**0.04874*****	**0.10981*****	**0.12392*****
1998-1999	0.05052***	0.12425***	0.15930***	0.02138***	0.07024***	0.08578***	0.03707***	0.08885***	0.09225***
1999-2000	0.03500***	0.07249***	0.08293***	0.00800**	0.02465***	0.03296***	0.02638***	0.05733***	0.05794***
2000-2001	0.04920***	0.04920***	0.11395***	0.01400***	0.03588***	0.04202***	0.00559	0.02217**	0.02685**
2001-2002	0.02452***	0.05311***	0.05752***	0.00873***	0.02710***	0.03214***	0.01816***	0.03574***	0.02944***
2002-2003	0.02045***	0.05498***	0.06244***	0.00413	0.01031*	0.01287**	0.02491***	0.05012***	0.05288***
2003-2004	0.02228***	0.05527***	0.05893***	-0.00031	0.01366**	0.02089**	0.02897***	0.06244***	0.07005***
2004-2005	0.02784***	0.0650***	0.06707***	0.00287	0.02108***	0.02904***	0.02293***	0.04584***	0.04967***
2005-2006	0.03238***	0.07111***	0.07469***	0.01749***	0.05096***	0.06222***	0.05982***	0.12230***	0.12560***
2006-2007	0.02707***	0.07559***	0.08650***	0.01137***	0.04501***	0.05398***	0.05636***	0.12208***	0.13272***
2007-2008	0.03039***	0.08183***	0.09673***	0.02411***	0.08994***	0.11846***	0.06141***	0.12382***	0.13671***
2008-2009	0.04574***	0.10137***	0.11533***	0.01286***	0.06060***	0.07961***	0.04716***	0.09318***	0.09715***
2009-2010	0.04026***	0.09312***	0.10715***	0.01082***	0.05379***	0.07404***	0.03710***	0.08655***	0.10054***
2010-2011	0.02566***	0.06465***	0.07504***	0.00753**	0.02909***	0.03696***	0.03326***	0.06924***	0.06906***
2011-2012	0.01216***	0.03103***	0.03419***	0.00763**	0.02982***	0.03652***	0.03296***	0.06955***	0.06898***
2012-2013	0.01521***	0.03176***	0.03437***	0.00390	0.01531**	0.02088***	0.01285***	0.02886***	0.03334***
2013-2014	0.03244***	0.06449***	0.06718***	0.00690**	0.03004***	0.04022***	0.01071***	0.02081***	0.02512***
2014-2015	0.03257***	0.08251***	0.09660***	0.01604***	0.05153***	0.06204***	0.00938***	0.01461**	0.01385**
2015-2016	0.03609***	0.09697***	0.11174***	0.01604***	0.05153***	0.06204***	0.01547***	0.03634***	0.03728***
2016-2017	0.04920***	0.11395***	0.12517***	0.01313***	0.04004***	0.04964***	0.01257***	0.04404***	0.04932***
REMARK	INEFFICIENT			INEFFICIENT			INEFFICIENT		
	MOSENEW			**TUSISE**					
Full sample	**0.033383*****	**0.081181*****	**0.092575*****	**0.029524*****	**0.065919*****	**0.070903*****			
1998 -1999	0.026121***	0.063461***	0.074513***	NA	NA	NA			
1999-2000	0.039020***	0.093268***	0.112677***	NA	NA	NA			
2000-2001	0.042567***	0.091463***	0.105479***	0.040409***	0.093543***	0.099858***			
2001-2002	0.040550***	0.088302***	0.102597***	0.030557***	0.072565***	0.080213***			
2002-2003	0.027415***	0.080826***	0.087704***	0.021723***	0.051485***	0.062281***			
2003-2004	0.023692***	0.064822***	0.068100***	0.024184***	0.056518***	0.056955***			
2004-2005	0.030597***	0.072962***	0.079677***	0.019471***	0.044081***	0.040404***			
2005-2006	0.029940***	0.082299***	0.110389***	0.012904***	0.029757***	0.028194***			
2006-2007	0.021478***	0.054560***	0.066818***	0.013681***	0.034816***	0.036839***			
2007-2008	0.030467***	0.091014***	0.099501***	0.037993***	0.078711***	0.086798***			
2008-2009	0.032182***	0.082987***	0.090750***	0.035000***	0.066148***	0.065184***			
2009-2010	0.026501***	0.055448***	0.057532***	0.031919***	0.060942***	0.061673***			
2010-2011	0.031973***	0.065726***	0.070277***	0.066088***	0.141463***	0.153580***			
2011-2012	0.024686***	0.058168***	0.064828***	0.050428***	0.110485***	0.118575***			
2012-2013	0.015223***	0.038004***	0.039969***	0.021693***	0.058209***	0.062937***			
2013-2014	0.017886***	0.034589***	0.036427***	0.024507***	0.055441***	0.058229***			
2014-2015	0.016003***	0.033512***	0.033883***	0.020070***	0.048828***	0.050072***			
2015-2016	0.020358***	0.050403***	0.050413***	0.021879***	0.051569***	0.055604***			
2016-2017	0.035212***	0.072899***	0.078274***	0.017658***	0.041748***	0.043675***			
REMARK	INEFFICIENT			INEFFICIENT			N/A		

The first row reports the dimensions. Reported values are the BDS statistics. ***, **, * indicate significance of *p*-value at 1%, 5% and 10%. A p-value < 0.05 means that the H_0 of a random walk is rejected at the 5% level, in favour of the H_1 that the returns are serially correlated.

Table 5.8: BDS statistics from BDS test on the AR-GARCH filtered stock returns

Dimension	**2**	**4**	**6**	**2**	**4**	**6**	**2**	**4**	**6**
	NGSEINDX			**JALSH**			**SEMDEX**		
Full sample	**0.00756*****	**0.01605*****	**0.01403*****	**-0.00231****	**-0.00158**	**-0.00023**	**0.00683*****	**0.012013*****	**0.0081*****
1998 -1999	0.00840**	0.01191*	0.01027	-0.00251	-0.00038	0.00315	0.00070***	0.01065***	0.01189***
1999-2000	0.00394	0.00203	-0.00234	-0.00281	-0.00162	0.00089	-0.00120	-0.00155	-0.00341
2000-2001	0.00730**	0.01115*	0.00749	0.00157	0.00698	0.00583	-0.00106	-0.00306	-0.00822
2001-2002	0.01022***	0.01415**	0.01341**	0.00083	0.00421	0.00452	0.00209	0.00126	0.00910
2002-2003	0.01354***	0.0255***	0.02373***	-0.00206	-0.00700	-0.00530	0.00867*	0.00852	0.00016
2003-2004	0.01431***	0.02968***	0.02835***	-0.00681**	-0.00836	-0.00509	0.01245**	0.01003	0.00084
2004-2005	0.00930**	0.01617**	0.01159	-0.00348	-0.00609	-0.00449	0.01438**	0.01354	0.00992
2005-2006	0.00618*	0.01744**	0.01798**	0.00160	0.00171	0.00191	0.01983***	0.02684***	0.01674*
2006-2007	0.00097	0.00989	0.01365*	0.00018	0.00576	0.00630	0.02116***	0.03579***	0.02998***
2007-2008	0.004241	0.02248**	0.02236**	0.00043	0.00532	0.00771	0.02062***	0.04566***	0.04414***
2008-2009	0.01230***	0.03011***	0.02542***	-0.00640**	-0.00782	-0.00850*	0.01416***	0.02337***	0.01761**
2009-2010	0.01036***	0.02968***	0.02960***	-0.00307	-0.00429	-0.00486	0.00854**	0.0076	0.00191
2010-2011	0.00593	0.02061**	0.02305**	-0.00084	-0.00056	0.00039	0.01148***	0.01744***	0.01110
2011-2012	0.00594	0.01092	0.00764	-0.00499	-0.00513	-0.00537	0.00862***	0.02073***	0.01554**
2012-2013	0.00518	0.00419	0.00021	-0.00211	-0.00406	-0.00420	-0.00021	0.00110	0.00383
2013-2014	0.00746**	0.00637	0.00048	-0.00233	0.00150	0.00129	-0.00101	-0.01081	-0.00756
2014-2015	0.00490	0.00971	0.00686	0.00150	0.00702	0.00598	-0.00335	-0.01426**	-0.01522**
2015-2016	0.00298	0.00779	0.00702	0.00054	0.00204	0.00426	-0.00459	-0.00399	-0.00560
2016-2017	0.01599***	0.02966***	0.02490***	0.00054	0.00204	0.00426	-0.00640	0.00170	-0.00078
REMARK	ADAPTIVE			ADAPTIVE			ADAPTIVE		

	MOSENEW			**TUSISE**			
Full sample	**0.007307*****	**0.013361*****	**0.011944*****	**0.000314**	**-0.000799**	**-0.001018**	
1998 -1999	0.014451***	0.030957***	0.036911***				
1999-2000	0.017544***	0.036184***	0.041344***				
2000-2001	0.010960***	0.016769**	0.016625**	0.004966	0.001938	-0.004195	
2001-2002	0.009178**	0.020043**	0.019623**	9.90E-05	0.001335	0.001605	
2002-2003	0.007779*	0.025416***	0.024152***	-0.006497*	-0.007953	-0.001134	
2003-2004	-0.000127	0.002155	-0.000443	-0.002433	-0.001706	-0.003768	
2004-2005	0.005984	0.012585*	0.008608	0.001559	0.000976	-0.003699	
2005-2006	0.003239	0.005631	0.004525	-0.002740	-0.011733*	-0.014361**	
2006-2007	0.002392	0.001522	-0.000304	-0.007195**	-0.013394**	-0.012596*	
2007-2008	0.007760**	0.018319***	0.011279	0.000758	-0.004880	-0.005252	
2008-2009	0.006322*	0.006675	0.000383	0.001363	-0.008962	-0.011943	
2009-2010	0.006556*	0.003811	0.002284	0.005825*	0.002886	0.000521	
2010-2011	0.009527**	0.011474*	0.008021	0.012709***	0.023810***	0.020320***	
2011-2012	0.008819***	0.010830*	0.007080	0.003926	0.011358*	0.009667	
2012-2013	-0.000247	-0.001691	-0.003839	-1.07E-05	-6.46E-05	-0.000202	
2013-2014	0.005229	0.005513	0.001963	0.000588	0.003618	0.006370	
2014-2015	0.004287	0.007266	0.002202	-5.17E-05	0.001568	0.002480	
2015-2016	0.000957	0.007074	0.007726	0.001512	0.003176	0.003467	
2016-2017	0.007756**	0.010265	0.008237	-0.000896	-0.001470	-0.003313	
REMARK	ADAPTIVE			ADAPTIVE			N/A

The first row reports the dimensions. Table values are the BDS statistics. ***, **, * indicate significance of *p*-value at 1%, 5% and 10%. A p-value < 0.05 means that the H_0 of a random walk is rejected at the 5% level, in favour of the H_1 that the returns are serially correlated.

TUSISE does not have nonlinear dependence in all windows except 2005-2006, 2006-2007 and 2010-2011. Suffice to state that there are cycles of nonlinear dependence and independence in the five markets as pointed out by AMH and that the majority of dependence observed in AR (*p*) filtered returns are due to conditional heteroscedasticity.

The time plots of the average *p*-values of BDS statistics over 2, 3, 4 and 5 dimensions are presented in Figure 5.2. It presents BDS *p*-values via rolling window analysis on NGSEINDX GARCH whitened returns. The *p*-values are not significant (above 0.05) in 1999-2000 window but become significant from 2000 to 2005 suggesting that returns are predictable in the latter period. There is statistically insignificant *p*-value and unpredictability in 2006-2007. The NGSEINDX is predictable from 2008 to 2011 and unpredictable from 2011 to 2016. JALSH BDS *p*-values are plotted in Figure 5.2. Over the 19 rolling windows, significant *p*-values are only observed in windows 2003-2004 and 2008-2009 indicating inefficiency or significant predictability. This implies that JSE ALSI is efficient or unpredictable for most of the periods as *p*-values are not statistically significant during 17 windows.

Figure 5.2 presents the *p*-values of the BDS through time for SEMDEX showing that the return is unpredictable from the first window in 1998 to the fifth window in 2002-2003 as the *p*-values are statistically insignificant. Nine windows of statistically significant return predictability follow from 2003 to 2012. Market efficiency is observed thereafter except for a window of inefficiency or predictability in 2014-2015. MOSENEW average *p*-values are statistically significant over the first four windows from 1998 to 2002. The nonlinear predictability was only intercepted in 2007-2008, 2010-2011 windows with remaining periods showing significant unpredictability. Figure 5.2 shows that TUSISE rolling BDS test has many windows during which market is efficient (with average *p*-values above 5 percent) and a few windows when it is inefficient (with *p*-values below 5 percent). Thus, nonlinear predictability can be found in 3 windows (2006-2007, 2010-2011 & 2011-2012) but absent in 14 windows. Generally, the BDS tests of the AR-GARCH filtered returns in rolling window reveal periods of return predictability and unpredictability through time, which is in line with the AMH.

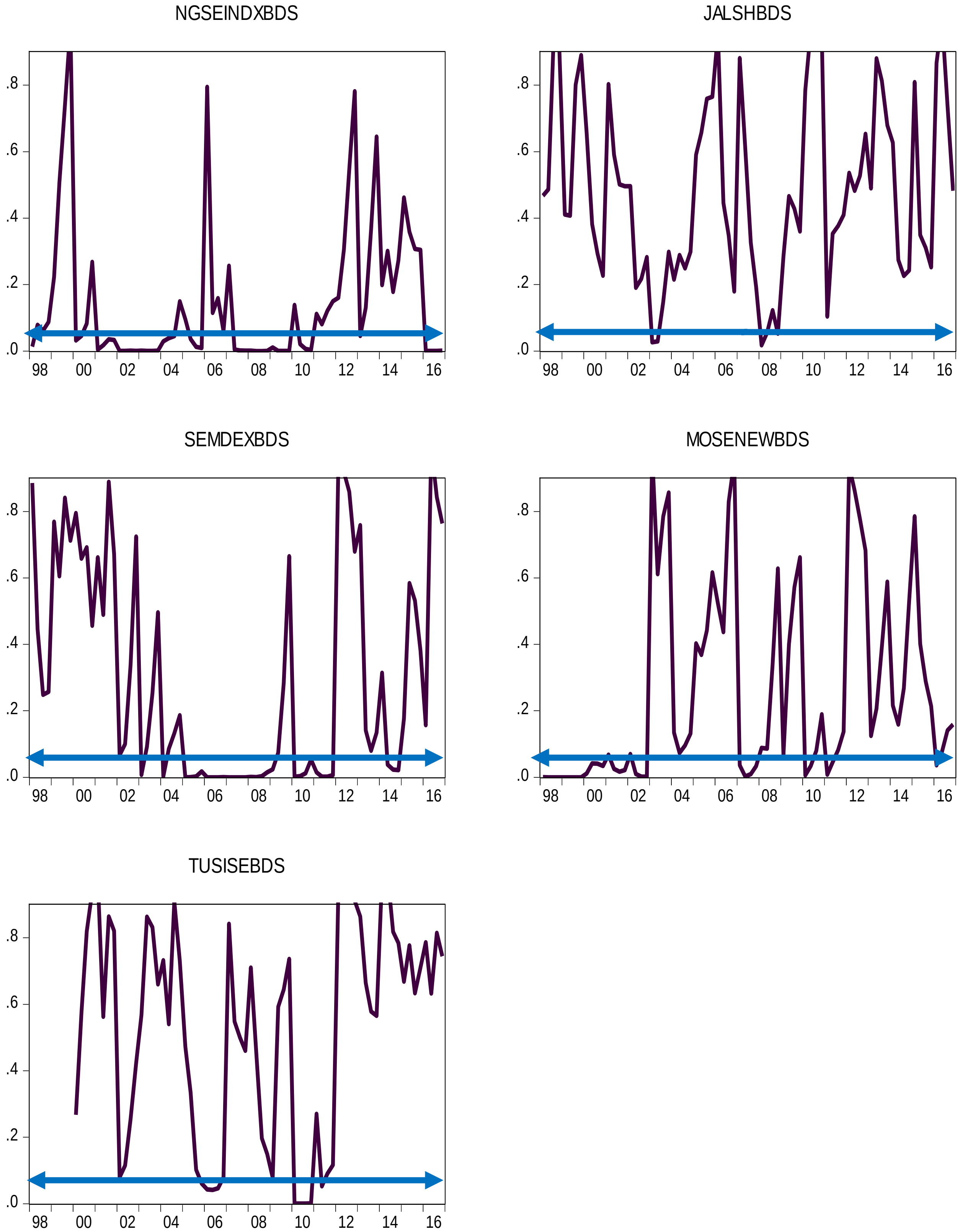

Figure 5.2: BDS P-VALUES (two-year window; rolled forward by one month)

Red line implies 5% significant level.

In summary, it was observed that most of the earliest studies (Working 1934; Kendall 1943; Osborne, 1962; Samuelson, 1965; and Fama, 1965, 1970) on market efficiency (notably from 1960 to 1980) support EMH, while subsequent (1988-2004) findings cast doubt on its validity (Kim *et al.,* 2011). This study investigates predictability of returns of the selected African stock exchange indices, namely the NGSEINDX, JALSH, SEMDEX, MOSENEW and TUSISE using daily data from January 1998 to February 2018. The study employs the BDS test as nonlinear predictability tool in addition to the linear VR test, the autocorrelation test and the unit root tests commonly used in the investigation of market efficiency particularly in the available African stock market studies. Varying levels of efficiency are tracked by estimating the two tests in two-year fixed-length rolling window, rolled forward by one year and by observing the significance of VR and BDS *p*-values over time. Doing so, the study contributes to the growing knowledge on AMH by documenting how stock return predictability has behaved over time via a combination of linear and nonlinear tests. Findings from this study, as summarised in Table 5.9, show that:

i. VRT tests show that NGSEINDX is an adaptive market; Linear autocorrelation shows that JALSH is an adaptive market; VRT and linear autocorrelation tests show that SEMDEX and MOSENEW are adaptive markets;
ii. ADF tests imply that all the markets are efficient over time, KPSS unit root tests, however, show that NGSEINDX, SEMDEX, MOSENEW and TUSISE return series pass through periods of stationarity and non-stationarity, suggesting cycles of efficiency and inefficiency in consonance with the proposition of the AMH in four of the five markets;
iii. Nonlinear BDS tests on the AR(*p*) filtered returns provide proof of significant return dependence in the five markets in spite of the removal of linear autocorrelations;
iv. However, it has been established in the literature that nonlinear dependence in return series could result from conditional heteroscedasticity, which cannot be filtered by ordinary AR(K) models, but by ARCH-type model. BDS results on the standardised residuals of AR-GARCH (1,1) model reveal that all the markets undergo phases of return predictability and unpredictability over time, in line with the AMH.

Table 5.9: Summary of Findings I

TEST	NGSEINDX	JALSH	SEMDEX	MOSENEW	TUSISE
VR	Adaptive	Inefficient	Adaptive	Adaptive	Inefficient
ADF	Efficient	Efficient	Efficient	Efficient	Efficient
KPSS	Adaptive	Efficient	Adaptive	Adaptive	Adaptive
ACF	Adaptive	Adaptive	Adaptive	Adaptive	Inefficient
AR-GARCH BDS	Adaptive	Adaptive	Adaptive	Adaptive	Adaptive

Table 5.9 reveals that NGSEINDX, SEMDEX and MOSENEW exhibit similar behaviour. In addition, JALSH appears as the most efficient series while TUSISE seems to be the most inefficient. Overall, there are more reasons to admit that all the markets (apart from TUSISE) are adaptive as opposed to inefficient. This finding permits the analyses of market conditions that favour return predictability.

5.4 Return Predictability and Market Condition

AMH explains that market is not always efficient, as inefficiencies exist due to changes in market and other environmental conditions. In other words, seasons of efficiencies and inefficiencies occur in turn repeatedly as conditions surrounding the market change. One of the implications of AMH is that market is not static but dynamic and that abnormal profits can arise and be predicted over time as a result of changing market conditions. In other words, predictability of stock returns changes under different market conditions. Markets and participants do not operate in isolation but they are influenced by factors and conditions such as technological revolution, economic condition, regulatory framework, psychology of market operators, market fundamentals and political environment (Kim, Doucouliagos & Stanley, 2014). Lo (2017) argues that investors' behaviour and market dynamics are affected by different environmental factors all of which impact on the behaviour of market returns. Since the analysis has established variations in efficiency in the previous section, the study probes further the explanatory power of prevailing market and economic conditions on return predictability in the selected African stock markets, since findings from developed markets might not provide a good approximation of what was obtained in the African stock markets.

For the examination of the effect of market conditions on return predictability in the selected African stock markets, monthly measures[35] of return predictability are generated (the measures are plotted in Figures 5.3 & 5.4) and specified as dependent on a host of dummies of market conditions. The figures present the monthly joint VR and average BDS *p*-values for the five markets over time (two-year rolling windows rolled forward by one month). The arrangement produced 204 monthly samples (*p-values*) for TUSISE over 1999:4 to 2018:2 and 219 for other markets, which are used as monthly measures of return predictability for the purpose of regression analyses. It is evident from the graphs that *p*-values undergo cycles over time as already established in the previous section. Having generated the *p*-values as monthly measures of return predictability, the essence here is to determine the response of these measures to changing market conditions.

[35]Procedure for generating predictability and market conditions are elucidated in Chapter 4 (Section 4.3.2.1).

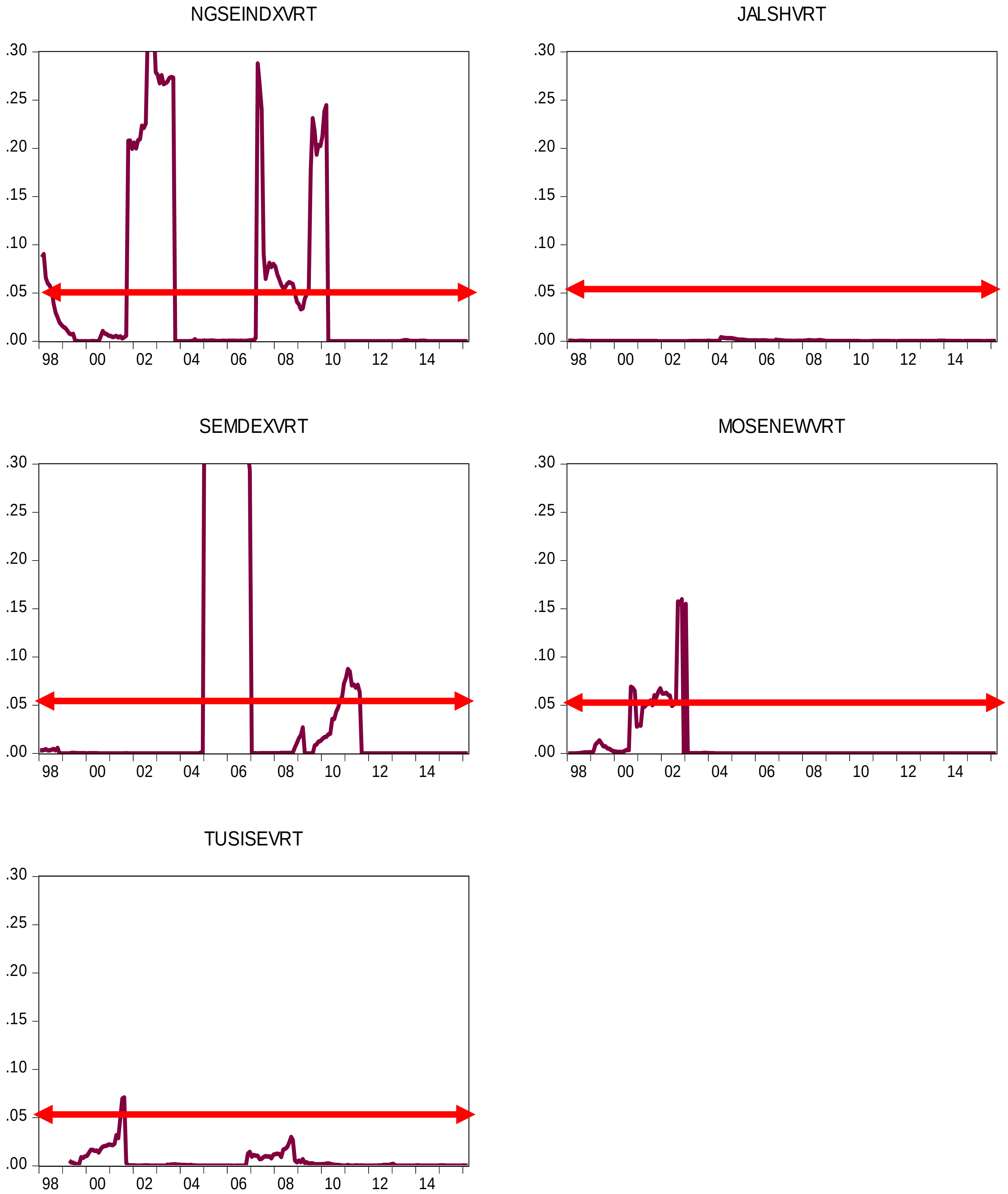

Figure 5.3: Linear Return Predictability

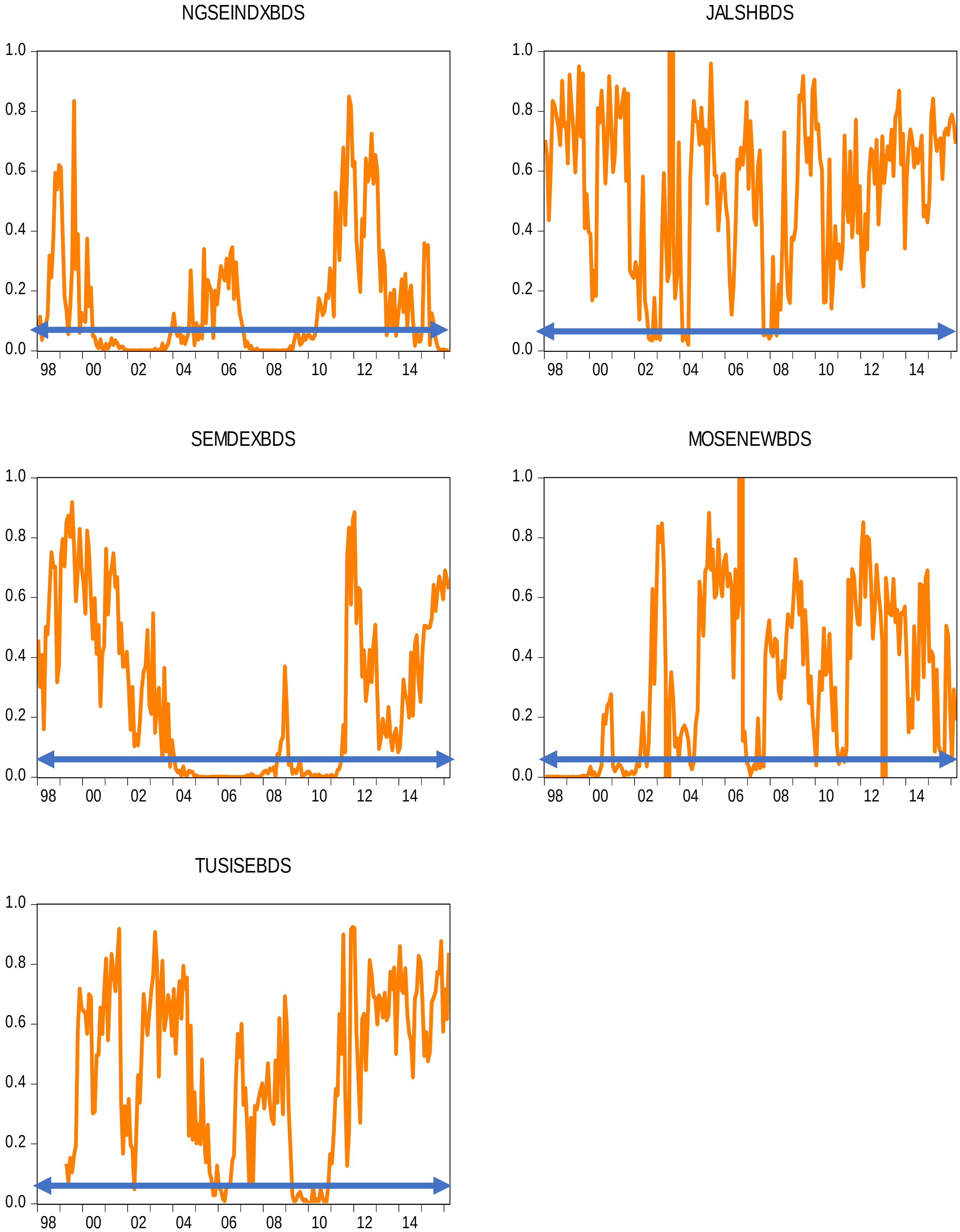

Figure 5.4: Nonlinear Return Predictability

Following the procedure described in Chapter 4 (Section 4.3.2.2), the number of up months, down months, bull months, bear months and normal months generated from the two definitions of market conditions for NGSEINDX, JALSH, SEMDEX, MOSENEW and TUSISE are shown in Table 5.10.

Table 5.10: Number of Months (windows) Characterised as Market Conditions

MARKET CONDITION	**NGSEINDX**	**JALSH**	**SEMDEX**	**MOSENEW**	**TUSISE**
UP	155	208	156	137	164
DOWN	64	11	63	82	40
BULL	62	76	66	57	65
BEAR	45	25	55	54	40
NORMAL	112	118	98	108	99
TOTAL	**219**	**219**	**219**	**219**	**204**
FINANCIAL CRISIS	19	19	19	19	19

In addition, realised volatility is obtained by taking the square root of sum of squared daily returns. The study, therefore, evaluates how the level of predictability of stock returns changes under different market conditions.

The results of the dummy regressions (equations 26 & 27 in Chapter 4) of monthly measures of return predictability fitted against an array of market conditions are presented in Table 5.11. The regression analysis is based on the two definitions (up, down & bull, bear, normal) of market conditions and of return predictabilities (VR and BDS). The two models are estimated and the right model is selected using the information criteria and diagnostic tests (both reported in appendix I). In the case of autocorrelation of unknown form, Newey-West HAC (heteroscedasticity and autocorrelation consistent) procedure is employed to correct the standard errors for possible autocorrelation (Newey & West, 1987).

Table 5.11 shows that the information criteria favour the bull, bear and normal condition definition in NGSEINDX as indicated by * symbol. Linear predictability regression model (VR *p*-values as dependent variable) results of NGSEINDX show that bull, bear and normal conditions have negative and significant coefficients. The NGSEINDX is associated with high linear return predictability under the bull, bear and normal market conditions, although return predictability is a bit higher during the bull (more negative -0.225505) than bear and normal period. A significant and positive coefficient of VOL in the VR equation indicates that linear predictability is low during period of high volatility. Nonlinear predictability regression (BDS *p*-values as dependent variable) results for NGSEINDX reveal that the bull, bear and normal market conditions have positive and significant coefficients, indicating that there is low non-linear predictability during bull, bear and normal market conditions. However, the nonlinear predictability is lower (more positive 0.161927) during the bull than bear or normal period. Negative signs of volatility depict high non-linear return predictability during the volatile period. The coefficient of financial crisis remains insignificant at 5 percent conventional level of significance, implying that the global financial crisis does not have a force to bear with return predictability in NGSE.

The JALSH regression results show that the up and down model minimises information criteria as indicated by * symbol. The up and down, financial crisis and volatility periods produce insignificant coefficients. The results hold both for the linear and nonlinear predictability models. Regression results disclose that the linear and non-linear return predictability is not associated with any market conditions for JALSH because none of the market condition dummies were found to have a significant coefficient. It means that market conditions do not have a significant effect on return predictability in JSE or the weak-form efficiency of JSE does not change with market conditions.

The up and down definition of market condition produces the best model for SEMDEX. VR-based regression results indicate high predictability during the financial crisis, while other conditions have no relationship with linear predictability. Based on the BDS test, there is a significantly low degree of predictability in the up and down periods (however, lower in up (more positive 0.404653***) than the down condition) whereas the nonlinear predictability is high during the period of high volatility.

SEMDEX BDS result is similar to that of NGSEINDX in terms of non-linear predictability, with significantly low linear predictability under all the market conditions, other than the global financial crisis period, where non-linear predictability is statistically significant and high.

From the MOSENEW results, the up and down model is also selected as the best model as indicated by information criteria. The degree of predictability is high during the financial crisis according to the joint VR test while the up and down period do not have a significant effect on return predictability. The coefficients of all the market conditions are not statistically significant according to the BDS results, meaning that the nonlinear predictability is not influenced by the market conditions.

The TUSISE results show that there is high and significant predictability during both up and down periods based on the VR tests, as the two conditions have significant negative coefficient estimates; although return predictability is a little higher (more negative -0.019624) during the up than the down market conditions. Thus, the return is more predictable during the up than the down market condition. VR results also demonstrate significantly low linear predictability during the high volatility periods. However, the financial crisis bears no relationship with return predictability. The predictability is low in both periods as suggested by BDS results; the BDS regression results disclose significant positive coefficients in both the up and down market conditions. It implies that nonlinear predictability is low irrespective of the market being in up or down condition. Although up and down market conditions are associated with low nonlinear predictability, it must also be noted that predictability is lower (more positive 0.267523) in the down than in the up months. This again shows that return is less predictable during the down than the up market condition in TUSISE. Results show significantly high nonlinear predictability during high volatility periods. The statistical insignificance of financial crises dummy in all regression results hints that the linear and nonlinear predictability are not influenced by financial crises.

Table 5.11: Regression Results: Return predictability and market condition dummies

Equation (24)			**Equation (25)**		
NGSEINDX					
CONDITIONS	**VRT**	**BDS HAC**	**CONDITIONS**	**VRT**	**BDS HAC**
UP	-0.180764***	0.449920***	BULL	-0.225505***	0.161927***
DOWN	-0.188801***	0.446507***	BEAR	-0.219078***	0.116758***
FC	-0.008226***	-0.016255	NOR	-0.223511***	0.154857***
VOL	0.010377***	-0.012588***	FC	-0.012276	0.030473*
	NA	NA	VOL	0.011482***	-0.005005***
JALSH					
CONDITIONS	VRT	BDS HAC	CONDITIONS	VRT	BDS HAC
UP	-0.001799	36.98990	BULL	-0.001734	42.31493
DOWN	-0.001859	46.60149	BEAR	-0.001689	31.73123
FC	-0.000177	4.805120	NOR	-0.001748	26.70194
VOL	8.50E-05	-1.207696	FC	-0.000203	8.263355
	NA	NA	VOL	8.26E-05	-1.049114
SEMDEX					
CONDITIONS	VRT	BDS HAC	CONDITIONS	VRT	BDS HAC
UP	0.062988	0.404653***	BULL	0.065799	0.389974***
DOWN	0.068659	0.332923***	BEAR	0.062773	0.379482***
FC	-0.147935***	0.001497	NOR	0.064120	0.402698***
VOL	NA	-0.007940**	FC	-0.147888***	-0.003940
AR(1)	NA	NA	VOL	NA	-0.008638**
MOSENEW					
CONDITIONS	VRT HAC	BDS	CONDITIONS	VRT HAC	BDS
UP	-0.002338	1300.872	BULL	-0.012227	733.0323
DOWN	-0.001705	581.9306	BEAR	-0.006886	703.0079
FC	-0.004803**	-364.5955	NOR	-0.005392	1689.260
VOL	0.000346	-30.19314	FC	-0.010256**	-385.2138
	NA	NA	VOL	0.001113	-39.94240
TUSISE					
CONDITIONS	VRT HAC	BDS	CONDITIONS	VRT HAC	BDS
UP	-0.019624**	0.245729***	BULL	-0.020698***	0.305625***
DOWN	-0.018833**	0.267523***	BEAR	-0.022889***	0.361234***
FC	-0.002911	-0.019363	NOR	-0.020932***	0.282563***
VOL	0.002057***	-0.010724**	FC	-0.003369	0.005815
	NA	NA	VOL	0.002213***	-0.014694***

P-values are symbolised as. ***, **, * which signify significance at 1%, 5% & 10% in that order.

In summary, this study investigates the AMH in African stock markets with a focus on market conditions using daily NGSEINDX, JALSH, SEMDEX, MOSENEW and TUSISE indices returns. The study contributes to the literature by becoming the first study to investigate predictability-cum-market conditions in the selected African stock markets. The *p*-values of joint VR test and BDS test, generated by implementing the tests in two-year rolling window rolled forward by one-month, are adopted as monthly measures of linear and non-linear predictability. Having established that the *p*-values undergo cycles over time, the study further examines the relationship between different market conditions and the cycles of efficiency. Findings from the regression analyses (as summarised in Table 5.12) of return predictability against series of up, down, bull, bear, normal, volatile and financial crisis market conditions dummies performed to determine the market condition that is associated with high predictability or otherwise show that:

i. NGSEINDX and TUSISE undergo high linear predictability in bull/up and bear/down market but the predictability is higher in bull/up than bear/down market respectively; while other markets are not influenced by up and down conditions;
ii. NGSEINDX and TUSISE undergo low linear predictability during high volatility; while other markets are not influenced by high volatility;
iii. There is high linear predictability in MOSENEW and TUSISE during financial crisis while there is no relationship between linear predictability and financial crisis in other markets;
iv. Linear predictability of JALSH returns has no relationship with market conditions.

From the nonlinear predictability regression results, we found that:

i. NGSEINDX, SEMDEX and TUSISE undergo low nonlinear predictability in bull/up and bear/down market; while other markets are not influenced by up and down conditions;
ii. NGSEINDX, SEMDEX and TUSISE undergo high nonlinear predictability during volatile period; while other markets are not influenced by volatility conditions;

iii. JALSH and MOSENEW show no relationship between nonlinear predictability and all the market conditions;

iv. There is no relationship between financial crisis and nonlinear predictability in all the market.

Table 5.12: Summary of Findings II

5.12A: Linear predictability (VR P-value)					
Conditions	**NGSEINDX**	**JALSH**	**SEMDEX**	**MOSENEW**	**TUSISE**
UP/BULL	High	-	-	-	High
DOWN/BEAR	High	-	-	-	High
NORMAL	High	*N/A*	*N/A*	*N/A*	*N/A*
FC	-	-	High	High	-
VOL	Low	-	-	-	Low
5.12B: Non-linear predictability (BDS *P-value*)					
Conditions	**NGSEINDX**	**JALSH**	**SEMDEX**	**MOSENEW**	**TUSISE**
UP/BULL	Low	-	Low	-	Low
DOWN/BEAR	Low	-	Low	-	Low
NORMAL	Low	*N/A*	*N/A*	*N/A*	*N/A*
FC	-	-	-	-	-
VOL	High	-	High	-	High

N/A implies not applicable

The findings show that the NGSEINDX, SEMDEX, MOSENEW and TUSISE return predictability is influenced by changes in market conditions in line with the AMH. However, both linear and nonlinear predictabilities are not influenced by market condition in JALSH. Hence, the hypothesis of market efficiency being influenced by changing market conditions holds in selected African Markets with the exception of JALSH.

5.5 Time Varying Calendar Anomalies

The main argument of the EMH is that stock returns or changes in stock prices are independent and unpredictable. However, several deviations and various types of patterns have been discovered in asset returns, which are contrary to the EMH and are hence, termed efficient market anomalies. One category of these anomalies, known as calendar anomalies, is examined in this section. Specifically, the DOW, MOY and HOM are examined with a view to determine whether its behaviour swings with time in line with AMH.

It is necessary to establish whether the returns are significantly different across the selected calendar periods (days, months and halves of the month) before embarking on the evaluation of calendar anomalies. The study employs *F*-test and Kruskal-Wallis (KW) tests of the difference in mean returns and Levene test for the difference in variance. KW and *F*-test test the null hypothesis of no significant difference in mean returns, while the Levene test tests the null hypothesis of no significant difference in variances across DOW, MOY and HOM. The tests are carried out in five-year rolling window, rolled forward by one-year. From the AMH point of view, one would expect windows where returns are significantly different and windows where they are not. The results of the full sample and rolling window analyses are presented separately for DOW, MOY and HOM.

5.5.1 Rolling ANOVA Results

The DOW *F*-test, KW and Levene tests are reported in Table 5.13. KW shows that NGSEINDX DOW returns are significantly different at 5 percent level of significance in full sample while other tests reveal that they are not. The rolling window *F*-test and KW results show that there exists no evidence of difference in mean returns for NGSEINDX but Levene test reveals that variances are significantly different in 2005-2009 and 2012-2016 windows. JALSH KW results reject the hypothesis of no significant difference among MON, TUE, WED, THUR and FRI returns in full sample while, other tests fail to reject the null hypothesis. Rolling window KW results, however, provide evidence of no difference in mean returns except for 1999-2003, 1991-2005 and 2003-2007 windows.

Table 5.13: F-test, Kruskal-Wallis statistics and Levene equality tests for DOW returns

Period	*F*-test	KW	Levene	*F*-test	KW	Levene
	NGSEINDX			JALSH		
Full sample	**0.749559**	**10.997*** **	**0.953491**	**1.852969**	**15.93906*** **	**15.93906**
1998-2002	0.585183	3.585531	0.398986	1.026309	7.565468	0.871434
1999-2003	0.085138	0.844342	0.074343	1.926218*	11.27476**	0.719170
2000-2004	0.299271	0.075553	0.077045	1.348082	7.286205	0.885681
2001-2005	0.121201	0.336754	0.156170	2.034333*	10.99359**	1.207349
2002-2006	0.453172	0.821498	0.290660	1.253308	6.496532	0.905446
2003-2007	0.510510	1.189858	0.414996	1.812699	10.73551**	1.089578
2004-2008	0.612167	2.423450	0.768623	0.571938	6.244648	0.749472
2005-2009	0.674957	4.761410	2.5345***	0.467873	5.708081	1.195102
2006-2010	0.752476	3.735647	1.259754	0.724672	6.654085	0.741830
2007-2011	0.739034	4.198151	0.616992	0.629960	3.741069	1.301551
2008-2012	0.415859	3.786872	0.433887	0.668466	3.841278	1.588539
2009-2013	0.589277	5.710864	0.868191	0.446033	2.563522	1.338609
2010-2014	0.610284	5.599813	1.183415	0.903162	5.030455	1.198907
2011-2015	0.789850	3.924114	1.690607	0.500130	3.174268	0.904831
2012-2016	0.696666	5.256765	2.771413**	0.863453	3.557958	0.540576
2013-2017	0.977205	8.173453*	2.130886*	0.972076	5.289718	0.589867
	SEMDEX			MOSENEW		
Full sample	**1.744213**	**14.87634*** **	**1.2192**	**1.274692**	**6.314256**	**0.220706**
1998-2002	0.776807	4.028789	0.4776	3.2753***	25.1452***	1.310073
1999-2003	0.686696	4.320018	0.6803	2.4876**	14.548***	0.768003
2000-2004	0.756389	4.588537	0.6501	2.057747*	13.808***	0.933330
2001-2005	0.728568	3.843732	0.8467	0.854525	4.416255	0.537251
2002-2006	1.355957	5.142417	1.5451	0.656406	4.034986	0.468731
2003-2007	1.326470	4.910472	1.1886	0.423365	2.421279	0.745785
2004-2008	1.234436	5.313318	1.6087	0.188218	2.208188	0.777185
2005-2009	1.297223	7.041456	1.2228	0.223704	2.632496	1.263059
2006-2010	1.101936	6.721185	1.0186	0.069902	1.106941	1.297038
2007-2011	0.754808	7.264005	0.2028	0.051366	0.750288	1.202675
2008-2012	0.759008	7.549177	0.4598	0.678423	2.906282	0.421828
2009-2013	1.377731	6.322894	1.1219	2.048861*	8.055162*	1.350005
2010-2014	2.7395**	8.024727*	0.4561	2.010416*	7.038763	3.0349***
2011-2015	1.546173	4.391075	0.9357	2.095687*	7.877932*	4.2475***
2012-2016	1.907377	3.788705	0.5989	0.557860	2.444315	3.9737***
2013-2017	2.098516*	6.389200	0.0414	0.841976	3.543476	2.208989*
	TUSISE					
Full sample	**3.4844*** **	**31.2107*** **	**0.458587** **			
2000-2004	0.580317	1.730301	0.058292			
2001-2005	0.434610	2.435901	0.154181			
2002-2006	1.047264	6.900377	0.216663			
2003-2007	2.59875**	11.14700**	0.113853			
2004-2008	2.4717**	8.826380*	0.728052			
2005-2009	1.910224	16.36742***	0.491617			
2006-2010	2.62315**	22.95977***	0.514186			
2007-2011	2.40489**	23.32070***	0.332679			
2008-2012	2.003648*	20.96485***	0.397546			
2009-2013	1.980664*	22.92868***	0.358328			
2010-2014	2.51123**	20.42340***	0.718205			
2011-2015	2.074286*	15.68575***	0.465927			
2012-2016	1.935739*	10.59920**	0.569610			
2013-2017	1.987155*	6.945931	0.267839	NA		

P-values are symbolised as. ***, **, * which signify significance at 1%, 5% & 10% and 10% in that order.

SEMDEX DOW returns are significantly different in full sample based on KW only but they are not different in rolling except for *F*-test result in 2010-2014 window. Results of the three tests show that the hypothesis of no significant difference cannot be rejected for MOSENEW in full sample at 5 percent level of significance. The rolling windows, however, show that there are three windows where mean returns (1998-2002, 1999-2003, 2000-2004) and variance (2010-2014, 2011-2015, 2012-2016) are statistically different. All the tests in full sample reject the hypothesis of no significant difference in mean and variance for TUSISE but there are windows of differences and similarities in DOW return. Overall, the tests show that there are windows when DOW mean returns are significantly different and windows when means are equal in compliance with AMH, except for NGSEINDX and SEMDEX, which support equality of mean all through.

Table 5.14 reports the MOY ANOVA results for the selected African stock markets. The full sample results show that NGSEINDX MOY returns and variance are significantly different across months of the year. Rolling window analyses, however, reveal that MOY returns are not significantly different in three windows from 2001-2005 to 2003-2007 while other windows are significantly different at 5 percent level of significance, based on *F*-test and KW test. It suggests that the market is adaptive. Conversely, the Levene test reveals that the variances of return are significantly different throughout at 5 percent significance level.

The JALSH result for the full sample period rejects the hypothesis of significant difference in mean and variance based on the three tests. The same result holds for *F*-test of difference in mean in rolling windows. The KW tests, however, show that mean returns are significantly different in 2000-2004 and 2001-2005 windows. Levene test discloses that variance is significantly different from 1998-2002 window through 2004-2008 window, not significantly different in 2005-2009, 2006-2010, 2008-2012, 2012-2016 and 2013-2017 while other windows are different in variances. Hence, the KW and Levene tests provide support for the AMH.

Table 5.14: F-test, Kruskal-Wallis statistics and Levene equality tests for MOY returns

Period	*F*-test	KW	Levene	*F*-test	KW	Levene
	NGSEINDX			JALSH		
Full sample	**3.929093*** **	**52.69568*** **	**4.846235*** **	**0.836070**	**13.86597**	**1.573238* **
1998-2002	3.554613***	35.82399***	6.601766***	1.339574	17.50030*	3.003715***
1999-2003	2.60760***	43.69079***	2.297988***	1.483796	18.58532*	2.714322***
2000-2004	1.814201**	34.91377***	0.0123***	1.626039*	19.75010**	1.829609**
2001-2005	1.630176*	24.47538***	2.409915***	1.730731*	22.30466**	2.445799***
2002-2006	0.926350	16.31509	4.973045***	0.774610	11.42188	2.259184***
2003-2007	1.232781	16.27164	6.221326***	0.563348	8.584278	2.548124***
2004-2008	2.013295**	24.17991***	6.558926***	0.265050	4.642293	2.324030***
2005-2009	2.720038***	26.90597***	3.404299***	0.217079	4.802165	1.159662
2006-2010	2.161071***	32.24529***	3.015445***	0.324732	7.878617	0.696872
2007-2011	2.896905***	47.27783***	2.140909**	0.437732	10.64376	1.768187**
2008-2012	2.250119***	31.25727***	2.039414**	0.351428	8.084422	1.591878
2009-2013	3.044787***	40.05947***	4.212615***	0.958648	11.16358	4.322552***
2010-2014	2.160629***	27.53484***	1.801565**	0.518168	5.765206	2.298248***
2011-2015	2.256168***	24.52610***	2.920128***	0.585883	7.880507	2.126648**
2012-2016	2.994187***	29.11568***	4.295286***	0.294268	4.056440	1.399426
2013-2017	3.271446***	33.54405***	4.971367***	0.588429	7.150462	2.277523
	SEMDEX			MOSENEW		
Full sample	**1.205283**	**27.07974*** **	**1.305379**	**2.620027*** **	**45.26267*** **	**3.859451*** **
1998-2002	0.0960*	27.61691***	2.222286***	1.771816**	26.38679***	2.496079***
1999-2003	3.103823***	38.36817***	1.711829*	1.678863*	16.33191	2.617382
2000-2004	3.771085***	39.35248***	3.344754***	2.478707***	26.29207***	3.151584***
2001-2005	3.687104***	39.56578***	2.505795***	2.358023***	35.98678***	3.306875***
2002-2006	1.215441	57.00166	3.479206***	1.949246**	36.85283***	1.927027**
2003-2007	1.135327	39.48213***	2.753414***	2.966897***	38.96177***	5.026463***
2004-2008	0.375317	31.21486***	3.357865***	2.950375***	44.41547***	6.099666***
2005-2009	0.472884	25.86043***	1.919465**	1.734018*	32.98280***	4.928189***
2006-2010	0.580715	18.65442*	1.976783**	2.278223***	38.33787***	5.175714***
2007-2011	1.180899	15.99618	1.467770	1.588711*	38.00432***	4.854776***
2008-2012	1.779433**	26.44237***	1.608358*	1.751422*	34.77406***	4.342654***
2009-2013	2.999264***	27.48320***	2.392810***	1.476528	24.76033***	3.888213***
2010-2014	1.453789	15.02385	4.084492***	1.253090	20.10647**	2.830811***
2011-2015	1.055833	11.71636	4.165456***	1.749529**	20.00363**	2.855585***
2012-2016	1.067160	12.35759	4.211069***	0.860379	10.84397	1.856115**
2013-2017	1.048104	10.87853	2.697881***	0.877216	12.73186	3.157458***
Period	TUSISE					
Full sample	**2.336475*** **	**2.336475** **	**4.470864*** **			
2000-2004	1.123250	15.06275	3.211507***			
2001-2005	2.150881***	23.28775***	4.385007***	NA		
2002-2006	2.703787***	22.25899**	6.161438***			
2003-2007	3.236688***	21.56504**	2.967003***			
2004-2008	2.423687***	21.25612**	3.315420***			
2005-2009	3.070024***	23.63168***	4.695464***			
2006-2010	3.356813***	30.61816***	7.100444***			
2007-2011	2.622053***	40.61631***	6.742785***			
2008-2012	3.967012***	51.25414***	6.767527***			
2009-2013	2.359824***	35.00279***	4.388572***			
2010-2014	0.888690	21.46794**	4.274227***			
2011-2015	1.160167	24.98152***	4.213432***			
2012-2016	3.098322***	38.72109***	2.850052***			
2013-2017	2.950707***	41.59891***	2.750322***			

P-values are symbolised as. ***, **, * which signify significance at 1%, 5% & 10% and 10% in that order.

SEMDEX full sample results show that MOY mean returns and their variances are not statistically different at 5 percent using *F*-test and Levene tests, while KW test shows that returns are significantly different. Conversely, the three tests in rolling window reveal that the acceptance and rejection of the hypothesis of no significant difference in mean and variance occur in turn repeatedly in line with AMH. *F*-test implies significant difference in return in 1999-2003 through 2001-2005 windows and in 2008-2012 and 2009-2013 windows. KW implies no significant difference in 2002-2006, 2006-2010 and the remaining windows from 2010-2014 through 2013-2017. Levene test shows that variances are significantly different in all except 1999-2003, 2007-2011, 2008-2012 windows.

The three tests in full sample reveal that returns and variance are significantly different for MOSENEW. Rolling window analyses reveal that there are few windows without evidence of significant difference. TUSISE result shows strong evidence that mean and variance differ across MOY. *F*-test and KW tests, however, show that MOY returns are not different in 2000-2004 and 2000-2004, 2010-2014, 2011-2015 windows respectively. The presence of windows of significant difference and similarity in MOY mean returns and variances also conforms to the AMH.

Table 5.15 reports the intra-month or HOM *F* -test, KW and Levene tests in full sample and rolling window. The full sample results show that HOM mean returns and variance are not significantly different at 5 percent in the five markets, except in TUSISE where Levene test shows significant difference in variances. Rolling window analyses, however, reveal that NGSEINDX HOM returns are significantly different in eight windows from 2000-2004 through 2006-2010 and 2011-2015 through 2013-2017, while other windows are not significantly different. The JALSH results show that first and second half of the months are significantly different in three windows over 1999-2003 to 2001-2005, while others are not. SEMDEX results reveal that returns are significantly different in 1998-2002 windows and from 2005-2009 to 2009-2013 windows, while other windows are not. MOSENEW and TUSISE HOM returns are not significantly different over the entire windows. NGSEINDX, JALSH and SEMDEX results indicate a rejection of the hypothesis of no significant difference in variances in rolling windows analyses.

Table 5.15: F-test, Kruskal-Wallis statistics and Levene equality tests for HOM returns

Period	*F*-test	KW	Levene	*F*-test	KW	Levene
	NGSEINDX			JALSH		
Full sample	**3.504036***	**1.296156**	**1.482347**	**0.208138**	**1.841337**	**1.802235**
1998-2002	0.010141	1.876671	0.562374	2.228201	3.699950*	0.024354
1999-2003	2.397227	0.220349	1.991584	11.77090***	11.02434***	0.573106
2000-2004	10.53487***	5.862756**	0.450718	5.957327**	4.933108**	0.037245
2001-2005	14.06896***	11.48664***	0.449939	5.819255**	5.451198**	0.114964
2002-2006	18.88392***	20.64335***	0.700192	1.574119	2.690347	0.006302
2003-2007	20.61559***	21.99179***	0.942775	0.009547	0.803312	0.548726
2004-2008	16.27951***	14.79035***	0.023997	2.375760	0.418061	0.215101
2005-2009	4.561873**	4.773029**	1.14E-06	0.322477	0.024704	0.250789
2006-2010	5.733498**	6.550470**	0.025310	0.049036	0.225831	1.489886
2007-2011	2.669291	1.874283	0.007973	0.077495	0.761672	0.709456
2008-2012	1.761682	1.515147	0.000300	0.230359	0.730315	0.501508
2009-2013	0.581116	0.309171	0.203850	1.992924	1.688241	0.267076
2010-2014	0.064118	0.009742	0.008063	0.194342	0.535800	0.201558
2011-2015	4.418374**	2.884326*	0.734089	1.249494	0.196936	0.732171
2012-2016	6.422636**	4.473753**	0.567400	2.101014	0.769483	1.726784
2013-2017	5.700117**	6.734512***	1.096012	3.526666*	1.430087	2.088432
	SEMDEX			MOSENEW		
Full sample	**1.683186**	**0.694571**	**0.054090**	**0.113953**	**0.304826**	**0.002228**
1998-2002	4.087571**	2.199539	1.002899	1.601492	0.349723	1.588745
1999-2003	3.083210*	2.183538	1.049436	1.490040	0.732676	2.268370
2000-2004	0.081924	0.036412	0.545146	0.484121	1.659054	2.458688
2001-2005	0.397085	0.733132	0.057948	0.324194	0.215548	2.446368
2002-2006	0.056748	0.049236	0.160647	0.994870	1.018090	0.112526
2003-2007	0.779972	0.783583	0.349782	0.565462	1.296982	2.574726
2004-2008	2.571835	4.393325**	0.359343	0.984550	1.878334	0.279272
2005-2009	4.296182**	6.525035**	0.013143	0.272450	0.003396	2.811861*
2006-2010	5.082626**	10.00746***	0.001002	0.252739	0.053463	3.104546*
2007-2011	6.950451***	8.499899***	0.242817	0.009044	0.244110	1.640343
2008-2012	5.876126**	8.506065***	0.266729	0.000890	0.112076	0.074816
2009-2013	5.063069**	5.534647**	2.284853	1.316267	2.391015	0.420007
2010-2014	0.864410	1.108383	0.359425	0.431729	2.226863	0.589678
2011-2015	0.013520	0.178283	0.091729	0.415457	2.574507	0.573835
2012-2016	0.259775	0.736747	0.221051	1.783313	0.830755	4.051883**
2013-2017	0.996068	1.943124	0.260001	1.783272	0.963298	2.381959
Period	TUSISE			NA		
Full sample	**0.585093**	**0.455855**	**4.777500****			
2000-2004	0.314119	0.469725	3.038280*			
2001-2005	0.008391	0.000864	2.189939			
2002-2006	0.503567	0.155955	4.553909**			
2003-2007	0.087565	0.596253	0.010986			
2004-2008	0.074975	0.671647	1.961189			
2005-2009	0.967229	1.331109	8.810859***			
2006-2010	0.602738	0.734379	10.58113***			
2007-2011	0.155558	0.146924	16.71245***			
2008-2012	0.244838	0.001344	11.45550***			
2009-2013	0.327643	0.022561	8.405829***			
2010-2014	0.396112	1.042076	3.309114*			
2011-2015	1.144672	1.428593	2.097269			
2012-2016	0.064916	0.014714	1.187944			
2013-2017	0.030094	0.073267	1.646989			

P-values are symbolised as. ***, **, * which signify significance at 1%, 5% & 10% in that order.

Moreover, the first and second half variances differ in 2012-2016 for MOSENEW and 2002-2006, 2005-2009,2006-2010, 2007-2011, 2008-2012, 2009-2013 in TUSISE. Based on the results of the *F*-test, KW and Levene tests, there are evidences that returns are significantly different in most cases but there are also periods of insignificant difference. Hence, the results support AMH in most cases. Since the ANOVA tests performed in this section only provide information as to whether cycles of significant difference (inefficiency/anomaly) alternate those of equality in mean returns (efficiency), they are not sufficient in the examination of calendar anomalies (as discussed in Section 4.3.3), because they do not provide specific information on each day or months. The study thus proceeds to the analyses of the behaviour of the three calendar anomalies, using GARCH estimations, which take into account the relevant features of stock returns. The possibility of time-changing behaviours is taken into consideration using rolling GARCH estimations.

5.5.2 Rolling GARCH Results

Given the motivation for GARCH models in the methodology section and the discovery of ARCH effect in the OLS regression (not reported), this study estimates the three calendar anomaly (DOW, MOY and HOM) models using the GARCH(1,1), EGARCH and TGARCH with student t distribution. The selected models are those that minimise information criteria (AIC and BIS as reported in Appendix II) and in which the estimated and model parameters are significant. The three GARCH models (GARCH (1, 1), EGARCH & TGARCH) are estimated for every window with the aim of capturing possible changes in asymmetry across windows. It is assumed that the model may change with windows, since windows are susceptible to change in sample size. The adequacy of the estimated models is evaluated using diagnostic tests as explained in Section 5.5.3.

The DOW GARCH results are given in Table 5.16, in which the mean equation results of the selected models for each window are reported since the objective focuses on the average returns across calendar periods. The columns of Table 5.16 contain window size, selected model, DOW coefficients (mean daily returns for each day), the ARCH parameters (A-alpha), leverage term (**γ**) and GARCH parameters (B-beta) respectively. From the DOW result in Table 5.16, leverage effect (γ) is not significant in all the windows for NGSEINDX, present in all windows for JALSH, in one window for SEMDEX, two windows for MOSENEW and four windows for TUSISE. Hence, the sign and magnitude of the asymmetry term is not the same across windows and markets. Such variation suggests different reactions of investors to new information.

From the full sample result in Table 5.16, it can be seen that there is presence of the weekend effect in African stock markets, characterised by negative Monday and positive Friday except in the JSE where the reverse of weekend effect is the case. Information criteria select mixture of EGARCH and GARCH (1, 1) models for different windows in NGSEINDX as shown in column 2 of Table 5.16. Neither the full sample nor the rolling windows display significant leverage effect (γ). In NGSEINDX returns, though most of the windows have negative Monday effect, significant negative Monday effect is found in 1998-2002, 2000-2004 and 2008-2012 windows and it shifts to negative Tuesday from 2007-2011 to 2009-2013 window. Weekend or Friday effect is fluctuating over time as shown by six (out of 16) windows of statistically significant coefficients.

Information criteria favour EGARCH model for JALSH in full sample and rolling windows except of 1999-2003 and 2010-2014 windows. All the windows are characterised with significant leverage effect (negative and significant signs of γ) suggesting that the negative shock causing volatility to increase by more than a positive shock of the same magnitude all the time. There is the DOW effect in JALSH, especially the positive Monday and Thursday effects. These DOW effects fluctuate in rolling windows. JALSH results show the opposite of weekend effect in full sample, evidenced by significantly positive and higher Monday returns. In addition, the positive Monday effect was present in the first nine windows except 2004-2008. The effect disappears in 2007-2011, 2008-2012, 2009-2013, 2011-2015 and 2012-2016. Thus, the rolling EGARCH results provide stronger proof of fluctuation in DOW (Monday and Thursday) effects.

EGARCH is selected for most of the windows in the SEMDEX, although there are five windows and three windows where GARCH and TGARCH are selected respectively. There is a significant asymmetric effect in 2007-2011 window when negative shock causes volatility to increase by more than a positive shock of the same magnitude. SEMDEX results show the presence of DOW and weekend effect in full sample. Friday returns are higher than other weekdays and the coefficients are significant except Monday and Tuesday, suggesting presence of weekend effect. Rolling window results reveal that there is no DOW effect in the first two windows (1998-2002; 1999-2003) and the last three windows (2011-2015; 2012-2016; 2013-2017), which implies that the SEMDEX switches between periods of anomaly and efficiency, hence, they are adaptive. In addition, Tuesday seems to be more negative than Monday. These results provide a stronger evidence of adaptive DOW effects.

Information criteria equally select EGARCH for most of the windows and there are only two windows (1998-2002 and 1998-2012) of significant leverage effect for MOSENEW. MOSENEW results also show that there is DOW effect characterised by weekend anomalies in full sample. There is no DOW effect for seven windows from 2007-2011 to 2012-2016. The negative Monday/Tuesday effects vary from significant negative in the first three windows to insignificant effect in 2001- 2005 and 2002-2006, to significant positive effect in 2003-2007 2004-2008 and 2005-2009 windows. Friday effect is not found before and after 2002-2006 to 2006-2010 windows. These results show that DOW effects vary over time as suggested by AMH.

TUSISE results are based on the combination of the two asymmetric models and the results show that there are at least four windows having significant leverage effect while others are not significant at 5 percent. Return displayed DOW and weekend effects in full sample as evidenced by significant high Friday returns and low and insignificant Monday and Tuesday returns. The effects, however, move between era of significance and insignificance in rolling window. Negative Monday effect is insignificant for most windows and there is significant positive Monday in 2006-2010. At least four windows are not associated with DOW effect; hence adaptive.

Table 5.16 GARCH results for DOW calendar anomaly for NGSEINDX, JALSH, SEMDEX, MOSENEW and TUSISE

SAMPLE	MODEL	MON	TUE	WED	THU	FRI	A	Γ	B
					NGSEINDX				
FULL	**EGARCH(1,1)**	**-0.0436*** **	**-0.0136**	**0.0001**	**0.0106**	**0.0511*** **	**0.3958*** **	**0.0222**	**0.9534*** **
1998-2002	GARCH(1,1)	-0.0666***	0.0074	-0.0250	-0.0126	0.0144	0.1647***	-	0.8547***
1999-2003	GARCH(1,1)	0.0064	0.0602	0.0489	0.0737*	0.0695	0.2457***	-	0.7160***
2000-2004	GARCH(1,1)	0.0851*	0.1077**	0.0749	0.1354***	0.1158***	0.3018***	-	0.6074***
2001-2005	EGARCH(1,1)	0.0397	0.0661	0.0591	0.1114***	0.0723	0.4368***	0.0590	0.8286***
2002-2006	EGARCH(1,1)	0.0035	0.0679	0.0060	0.0998**	0.1047**	0.4295***	0.0530	0.8689***
2003-2007	EGARCH(1,1)	0.0465	0.081297*	0.0832*	0.0988**	0.1482***	0.4275***	0.0667*	0.8781***
2004-2008	EGARCH(1,1)	0.0069	0.0015	-0.0111	-0.0080	0.0690	0.4154***	0.0086	0.8954***
2005-2009	EGARCH(1,1)	-0.0192	-0.0548	-0.0399	-0.0206	0.0796	0.4338***	-0.0013	0.9156***
2006-2010	EGARCH(1,1)	-0.0150	-0.0593	-0.0248	-0.0517	0.1019**	0.5054***	0.0022	0.8894***
2007-2011	EGARCH(1,1)	-0.0840	-0.1578***	-0.0426	-0.0869	0.0527	0.5047***	-0.0155	0.8773***
2008-2012	EGARCH(1,1)	-0.1225***	-0.1531***	-0.0296	-0.0443	0.0196	0.4931***	-0.0284	0.8735***
2009-2013	EGARCH(1,1)	-0.0608	-0.0782*	0.0701	0.0619	0.1161***	0.4535***	-0.0479	0.8962***
2010-2014	GARCH(1,1)	-0.0467	-0.0372	0.083211**	0.0194	0.0960**	0.2260***	-	0.6682***
2011-2015	GARCH(1,1)	-0.0414	-0.0678	0.0186	0.0064	0.0737	0.1760***	-	0.7572***
2012-2016	GARCH(1,1)	-0.0331	-0.0487	0.0149	0.0391	0.0745	0.2114***	-	0.7333***
2013-2017	GARCH(1,1)	-0.0383	-0.1001	0.0082	0.0364	0.0809	0.3450***	-	0.6044***
REMARK					**ADAPTIVE**				
					JALSH				
1998-2016	**EGARCH(1,1)**	**0.1826*** **	**0.0264**	**0.0204**	**0.1049*** **	**0.0327**	**0.1468*** **	**-0.0777*** **	**0.9834*** **
1998-2002	EGARCH(1,1)	0.2859***	0.0016	-0.0312	0.0751	0.0184	0.1503***	-0.0680***	0.9617***
1999-2003	TGARCH(1,1)	0.2601***	0.0086	-0.0900	0.0595	0.0651	0.0308***	0.0949***	0.8559***
2000-2004	EGARCH(1,1)	0.1350**	0.0578	-0.0903	0.0659	0.0467	0.1120***	-0.0751***	0.9739***
2001-2005	EGARCH(1,1)	0.2010***	-0.0125	-0.0544	0.1719***	0.1068*	0.1379***	-0.0671***	0.9763***
2002-2006	EGARCH(1,1)	0.1957***	0.0022	0.0160	0.1335***	0.1475***	0.1150***	-0.0787***	0.9781***
2003-2007	EGARCH(1,1)	0.2356***	0.0058	0.0228	0.1598***	0.1629***	0.1354***	-0.0910***	0.9724***
2004-2008	EGARCH(1,1)	0.2027***	0.0024	0.0379	0.2126***	0.0833	0.1439***	-0.1061***	0.9832***
2005-2009	EGARCH(1,1)	0.2860***	-0.0644	0.0609	0.1967	0.0684	0.1341***	-0.1025***	0.9845***
2006-2010	EGARCH(1,1)	0.2627***	-0.0537	0.0915	0.1624***	-0.0833	0.1340***	-0.1194***	0.9820***
2007-2011	EGARCH(1,1)	0.1254*	-0.0803	0.0365	0.0870	-0.0939	0.0756***	-0.1239***	0.9864***
2008-2012	EGARCH(1,1)	0.0690	-0.0066	0.0677	0.1142**	-0.0810	0.0894***	-0.1172***	0.9914***
2009-2013	EGARCH(1,1)	0.0810	0.0361	0.0590	0.1416***	-0.0094	0.0819***	-0.1032***	0.9899***
2010-2014	TGARCH(1,1)	0.0985**	0.0645	0.0186	0.0945**	-0.0158	-0.037***	0.1630***	0.9378***
2011-2015	EGARCH(1,1)	0.0370	0.0721	0.0005	0.0971**	0.0095	0.0449***	-0.1384***	0.9846***
2012-2016	EGARCH(1,1)	0.0633	0.0557	0.0032	0.0899**	0.0012	0.0614***	-0.1400***	0.9817***
2013-2017	EGARCH(1,1)	0.1458**	0.0404	-0.0139	0.0231	-0.0096	0.1072***	-0.1432***	0.9751***
REMARK					**ADAPTIVE**				
					SEMDEX				
1998-2016	**EGARCH(1,1)**	**0.0100**	**0.0092**	**0.0263*** **	**0.033358*** **	**0.0366*** **	**0.4450*** **	**0.0102**	**0.9324*** **
1998-2002	EGARCH(1,1)	0.0064	-0.0048	0.0052	0.0042	0.0337*	0.3527***	0.0243	0.9203***
1999-2003	EGARCH(1,1)	0.0091	-0.0167	0.0122	-0.0007	0.0328*	0.2161***	0.0318	0.9679***
2000-2004	GARCH(1,1)	0.0062	0.0049	0.0094	0.0246	0.0544***	0.1141***	-	0.8935***
2001-2005	EGARCH(1,1)	0.0519***	0.0173	0.0292	0.0533***	0.0838***	0.4052***	0.0637	0.8395***
2002-2006	GARCH(1,1)	0.0813***	0.0341	0.0563***	0.0780***	0.0942***	0.5475***	-	0.5142***
2003-2007	GARCH(1,1)	0.0884***	0.0544**	0.0795***	0.1005***	0.0938***	0.6702***	-	0.4521***
2004-2008	EGARCH(1,1)	0.0758***	0.0386	0.0611***	0.1012***	0.1016***	0.6531***	0.0289	0.8896***
2005-2009	EGARCH(1,1)	0.0741***	0.0216	0.0731***	0.0637**	0.1018***	0.7186***	0.0155	0.8859***
2006-2010	EGARCH(1,1)	0.0556*	0.0488	0.0885***	0.0933***	0.1289***	0.6231***	-0.0040	0.8705***
2007-2011	EGARCH(1,1)	-0.0439	0.0245	0.0526*	0.0528*	0.1115***	0.6261***	-0.0834**	0.8774***
2008-2012	EGARCH(1,1)	-0.0366*	-0.0206	0.0147	-0.0046	0.0638**	0.4328***	-0.0286	0.9516***
2009-2013	TGARCH(1,1)	0.0007	0.0226	0.0438**	0.0422*	0.0597***	0.2253***	0.0067	0.7541***
2010-2014	TGARCH(1,1)	-0.0201	0.0080	0.0237	0.0409**	0.0374**	0.2125***	0.0631	0.6158***
2011-2015	TGARCH(1,1)	-0.0330*	-0.0112	-0.0041	0.0190	0.0080	0.1389***	0.0890	0.5596***
2012-2016	GARCH(1,1)	-0.0124	-0.0150	0.0072	0.0229	0.0037	0.1077***	-	0.7077***
2013-2017	GARCH(1,1)	-0.0072	0.0121	0.0234	0.0403***	0.0119	0.0845***	-	0.7461***
REMARK					**ADAPTIVE**				
					MOSENEW				
1998-2016	**EGARCH(1,1)**	**-0.028380** **	**-0.015828**	**0.030990** **	**0.022183**	**0.043149*** **	**0.484487*** **	**-0.026473**	**0.894795*** **
1998-2002	EGARCH(1,1)	-0.114599***	-0.117220***	-0.030110	-0.024723	0.005806	0.602857***	-0.087232**	0.836421***
1999-2003	EGARCH(1,1)	-0.103210***	-0.108930***	-0.022297	-0.026698	-0.015810	0.589486***	-0.057504	0.827341***
2000-2004	EGARCH(1,1)	-0.072155***	-0.065181***	0.013499	0.023709	-0.012039	0.615753***	-0.030995	0.746731***
2001-2005	EGARCH(1,1)	0.003135	0.008796	0.054194*	0.070288***	0.053778*	0.604563***	-0.022939	0.692694***
2002-2006	EGARCH(1,1)	0.050767	0.065589**	0.091253***	0.092512***	0.098383***	0.496761***	0.022355	0.891982***
2003-2007	EGARCH(1,1)	0.118827***	0.133628***	0.122847***	0.096654***	0.129556***	0.398473***	0.039548	0.949950***
2004-2008	EGARCH(1,1)	0.089927***	0.111846***	0.062799*	0.112580***	0.132449***	0.526789***	0.009998	0.961114***
2005-2009	EGARCH(1,1)	0.102163***	0.127458***	0.027607	0.079036**	0.115477***	0.383795***	0.006567	0.947476***
2006-2010	TGARCH(1,1)	0.007794	0.081760**	0.017555	0.080327**	0.085965**	0.249964***	-0.033107	0.710854***
2007-2011	TGARCH(1,1)	0.001430	0.032516	0.011299	0.008078	0.043135	0.275950***	0.147423	0.510323***
2008-2012	TGARCH(1,1)	-0.059195	-0.026034	0.003055	-0.013939	-0.047925	0.171260***	0.267026***	0.583284***
2009-2013	GARCH(1,1)	0.001071	-0.002418	0.048696	-0.020193	-0.064720**	0.254110***	-	0.462750***
2010-2014	TGARCH(1,1)	-0.008092	-0.024274	0.050333	-0.021991	-0.031125	0.251748***	0.045656	0.504658***
2011-2015	TGARCH(1,1)	0.002236	-0.067486**	0.036258	-0.040874	-0.021874	0.130552***	0.098625*	0.672183***
2012-2016	TGARCH(1,1)	0.006443	-0.010616	0.041904	0.020676	0.013767	0.364207***	0.004404	0.808907***
2013-2017	EGARCH(1,1)	0.008823	0.006516	0.061723**	0.017084	0.071025***	0.272458***	-0.098654	0.534618***
REMARK					**ADAPTIVE**				
					TUSISE				
1998-2016	**TGARCH(1,1)**	**0.020827**	**-0.019413**	**0.019320**	**0.047864*** **	**0.086869*** **	**0.246456*** **	**0.077946***	**0.568821*** **
1998-2002	NA	NA	NA	NA	NA	NA	NA	NA	NA
1999-2003	EGARCH(1,1)	0.005496	-0.054546*	0.002701	0.016198	0.039552	0.382208***	0.039610	0.872675***
2000-2004	EGARCH(1,1)	0.002944	-0.064495***	-0.012060	-0.006953	0.011159	0.434497***	-0.016564	0.854674***
2001-2005	EGARCH(1,1)	-0.019542	-0.066444***	-0.032261	0.016323	0.031778	0.436279***	-0.041789	0.862468***
2002-2006	EGARCH(1,1)	0.033929	-0.034864	-0.001333	0.068581***	0.072577***	0.327479***	-0.007111	0.844195***
2003-2007	EGARCH(1,1)	0.037778	-0.006661	0.037939	0.070238***	0.113653***	0.358132***	-0.001078	0.828570***
2004-2008	EGARCH(1,1)	0.028940	-0.030133	0.039462	0.072094***	0.138907***	0.210994***	0.173627*	0.541411***
2005-2009	TGARCH(1,1)	0.045336	-0.010679	0.071254***	0.120501***	0.187763***	0.169728***	0.100736	0.655262***
2006-2010	TGARCH(1,1)	0.061307**	-0.003846	0.098109***	0.124722***	0.195640***	0.220957***	0.167167*	0.476138***
2007-2011	TGARCH(1,1)	0.032301	-0.032947	0.067983***	0.042805	0.158966***	0.171390***	0.183498**	0.606743***
2008-2012	TGARCH(1,1)	0.022013	-0.058208**	0.063962***	0.053098**	0.134077***	0.156113***	0.223758***	0.591428***
2009-2013	TGARCH(1,1)	0.003953	-0.029040	0.054679***	0.077338***	0.089654***	0.232501***	0.258971***	0.462821***
2010-2014	TGARCH(1,1)	-0.010433	-0.030799	0.014426	0.046935***	0.060437***	0.297393***	0.210489**	0.445810***
2011-2015	TGARCH(1,1)	-0.028015	-0.036258*	0.000177	0.024705	0.033171	0.300923***	0.160621	0.448796***
2012-2016	EGARCH(1,1)	-0.004778	-0.034420*	-0.021139	0.016798	0.038763*	0.479227***	0.004830	0.736342***
2013-2017	TGARCH(1,1)	0.018643	-0.007965	-0.019484	0.020802	0.055709***	0.237716	-0.036365	0.549346
REMARK					ADAPTIVE				

***, **, * signify significance at 1%, 5%, 10% level of significance. The ARCH parameters correspond to A (α-alpha), the leverage effect correspond to γ (Γ), the GARCH parameters to B (β-beta).

Additionally, the changing behaviour of MOY effects over time in selected African stock markets is also tracked with the aim of determining whether the effect changes in support of AMH as reported in Table 5.17. MOY coefficients in the table correspond to average return for each month. For NGSEINDX returns, a mixture of GARCH and EGARCH is selected and it can be seen in Table 5.17 that the MOY is not strong in full sample, albeit May and December effect at 10 percent level of significance. From rolling window analyses, there is no feasible MOY effect in 1998-2002, 2004-2008, 2011-2015 and 2015-2016 windows but other windows are associated with different MOY anomalies. In addition, the January effect is not predominant, although there are two windows (2003-2007; 2010-14) of significant positive January returns, which are dominated by December and May effect respectively. Thus, there is a significant positive May effect in 2003-2007 and 2013-2017, representing two windows. Positive June effect is found in four windows from 1999-2003 through 2002-2006, which turns negative in 2009-2013 while the effect is not found in other windows. Otherwise, significant negative August, September and October effects are found in four windows from 2005-2009 to 2008-2012. The results thus indicate changes in behaviour of identified MOY anomalies over time in line with the AMH.

Asymmetric models are selected for JALSH in full and rolling windows with significant leverage effect as shown in Table 5.17. JALSH results display the presence of MOY effects in full sample with positive and significant April, August, October, November and December effects. The MOY effect fluctuated in rolling windows. For instance, December/April effect is observed in the first two windows 1998-2003, August effect in five windows from 2000-2004 and 2005-2009, May effect in five windows from 2002-2006 to 2006-2010, January effect in 2006-2010 and October effect in six windows from 2008-2012 to 2013-2017. It supposes that the MOY effects vary over time and hence, adaptive. However, the popular January effect is not predominant in full and rolling windows

For SEMDEX, there are two windows (2007-2011 & 2008-2012) with significant leverage effect. Full sample results show that there are significant MOY effects, notably positive January, May, June, September and December, which are dominated by popular January effect. A look at the rolling window analyses reveals that the January effect is absent in the first two windows, appearing in six windows from 2000-2004 through 2006-2010 and evaporates thereafter. Thus, there are seven windows of significant positive January returns in which the first three windows are significantly higher than other months of the year. The positive September effect remains in eight windows from 2001-2005 to 2007-2011 and 2009-2013 although the effect is only dominant in the last five of the seven windows. There are also negative February and April effects in 2008-2012 and 2005-2009 windows respectively and March and July effects in 2003-2007 and 2005-2010 respectively. October has positive effect in three windows and November in two windows. The December effect remains in five windows and it is higher than other months from 2008-2012 to 2010-2014. These show that the effects identified in the full sample undergo fluctuations in rolling windows while the months without anomaly in full sample have few windows of anomaly. This behaviour supports the argument inherent in AMH.

For SEMDEX, Table 5.17 shows that significant leverage effect is found in four windows. It can also be seen that MOSENEW exhibits MOY effect in full sample notably positive January, February, April and August and negative June effects with August returns greater than other months of the year. However, the positive January, February and April effects are not present before and after 2002-2006 to 2008-2012 (seven) windows with January effect being particularly strong in three windows from 2005-2009 to 2007-2011. Significant negative June effect is only found in four windows while March also shows negative effect in 2008-2012 and 2009-2013 windows. The July, September, November and December effect, though absent in full sample, are found to have negative effect in 1999-2003, 2000-2004; 1998-2002; 2001-2005, 2002-2006, 2003-2007; 2001-2005 windows respectively and positive effect in 2013-2017; 2013-2017; 2007-2011; 2011-2015 respectively. All the evidences found here are different from the full sample results and show that MOY effects are fluctuating.

Table 5.17 reveals that leverage effect is found in full sample and five windows from 2001-2005 to 2010-2014. The TUSISE full sample results show that the MOY effect is present and the January effect is greater than other months.

Table 5.17 GARCH results for MOY calendar anomalies for NGSEINDX, JALSH, SEMDEX, MOSENEW and TUSISE

SAMPLE	MODEL	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEPT	OCT	NOV	DEC	A	γ	B
								NGSEINDX								
FULL	**EGARCH(1,1)**	**-0.0057**	**0.0069**	**-0.0307**	**0.0167**	**0.0759***	**0.0527**	**-0.0304**	**-0.0212**	**-0.0458**	**-0.0044**	**-0.0068**	**0.0693***	**0.3989*****	**0.020**	**0.9532*****
1998-2002	GARCH(1,1)	-0.0314	-0.0393	-0.0126	-0.0826	-0.0059	0.0676	-0.0361	-0.0213	-0.0709	0.0455	0.0252	0.0290	0.1664***	-	0.8527***
1999-2003	GARCH(1,1)	-0.0127	-0.0356	0.0448	0.0028	0.1145	0.339***	-0.1220	0.0663	-0.0428	0.0554	0.0713	0.1484*	0.2490***	-	0.7176***
2000-2004	GARCH(1,1)	0.2127*	0.1466	-0.0198	0.1534	0.1597	0.3318***	-0.0703	0.0106	-0.0314	0.0296	0.0616	0.2501***	0.3006***	-	0.6114***
2001-2005	EGARCH(1,1)	0.1033	0.0529	-0.0618	0.1854*	0.0993	0.2491***	-0.0417	-0.0623	0.0536	0.1006	0.0937	0.0852	0.4371***	0.060	0.8214***
2002-2006	EGARCH(1,1)	0.0237	0.0099	-0.1078	0.0824	0.1420	0.2480***	0.0312	0.1180	0.0482	-0.0213	0.0083	0.1575	0.4368***	0.052	0.8679***
2003-2007	EGARCH(1,1)	0.3761**	0.1556	-0.0469	0.2070	0.1498	0.1783	-0.0029	-0.0645	0.1751	0.1388	0.0148	0.5014***	0.2014***	-	0.7778***
2004-2008	EGARCH(1,1)	0.1477	0.2122*	-0.0821	-0.0057	0.0471	0.1694	0.0474	-0.2119*	-0.2025	-0.187539*	-0.0112	0.1418	0.4307***	0.004	0.8945***
2005-2009	EGARCH(1,1)	-0.0560	0.1776	-0.1006	-0.0476	0.0873	0.1392	0.0738	-0.1861	-0.2748**	-0.2251**	-0.0366	0.1209	0.4521***	-0.008	0.9128***
2006-2010	EGARCH(1,1)	-0.0421	0.2303*	-0.0411	-0.0125	0.1697	0.1581	0.0334	-0.3170***	-0.348***	-0.2474**	0.0305	0.0969	0.5342***	-0.002	0.8840***
2007-2011	EGARCH(1,1)	0.0151	0.2209*	-0.0279	0.0067	0.0553	-0.0856	-0.0790	-0.4822***	-0.384***	-0.1868*	-0.0369	0.0744	0.5351***	-0.020	0.8650***
2008-2012	EGARCH(1,1)	-0.0040	0.0524	-0.1352	-0.0237	0.0267	-0.1755	-0.0855	-0.2559**	-0.2514**	-0.2747***	-0.0537	0.0719	0.5002***	-0.034	0.8686***
2009-2013	EGARCH(1,1)	0.1387	-0.0512	-0.0509	0.1574	0.1605	-0.1772**	0.0446	-0.1597*	0.0186	0.1064	-0.0246	0.0748	0.4525***	-0.019	0.8951***
2010-2014	GARCH(1,1)	0.1628**	-0.0409	0.0369	0.1094	0.1763**	-0.0811	0.0210	-0.1202	-0.0015	0.0364	-0.0121	0.0583	0.2281***	-	0.6652***
2011-2015	GARCH(1,1)	0.0536	-0.0375	0.0212	0.1062	0.1327	-0.1141	-0.1082	-0.0856	0.0939	-0.0629	-0.0673	0.0918	0.1609***	-	0.7811***
2012-2016	GARCH(1,1)	0.0210	-0.0029	0.1004	0.0730	0.1331	-0.0867	-0.0923	-0.0302	0.1372*	-0.1280*	-0.0958	0.1440*	0.1992***	-	0.7453***
2013-2017	GARCH(1,1)	-0.0563	-0.0120	0.0928	0.0225	0.2910***	0.0040	-0.1000	-0.1121	0.0751	-0.1129	-0.0828	0.1031	0.3414***	-	0.5939***
								JALSH								
FULL	**EGARCH(1,1)**	**0.0599**	**0.0547**	**0.0693***	**0.1359*****	**0.0292**	**-0.0360**	**0.0719***	**0.0816****	**0.0497**	**0.1235*****	**0.0786****	**0.1187*****	**0.1452*****	**-0.07*****	**0.9837*****
1998-2002	EGARCH(1,1)	0.1375	0.0253	0.1855	0.3713***	-0.1663	-0.0599	-0.1433	0.0886	-0.1236	0.1058	0.1730	0.3821***	0.1085***	-0.087***	0.9664***
1999-2003	EGARCH(1,1)	-0.0077	-0.0609	0.0596	0.2764**	-0.0047	0.0001	-0.1390	0.1588	-0.1208	0.1311	0.1777	0.3736***	0.1303***	-0.076***	0.9474***
2000-2004	EGARCH(1,1)	0.0425	-0.0691	-0.0843	0.0242	0.1176	-0.1408	-0.1023	0.3153***	-0.0124	0.0199	0.2084**	0.1198	0.1140***	-0.089***	0.9744***
2001-2005	EGARCH(1,1)	-0.0152	0.0780	-0.0557	-0.0494	0.2375***	-0.1001	0.0715	0.2588***	0.1754*	0.0020	0.2139**	0.1419	0.1228***	-0.079***	0.9749***
2002-2006	EGARCH(1,1)	0.0768	0.0889	-0.0031	-0.0500	0.2804***	-0.0732	0.1253	0.2443***	0.1856**	0.0401	0.0937	0.0929	0.1089***	-0.090***	0.9764***
2003-2007	EGARCH(1,1)	0.0994	0.0962	0.0144	0.0082	0.2668***	-0.0580	0.1861	0.2334***	0.1911**	0.0869	0.0543	0.1406	0.1289***	-0.101***	0.9709***
2004-2008	EGARCH(1,1)	0.1153	0.1421	0.0193	0.0172	0.1615*	-0.0959	0.1899***	0.1921***	0.2043**	0.0413	0.0663	0.1041	0.1308***	-0.113***	0.9834***
2005-2009	EGARCH(1,1)	0.0980	0.1480	0.0805	0.0177	0.1906**	-0.0728	0.2140***	0.1309	0.1518	0.0938	-0.0276	0.1606	0.1228***	-0.108***	0.9849***
2006-2010	EGARCH(1,1)	0.1596**	0.0599	0.1620	0.1741*	0.0842	-0.1845*	0.1387	-0.0326	0.0461	0.1532*	-0.0392	0.0649	0.1037***	-0.131***	0.9833***
2007-2011	EGARCH(1,1)	-0.0306	0.0727	0.0697	0.1613*	-0.0807	-0.1990**	0.1394*	-0.0623	0.0352	0.1648	-0.0630**	-0.0358	0.0667***	-0.139***	0.9866***
2008-2012	EGARCH(1,1)	0.0273	0.0121	0.1011	0.1461*	-0.1069	-0.1325*	0.0815	0.0377	0.0898	0.1365**	-0.0116	0.0327	0.0709***	-0.124***	0.9929***
2009-2013	EGARCH(1,1)	0.0362	0.0172	0.130**	0.1481*	0.0891	-0.1750**	0.1020	0.0390	0.0804	0.1459**	0.0015	0.0889	0.0645***	-0.113***	0.9919***
2010-2014	TGARCH(1,1)	0.0291	0.0316	0.0474	0.1202*	0.0381	-0.0375	0.0470	0.0138	0.0814	0.1466***	-0.0018	0.0472	-0.044***	0.163***	0.9464***
2011-2015	EGARCH(1,1)	0.0117	0.0431	-0.0245	0.1110**	0.0267	0.0224	0.0218	0.0595	-0.0174	0.1236***	-0.0217	0.0633	0.0332**	-0.152***	0.9830***
2012-2016	EGARCH(1,1)	-0.0051	0.0670	0.0016	0.0828	0.0689	0.0552	0.0112	0.0281	0.0202	0.0747	-0.0053	0.1179**	0.0552***	-0.145***	0.9827***
2013-2017	EGARCH(1,1)	-0.0353	0.0297	-0.0028	0.0739	0.0621	0.0159	0.0540	0.0079	-0.0357	0.1328***	0.0693	0.0197	0.0895***	-0.145***	0.9805***
								SEMDEX								
FULL	EGARCH(1,1)	0.0541***	0.0039	0.0003	0.0122	0.0360***	0.0391***	0.0101	0.0014	0.0420***	0.0078	0.0143	0.0420***	0.4479***	0.010	0.9312***
1998-2002	EGARCH(1,1)	0.0011	0.0216	-0.0305	-0.0495	0.0314	0.0956***	-0.0393	0.0232	-0.0466	-0.0029	0.0454	0.0169	0.3459***	0.022	0.9199***
1999-2003	EGARCH(1,1)	0.0219	-0.0029	-0.0518	-0.0453	0.0489	0.0651*	-0.0715*	0.0081	-0.0143	0.0261	0.0434	0.0036	0.2079***	0.025	0.9706***
2000-2004	EGARCH(1,1)	0.0763***	0.0095	-0.0525	0.0293	0.0477	0.0370	-0.0498	-0.0189	0.0478	0.0460	0.0257	-0.0121	0.1651***	0.045	0.9732***
2001-2005	GARCH(1,1)	0.1314***	0.0426	0.0476	-0.0283	0.0644*	0.0561*	-0.0080	0.0093	0.1069**	0.0536	0.0751**	0.0225	0.2903***	0.065	0.8926***
2002-2006	**GARCH(1,1)**	0.2236***	0.0360	0.0505	-0.0699*	0.0500	0.0404	0.0441	0.0343	0.1721***	0.0986***	0.1067***	0.0889**	0.8415***	-	0.2377***
2003-2007	**GARCH(1,1)**	0.1528***	0.0756*	0.0842**	-0.0328	0.0647	0.0384	0.0473	0.0213	0.2592***	0.1444***	0.1214***	0.0798**	0.8209***	-	0.4332***
2004-2008	TGARCH(1,1)	0.1370***	0.0919*	0.0619	-0.0757	0.0204	0.0208	0.0717	0.0145	0.2404***	0.1058*	0.1108**	0.0557	1.1222***	-0.037	0.4238***
2005-2009	**EGARCH(1,1)**	0.1004***	0.0606	0.0598	-0.1226***	0.0406	0.0570	0.1292***	0.0747*	0.3077***	0.0780	0.0531	-0.0081	0.7785***	0.003	0.8974***
2006-2010	**EGARCH(1,1)**	0.0968*	0.0020	0.0434	0.0126	-0.0223	0.1089	0.1463***	0.0510	0.2821***	0.1286	0.0675	0.1058	0.6327***	-0.013	0.8725***
2007-2011	**EGARCH(1,1)**	0.1038	-0.0603	-0.0101	0.0766	0.0221	0.0877	0.0189	0.0081	0.1603**	0.0590	-0.0725	0.0649	0.6400***	-0.090**	0.8745***
2008-2012	**EGARCH(1,1)**	0.0154	-0.1841***	-0.0230	0.0589	0.0010	0.0068	-0.0358	-0.0756	0.0632	-0.0266	-0.0339	0.0974**	0.5283***	-0.067**	0.9446***
2009-2013	TGARCH(1,1)	0.0430	-0.0224	0.0593	0.0496	0.0086	0.0034	-0.0270	0.0167	0.0971**	0.0514	0.0058	0.1195***	0.2141***	0.005	0.7688***
2010-2014	TGARCH(1,1)	0.0273	-0.0204	0.0184	0.0240	0.0087	0.0054	-0.0136	0.0052	0.0619	0.0267	-0.0198	0.0820**	0.2141***	0.059	0.6220***
2011-2015	TGARCH(1,1)	-0.0326	-0.0060	0.0008	-0.0072	-0.0061	0.0094	-0.0283	-0.0235	0.0241	-0.0021	-0.0424	0.0529	0.1408***	0.076	0.5728***
2012-2016	GARCH(1,1)	-0.0311	-0.0232	0.0046	-0.0142	-0.0258	0.0078	0.0040	-0.0221	0.0457	-0.0085	-0.0065	0.0453	0.1050***		0.7036***
2013-2017	GARCH(1,1)	0.0198	0.0130	-0.0069	0.0324	-0.0013	0.0420	0.0338	0.0325	0.0359	-0.0210	-0.0200	0.0296	0.0805***		0.7518***
								MOSENEW								
FULL	**EGARCH(1,1)**	**0.0590****	**0.0624****	**-0.0029**	**0.0610****	**0.0151**	**-0.0659*****	**-0.0113**	**0.1045*****	**-0.0250**	**0.0042**	**-0.0498***	**-0.0068**	**0.4915*****	**-0.025**	**0.8893*****
1998-2002	EGARCH(1,1)	-0.0309	-0.0293	0.0148	-0.0924*	-0.0820*	-0.1298***	-0.1038*	0.1986***	-0.1002**	-0.0905**	-0.0827*	-0.0050	0.6145***	-0.088**	0.8329***
1999-2003	EGARCH(1,1)	-0.0211	-0.0684	-0.0657	-0.0846	-0.0869*	-0.1204**	-0.1254**	0.0804	-0.0736	-0.0354	-0.0327	0.0178	0.5942***	-0.049	0.8186***
2000-2004	EGARCH(1,1)	0.0232	0.0051	0.0028	-0.0303	-0.0448	-0.1181**	-0.1315**	0.0514	-0.0662	-0.0631	-0.0075	0.0937	0.6312***	-0.028	0.7389***
2001-2005	EGARCH(1,1)	0.0650	0.0937	-0.0402	0.0702	0.0176	-0.0812	-0.0314	0.1611***	-0.0707	0.0129	0.1478**	0.1200**	0.6152***	-0.021	0.6949***
2002-2006	EGARCH(1,1)	0.1296**	0.0891	0.0140	0.1287**	0.0317	-0.0559	0.0235	0.2161***	-0.0260	0.0635	0.2056***	0.1335*	0.5072***	0.028	0.8913***
2003-2007	EGARCH(1,1)	0.1708***	0.1910***	0.0256	0.1979***	0.1308**	-0.0170	0.0493	0.2571***	0.0006	0.0903*	0.1538***	0.0721	0.4215***	0.035	0.9456***
2004-2008	EGARCH(1,1)	0.1317***	0.1668***	0.0827	0.1015**	0.1073**	-0.0270	0.0460	0.1514***	-0.0160	0.0764	0.0667	0.0714	0.4427***	0.040	0.9395***
2005-2009	EGARCH(1,1)	0.2633***	0.1883**	-0.0499	0.1538**	0.1828***	-0.0432	0.0028	0.2374***	-0.0611	0.1387**	-0.0300	0.0635	0.4280***	-0.009	0.9353***
2006-2010	GARCH(1,1)	0.2803***	0.1580**	0.0188	0.1692***	0.0746	-0.0313	-0.0382	0.0934	0.0089	0.0801	-0.0662	0.0577	0.2811***		0.6500***
2007-2011	TGARCH(1,1)	0.2246***	0.1775***	-0.0575	0.1268**	0.1308**	-0.0884	-0.0473	0.0352	-0.0066	0.0331	-0.1312**	0.0353	0.2878***	0.195*	0.4684***
2008-2012	TGARCH(1,1)	0.1397*	0.1527**	-0.153***	0.0219	0.1329**	-0.1096*	-0.0821	-0.0154	-0.0728	-0.0342	-0.1196*	-0.0143	0.2015***	0.300***	0.5235***
2009-2013	TGARCH(1,1)	0.0765*	0.1046*	-0.1140**	0.0771	0.1213**	-0.0797	-0.0967*	-0.0094	-0.0130	0.0328	-0.0913	-0.0282	0.2121***	0.114	0.4601***
2010-2014	TGARCH(1,1)	0.0332	0.0810	-0.0526	0.0155	0.1083**	-0.1207***	-0.0208	0.0148	0.0612	0.0173	-0.0917	-0.0841*	0.2658***	0.039	0.4880***
2011-2015	TGARCH(1,1)	-0.0391	0.1026**	-0.0727	-0.0911*	0.0792	-0.0908*	-0.0064	0.0220	0.0115	0.0734*	-0.0918	-0.1245***	0.1214***	0.092***	0.6852***
2012-2016	EGARCH(1,1)	0.0165	0.0855**	-0.0082	-0.0090	0.0191	-0.0442	0.0804*	0.0109	0.0630	0.0830*	-0.0379	-0.0738	0.3722***	0.004	0.8192***
2013-2017	EGARCH(1,1)	0.0102	0.0599	0.0408	0.0399	0.0122	0.0086	0.1000**	0.0147	0.1032**	0.1000**	-0.0516	-0.0376	0.4010***	0.062*	0.7579***
								TUSISE								
FULL	**TGARCH(1,1)**	**0.0668*****	**0.03825**	**0.012469**	**0.0622*****	**0.0327**	**0.0533****	**0.0571*****	**0.0490****	**-0.002**	**0.0139**	**0.0049**	**-0.0114**	**0.2417*****	**0.089****	**0.5716*****
1998-2002	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
1999-2003	EGARCH(1,1)	-0.0986	-0.0632	-0.0369	-0.0268	0.0056	-0.0020	0.1242***	-0.0049	0.1422***	-0.0337	0.0125	0.0376	0.3732***	0.026	0.8780***
2000-2004	EGARCH(1,1)	-0.0727	-0.0638	0.0033	0.0197	-0.0366	-0.0278	0.0572	-0.0475	0.1110**	-0.0265	-0.0386	0.0416	0.4193***	-0.031	0.8589***
2001-2005	EGARCH(1,1)	-0.0725*	-0.0714	0.0192	0.1625***	-0.0374	-0.0502	0.0357	-0.0454	0.0742	0.0047	-0.0573	0.0109	0.4276***	-0.069*	0.8641***
2002-2006	EGARCH(1,1)	-0.0420	0.0258	0.0801	0.1478***	0.0448	-0.0485	0.0262	-0.0154	0.1470***	0.0259	-0.0250	0.0131	0.3105***	-0.029	0.8473***
2003-2007	TGARCH(1,1)	0.0628	0.0464	0.0918*	0.1604***	0.0181	-0.0334	0.0095	0.0266	0.1034**	0.0790	0.0339	0.0213	0.3572***	-0.018	0.8080***
2004-2008	TGARCH(1,1)	0.1461***	0.0343	0.3137***	0.0974*	0.0352	0.0033	-0.0221	0.0718	0.0821*	0.097**	0.0149	-0.0144	0.1855***	0.205**	0.5466***
2005-2009	TGARCH(1,1)	0.1221***	0.0544	0.0917*	0.1513***	0.0615	0.1198***	-0.0228	0.1174***	0.1473***	0.0841	0.0437	0.0266	0.1564***	0.128*	0.6312***
2006-2010	TGARCH(1,1)	0.2476***	0.0474	0.0592	0.1437***	0.0580	0.1127**	-0.0069	0.1864***	0.2250***	0.0571	0.0438	-0.0004	0.3041***	0.125*	0.6989***
2007-2011	TGARCH(1,1)	0.1797***	-0.0116	0.0067	0.0771*	0.0021	0.1204***	0.0307	0.1140***	0.1410***	0.0352	0.0187	-0.0219	0.1586***	0.240***	0.5894***
2008-2012	TGARCH(1,1)	0.0459	0.0071	0.0173	0.1035***	0.0087	0.1150***	0.0741**	0.0931***	0.1108***	-0.0110	-0.0157	-0.0394	0.1749***	0.251***	0.5450***
2009-2013	TGARCH(1,1)	0.0768	0.0106	0.0382	0.1240***	0.0106	0.1018**	0.1008**	0.0873**	0.0251	-0.0186	-0.0231	-0.0514	0.2328***	0.278***	0.4550***
2010-2014	TGARCH(1,1)	0.0880**	0.0677	0.0030	-0.0093	0.0236	0.0372	0.1245***	0.0440	-0.0639*	0.0091	-0.0416	-0.0724	0.3186***	0.217**	0.4340***
2011-2015	EGARCH(1,1)	0.0555	0.1186***	-0.0174	-0.0123	0.0225	0.0709*	0.0721*	-0.0046	-0.1113***	-0.0183	-0.0342	-0.0331	0.2846***	0.152	0.4923***
2012-2016	EGARCH(1,1)	0.0973***	0.0985***	-0.0166	-0.0061	0.0579	0.0133	0.0469	-0.0056	-0.1164***	0.0136	-0.0259	-0.0531	0.4807***	-0.017	0.7600***
2013-2017	EGARCH(1,1)	0.1123***	0.1040***	-0.0477	-0.0076	0.0644*	0.0662*	0.0390	0.0247	-0.1072***	0.0037	0.0221	-0.0392	0.3852***	0.003	0.7915***

. ***, **, * signify significance at 1%, 5%, 10% level of significance. The ARCH parameters correspond to Α (α-alpha), the leverage effect correspond to **γ** (Γ), the GARCH parameters to Β (β-beta).

Rolling window results, however, disclose that January effect has fluctuated between periods of insignificant effect in 1999-2003 to 2003-2007 (five) windows to significant effect in 2004-2008 to 2007-2011 and return to insignificance in 2008-2012 and 2009-2013. Specifically, positive September effect exists in 8 windows and is higher than other months in four windows, 1999-2003, 2000-2004 and 2005-2009 windows; April effect is found in seven windows and superior from 2001-2005 to 2003-2007; January effect is found in seven windows and dominant in 2004-2008, 2006-2010, 2007-2011 and 2013-2017; July effect in four windows and dominant in 2010-2014 and February effect in three windows from 2011-2015 to 2013-2017 windows in TUSISE. These results conform to the time varying behaviour of AMH. The full time results would imply that January effect is present at all times and fail to disclose periods where the effect disappear or is dominated by other months.

Furthermore, the GARCH results for HOM effect is given in Table 5.18 and coefficients correspond to average return of each half of the month. The full sample result shows that NGSEINDX average return is positive in the first half and negative in the second half but the coefficients are not statistically significant. It can be seen from the rolling window results that the HOM effect does not exist in the first two windows. The effect, however, occurs in 2004-2008, 2005-2009, 2006-2010 and 2007-2011 windows and disappears thereafter, meaning that the HOM effect is time varying. There is no significant leverage effect as reported in the DOW/MOY model.

In Table 5.18, JALSH results show that the HOM anomaly is present in full sample and the effect changes in cyclical version from rolling window reports. All the windows indicate presence of leverage effect (γ) in JALSH return with significant and appropriate signs as noted previously. The first halves of the months display significantly higher average returns from 1998-2002 windows to 2006-2010 windows but the HOM effect disappears in 2007-2011 and 2008-2012 windows. The effect reappears in 2009-2013 and 2010-2014 and disappear afterward, typical of the cyclical type of behaviour inherent in AMH. There are 7 windows of HOM effect.

Table 5.18: GARCH results for HOM calendar anomaly for NGSEINDX, JALSH, SEMDEX, MOSENEW and TUSISE

SAMPLE	MODEL	FIR	SEC	Α	Γ	Β	*Prob*	MODEL	FIR	SEC	Α	γ	Β
				NGSEINDX							JALSH		
FULL	**GARCH(1,1)**	**0.0077**	**-0.0069**	**0.3951*** **	**0.0219**	**0.9538*** **	**0.3122**	**EGARCH(1,1)**	**0.0876*** **	**0.0471*** **	**0.1456*** **	**-0.0788*** **	**0.9840*** **
1998-2002	GARCH(1,1)	-0.0276	-0.0012	0.16485***	-	0.8540***	0.1577	TGARCH(1,1)	0.1512***	-0.0189	0.0328**	0.0956***	0.8730***
1999-2003	GARCH(1,1)	0.0276	0.0769**	0.2431***	-	0.7214***	0.1633	TGARCH(1,1)	0.1876***	-0.0618	0.0333**	0.0967***	0.8543***
2000-2004	GARCH(1,1)	0.1173***	0.0905**	0.2987***	-	0.6095***	0.8360	EGARCH(1,1)	0.1169***	-0.0337	0.1202***	-0.0770***	0.9705***
2001-2005	EGARCH(1,1)	0.1169***	0.0209	0.4348***	0.0583	0.8279***	0.9540	TGARCH(1,1)	0.1488***	0.0088	0.0270***	0.1000***	0.9052***
2002-2006	EGARCH(1,1)	0.1368***	-0.0431	0.4133***	0.0555	0.8744***	0.9121	EGARCH(1,1)	0.1346***	0.0497	0.1179***	-0.0783***	0.9777***
2003-2007	EGARCH(1,1)	0.1591***	-0.0007	0.4150***	0.0696	0.8842***	0.6693	EGARCH(1,1)	0.1416***	0.0810**	0.1387***	-0.0902***	0.9717***
2004-2008	EGARCH(1,1)	0.0662	-0.0697	0.4190***	0.0061	0.8975***	0.3861	EGARCH(1,1)	0.1006***	0.0972***	0.1447***	-0.1033***	0.9833***
2005-2009	EGARCH(1,1)	0.0209	-0.0732	0.4384***	-0.0053	0.9168***	0.9600	EGARCH(1,1)	0.1233***	0.0844**	0.1352***	-0.0984***	0.9850***
2006-2010	EGARCH(1,1)	0.0276	-0.0694	0.5109***	-0.0047	0.8894***	0.7990	EGARCH(1,1)	0.1046**	0.0481	0.1310***	-0.1142***	0.9820***
2007-2011	EGARCH(1,1)	-0.0504	-0.1015**	0.5097***	-0.0248	0.8766***	0.7702	EGARCH(1,1)	0.0587	-0.0236	0.0676***	-0.1177***	0.9877**
2008-2012	EGARCH(1,1)	-0.0599	-0.0977**	0.4854***	-0.0394	0.8749***	0.9649	EGARCH(1,1)	0.0626	0.0003	0.0823***	-0.1148***	0.9920***
2009-2013	EGARCH(1,1)	0.0311	0.0016	0.4450***	-0.0134	0.8962***	0.8153	EGARCH(1,1)	0.0851***	0.0369	0.0788***	-0.1026***	0.9906***
2010-2014	TGARCH(1,1)	0.0148	0.0209	0.1836***	0.0891	0.6692***	0.7520	TGARCH(1,1)	0.0718***	0.0283	-0.039***	0.1600***	0.9423***
2011-2015	TGARCH(1,1)	-0.0236	0.0069	0.1145***	0.0881*	0.7868***	0.2673	EGARCH(1,1)	0.0295	0.0492*	0.0409**	-0.1451***	0.9844***
2012-2016	GARCH(1,1)	0.0016	0.0235	0.1978***	-	0.7487***	0.5913	EGARCH(1,1)	0.0318	0.0545**	0.0614***	-0.1417***	0.9818***
2013-2017	GARCH(1,1)	-0.0180	0.0225	0.3230***	-	0.6207***	0.9909	EGARCH(1,1)	0.0162	0.0516*	0.1112***	-0.1436***	0.9744***
				SEMDEX							MOSENEW		
FULL	**EGARCH(1,1)**	**0.0244*** **	**0.0208*** **	**0.4472*** **	**0.0101**	**0.9322*** **	**0.1371**	**EGARCH(1,1)**	**0.0175**	**0.0061**	**0.4841*** **	**-0.0248**	**0.8913*** **
1998-2002	EGARCH(1,1)	0.0082	0.0084	0.3518***	0.0250	0.9203***	0.4214	EGARCH(1,1)	-0.0560***	-0.053***	0.5947***	-0.0792**	0.8255***
1999-2003	EGARCH(1,1)	0.0057	0.0098	0.2143***	0.0313	0.9687***	0.5018	EGARCH(1,1)	-0.0482	-0.054***	0.5857***	-0.0423	0.8085***
2000-2004	EGARCH(1,1)	0.0258*	0.0184	0.1628***	0.0503**	0.9744***	0.2497	EGARCH(1,1)	0.0099	-0.0523**	0.6320***	-0.0198	0.7345***
2001-2005	EGARCH(1,1)	0.0429***	0.0467***	0.3689***	0.0599	0.8576***	0.7569	EGARCH(1,1)	0.0682***	0.0067	0.6082***	-0.0153	0.6950***
2002-2006	GARCH(1,1)	0.0670***	0.0645***	0.5744***	-	0.4812***	0.9922	EGARCH(1,1)	0.1081***	0.0493*	0.4935***	0.0266	0.8950***
2003-2007	GARCH(1,1)	0.0829***	0.0805***	0.6991***	-	0.4327***	0.9684	EGARCH(1,1)	0.1484***	0.0941***	0.4026***	0.0408	0.9492***
2004-2008	EGARCH(1,1)	0.0865***	0.0560***	0.6502***	0.0278	0.8904***	0.9288	EGARCH(1,1)	0.0929***	0.0545***	0.5522***	0.0504*	0.9634***
2005-2009	EGARCH(1,1)	0.0823***	0.0537**	0.6977***	0.0233	0.8814***	0.9506	EGARCH(1,1)	0.1140***	0.0754**	0.3878***	0.0051	0.9457***
2006-2010	EGARCH(1,1)	0.1026***	0.0511***	0.6286***	-0.0058	0.8682***	0.9647	TGARCH(1,1)	0.0568**	0.0520**	0.2502***	-0.0285	0.7065***
2007-2011	EGARCH(1,1)	0.0626***	0.0151	0.6159***	-0.0900**	0.8772***	0.8707	TGARCH(1,1)	0.0258	0.0133	0.2733***	0.1469	0.5110***
2008-2012	EGARCH(1,1)	0.0135	-0.0254	0.5265***	-0.0702**	0.9442***	0.0858	TGARCH(1,1)	-0.0366	-0.0215	0.1742***	0.2622***	0.5846***
2009-2013	TGARCH(1,1)	0.0431**	0.0251	0.2104***	0.0091	0.7692***	0.0550	TGARCH(1,1)	-0.0355	0.0083	0.1989***	0.0990	0.5061***
2010-2014	TGARCH(1,1)	0.0170	0.0195	0.2124***	0.0540	0.6259***	0.1251	TGARCH(1,1)	-0.0256	0.0125	0.2552***	0.0414	0.5045***
2011-2015	TGARCH(1,1)	-0.0116	0.0044	0.1367***	0.0778	0.5777***	0.1245	TGARCH(1,1)	-0.0387	0.0024	0.1430***	0.0963*	0.6445***
2012-2016	GARCH(1,1)	-0.0083	0.0099	0.1051***	-	0.7110***	0.4472	EGARCH(1,1)	0.0074	0.0237	0.3653***	0.0048	0.8108***
2013-2017	GARCH(1,1)	0.0077	0.0246*	0.0823***	-	0.7501***	0.4552	TGARCH(1,1)	0.0471***	0.0183	0.2806***	-0.1033	0.5155***
				TUSISE									
FULL	**TGARCH(1,1)**	**0.0377*** **	**0.0242*** **	**0.2468*** **	**0.0851** **	**0.562*** **	**0.3145**						
1998-2002	n/a	n/a	n/a	n/a	n/a	n/a	n/a						
1999-2003	EGARCH(1,1)	-0.0057	0.0090	0.3887***	0.0334	0.868***	0.8950						
2000-2004	EGARCH(1,1)	-0.0092	-0.0184	0.4324***	-0.0190	0.853***	0.7114						
2001-2005	EGARCH(1,1)	-0.0129	-0.0123	0.4320***	-0.0434	0.863***	0.7085						
2002-2006	EGARCH(1,1)	0.0163	0.0341	0.3256***	-0.0117	0.843***	0.7839						
2003-2007	EGARCH(1,1)	0.0568***	0.0430**	0.3554***	-0.0032	0.814***	0.6653				NA		
2004-2008	TGARCH(1,1)	0.0635**	0.0361*	0.2245***	0.1781*	0.507***	0.2068						
2005-2009	TGARCH(1,1)	0.0991***	0.0656***	0.1784***	0.1121	0.603***	0.1490						
2006-2010	TGARCH(1,1)	0.1089***	0.0774***	0.2200***	0.1724**	0.467***	0.1011						
2007-2011	TGARCH(1,1)	0.0646***	0.0408***	0.1859***	0.1870**	0.588***	0.8112						
2008-2012	TGARCH(1,1)	0.0449***	0.0395***	0.1873***	0.2236**	0.555***	0.7891						
2009-2013	TGARCH(1,1)	0.0435**	0.0345*	0.2463***	0.2720***	0.437***	0.9505						
2010-2014	TGARCH(1,1)	0.014709	0.0166	0.3095***	0.2205**	0.427***	0.9835						
2011-2015	TGARCH(1,1)	0.0033	0.0034	0.3018***	0.1409	0.462***	0.7948						
2012-2016	EGARCH(1,1)	0.0091	-0.0035	0.4759***	0.0004	0.734***	0.6695						
2013-2017	TGARCH(1,1)	0.0269	0.0020	0.2289***	-0.0299	0.549***	0.8677						

***, **, * signify significance at 1%, 5%, 10% level of significance. The ARCH parameters correspond to Α (α-alpha), the leverage effect correspond to **γ** (Γ), the GARCH parameters to Β (β-beta).

Similar to DOW and MOY results, leverage effects are observed in two windows. SEMDEX results show the presence of HOM effects in full sample, although the effect disappears and reappears in rolling windows. Notably, HOM effect is observed in 2001-2005 through 2007-2011 windows. The effect is not present before and after the identified windows. The result suggests that the HOM effect is not an all or nothing phenomenon. Table 5.18 shows that MOSENEW does not exhibit significant HOM effect in full sample but rolling results disclose HOM effect in cyclical version.

For MOSENEW, the anomaly cannot be found in the first three windows. It is found to be significant in six windows from 2001-2005 window to 2006-2010 window and become insignificant thereafter, until the last window in 2013-2017. Similarly, Table 5.18 reveals that TUSISE exhibits HOM calendar anomaly in full sample. The changing behaviour of the anomaly in TUSISE is reflected in its presence in seven of the possible 15 windows. The seven windows with significant HOM anomaly are the 2003-2007, 2004-2008, 2005-2009, 2006-2010, 2007-2011, 2008-2012 and 2009-2013 while the remaining eight windows are free from the HOM effect. Suffice to state that HOM is also time varying in TUSISE.

It is noteworthy that the asymmetry term (**γ**) in tables 5.16, 5.17 and 5.18 is significant in all windows for JALSH, in few windows for SEMDEX, MOSENEW and TUSISE. However, the asymmetry term is not significant in NGSEINDX. Therefore, this study documents significant leverage effect, indicating that negative news causes volatility to rise by more than positive news of the same magnitude at all time in JSE and on few occasions in SEM, MOSE and TSE.

5.5.3 Robustness Check

The robustness of the estimated GARCH models is performed to ensure model adequacy. The Ljung-Box Q statistics test on the standardised residuals of the selected GARCH model is carried out (associated *p*-values are presented in Appendix IIIA). The results show that there is no trace of serial correlation as the probability of Q statistics is greater than the 5 percent level of significance for each of the selected models. The test for heteroscedasticity is also carried out to establish a constant variance of the error terms or homoscedasticity of the fitted autoregressive conditional heteroscedasticity (GARCH) model. The result shows that F-statistic probability values (reported in appendix IIIB) are greater than 0.05, hence, the ARCH (1) tests indicate that there is no evidence of conditional heteroscedasticity in the residuals. Thus, the study establishes that the models have been successfully corrected and this implies that the fitted models are adequate. Therefore, there is no serial correlation or conditional heteroscedasticity in the standardised residuals of the fitted models.

The estimated GARCH term (**B**) is always significantly positive in the GARCH, EGARCH and TGARCH, respectively. As is typical of GARCH model estimates for financial asset returns data, the sum of the coefficients on the lagged squared error and lagged conditional variance is in most cases, very close to unity. This sum being close to unity implies that volatility converges to the steady state slowly. However, the high persistence of the conditional variance is captured by the magnitude of the beta coefficient.

In summary, this study examines time-varying calendar anomalies in the selected African stock markets with the aid of GARCH models. Changing magnitude of anomalies is tracked by estimating the selected GARCH model in five-year fixed length rolling window, rolled forward by one year and by observing the significance of the selected calendar anomalies over time. By so doing, the study presents further tests of the appropriateness of AMH in explaining the behaviour of calendar anomalies. Findings from the rolling ANOVA and GARCH model (summarised in Table 5.19) reveal that:

i. Kruskal Wallis test shows that NGSE and SEM pass through periods when MOY and HOM returns are significantly different (inefficient) and periods when they are not (efficient) in line with the AMH;
ii. Kruskal Wallis shows that MOSE and TSE go through periods when DOW and MOY returns are significantly different and when they are not;
iii. Kruskal Wallis shows that JSE goes through periods when DOW, MOY and HOM returns are significantly different and when they are not as put forth by the AMH;

iv. Rolling GARCH estimations show that calendar anomalies (DOW, MOY and HOM) disappear and reappear over time in line with the AMH in the selected African stock markets.

Table 5.19: Summary of Findings III

DOW effect					
TEST	**NGSEINDX**	**JALSH**	**SEMDEX**	**MOSENEW**	**TUSISE**
KW	Efficient	Adaptive	Efficient	Adaptive	Adaptive
GARCH models	Adaptive	Adaptive	Adaptive	Adaptive	Adaptive
MOY effect					
KW	Adaptive	Adaptive	Adaptive	Adaptive	Adaptive
GARCH models	Adaptive	Adaptive	Adaptive	Adaptive	Adaptive
Intra-Month effect					
KW	Adaptive	Adaptive	Adaptive	efficient	efficient
GARCH models	Adaptive	Adaptive	Adaptive	Adaptive	Adaptive

Table 5.19 shows beyond reasonable doubt that DOW, MOY and HOM effect are time varying and the selected African stock markets are adaptive. Having established time-changing calendar anomalies in the selected market, the study proceeds to test whether the changes in calendar anomalies are due to changing market conditions.

5.6 Calendar Anomalies and Market Condition: MSM

While much related literature exists on the application of MSM to finance, the model is rarely linked to the AMH or calendar anomalies. However, the MSM is suitable for the investigation of calendar anomalies cum market conditions as discussed in Chapter 4 (Section 4.3.4). For instance, it can provide information on the length of time a market spends in bull or bear condition/regime and generate regime-dependent results, which permit researchers to evaluate how a particular market's characteristic (such as anomaly) performs under each regime. Having established/provided evidences of time changing calendar anomalies through rolling window analyses in Section 5.5, the three calendar anomalies, namely the DOW, MOY and the HOM effects, are hereby subjected to regime switching regression with the aim of determining the regime (market condition) that favours significant calendar anomalies and *vice versa*. Determining the effect of market condition on calendar anomalies becomes necessary since the investigation of AMH does not stop at establishing the changing behaviour but also the condition that informed the changes or favours the anomalies. First, the study presents the probability of a market moving from one state or market regime (condition) to another as well as the probable expected duration in a particular state. The result is presented in Table 5.20.

5.6.1 Transition Probabilities and Constant Expected Durations

Table 5.20 contains the transition probability of being in bullish or bearish market for each of the markets under consideration. It can be seen that the probability of being in bear regime (0.955858) is higher than the probability of being in bull regime (0.880094) for the NGSEINDX. Thus, the NGSEINDX has higher tendency of undergoing bearish market than the bullish market. Hence, the NGSEINDX is expected to spend approximately 23 days in bear regime and 8 days in bull regime as revealed by the constant expected duration.

Table 5.20 shows that the transition probabilities of the JALSH following the bearish and bullish trends are 0.968184 and 0.986577 respectively. This implies that the JSE spends more time in the bull market than the bear market condition. This is corroborated by the constant expected duration of approximately 74 days in regime 2 compared to 31 days in regime 1. Therefore, JSE spends, in the bull regime, more than double of the period spent in the bear regime.

For the SEMDEX index return, the probability of remaining in the bear period (0.966459) is greater than that of being in the bull period (0.803481). In addition, the tendency for the market to transit from former (0.033541) to latter is also lower than the other way round (0.196519). The bear regime lasts about 30 days while the bull regime lasts for just 5 days in SEMDEX. Thus, SEMDEX has a higher likelihood of continuing in bearish trend or market than the boom, a similar behaviour with the NGSEINDX.

Table 5.20: Transition probabilities and constant expected durations

NGSEINDX			**JALSH**	
Transition probabilities	**Regime 1** $_{(t-1)}$	**Regime 2** $_{(t)}$	**Regime 1** $_{(t-1)}$	**Regime 2** $_{(t)}$
Regime 1 $_{(t-1)}$	0.955858	0.044142	0.968184	0.031816
Regime 2 $_{(t)}$	0.119906	0.880094	0.013423	0.986577
Constant expected durations (days)	22.65396	8.339853	31.43073	74.49844
	SEMDEX		**MOSENEW**	
Regime 1 $_{(t-1)}$	0.966459	0.033541	0.854576	0.145424
Regime 2 $_{(t)}$	0.196519	0.803481	0.043971	0.956029
Constant expected durations (days)	29.81447	5.088576	6.876462	22.74225
TUSISE				
Regime 1 $_{(t-1)}$	0.798889	0.201111		
Regime 2 $_{(t)}$	0.027131	0.972869		
Constant expected durations	4.972386	36.85858	NA	

Table 5.20 also discloses that the likelihood of the MOSENEW to be in up period (0.854576) is lower than that of down period (0.956029). However, the probability of moving from up regime (0.145424) to down regime is higher. The market is expected to stay in bull for about 7 days compared to 23 days in bear condition. It is noteworthy that there is high tendency of moving from bull to bear regime in all except JSE.

TUSISE results show that the probability that the stock market stays in the bullish and bearish state are 0.798889 and 0.972869 respectively. This means that the TSE has a tendency to remain in bear market conditions than bull market condition. Moreover, the market shows higher likelihood of moving from the bull condition to bear condition. This is in consonance with the constant expected duration, which reveals that market remains in the bearish state for approximately 37 days and in bullish state for about 5 days. The results of the regime shift in the three calendar anomalies are discussed in the subsequent subsections.

5.6.2 The DOW Effect (Weekend Effect)

The result of the regime shift in the DOW, MOY and HOM effects for the selected African stock markets is presented in Table 5.21, 5.22 and 5.23. Both three and two regimes MSMs are estimated and the appropriate model is selected using information criteria (reported in appendix IV). In most cases, three regimes are non-available. So, two regimes (bull and bear) MSM results are reported for the five markets in Tables 5.21, 5.22 and 5.23. The estimated DOW MOY and HOM coefficients correspond to average return for each day, month or half as the case may be. These coefficients are compared to determine the days that are significantly higher or lower and the significance of the estimated effect is taken at *p*-value less than 0.05. The hypothesis is tested for each regime to ascertain whether the calendar effect changes with regimes.

The MSM results of DOW effect for the selected African stock markets are presented in Table 5.21. The table shows evidence of weekend effect in bear market in NGSEINDX returns which is characterised with significantly low/negative Monday returns and positive/highest Friday returns. Tuesday and Thursday returns are also significantly negative and positive respectively but they are not as high as the weekend days. The weekend effect is not present in bull period, rather the opposite of Monday effect is found with positive and significant Monday return. The implication is that the weekend and DOW effect occurred during bear period and disappeared during bull period. It indicates that the appearance and disappearance of the DOW anomaly, reported in rolling window, occurs as market condition changes. This finding complies with the AMH.

JALSH result in Table 5.21 discloses that the bear period is not associated with significant DOW effect, while the bull period shows the opposite of popular weekend effect as Monday return is significantly positive and higher than those of the remaining days of the week, especially the Friday. In essence, presence of DOW effect is found in bull period but the effect is absent in bear period in line with the AMH, which states that profit opportunity appears during certain market condition and disappears during another. This also shows that the cyclical DOW effect found in rolling analyses is caused by changing conditions or regimes.

Regime switching is also present in the SEMDEX return series. The results in Table 5.21 reveal that apart from the Monday effect, DOW effect is found in bear period with Friday return significantly higher than other weekdays. The effect, however, disappears during the bull as all the week days possess insignificant coefficients at 5 percent level of significance. Thus, the variation in DOW effect observed in rolling window is informed by changing conditions. These again supports the assertion that profit opportunity found in one regime may evaporate as regime changes as pointed out by the proponents of the new AMH.

MOSENEW results in Table 5.21 reveal that the weekend effect is associated with bear market in which both Monday and Friday returns are positive and significant, although the former is lower than the latter as would be expected for weekend anomaly to hold. The weekend effect is absent in bull period in which Monday return is positive and significant while Friday return is insignificant. Hence, the negative Monday effect in rolling windows can be linked to bear condition and positive Monday effect to bull condition. Like the other markets, the results reveal that the DOW anomaly observed in one market regime is not present in the other regime as postulated by the AMH.

The TUSISE results show a switch between significant positive and insignificant negative Tuesday return in the bull and bear market respectively. The results also reveal the presence of weekend effect in the bear regime with Friday return significantly higher than other weekdays. Hence, the Friday effect found in rolling window is traceable to bear regime. The observed weekend effect is, however, absent in the bullish market.

Table 5.21: DOW MSM Results NGSEINDX, JALSH, SEMDEX, MOSENEW and TUSISE

	NGSEINDX				JALSH			
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
	Regime 1 BEAR				**Regime 1 BEAR**			
MON	-0.069192*	0.022131	-3.126515	0.0018	-0.089246	0.117129	-0.761952	0.4461
TUE	-0.053029*	0.021989	-2.411542	0.0159	0.085251	0.113472	0.751301	0.4525
WED	0.028481	0.021363	1.333154	0.1825	0.069415	0.120344	0.576809	0.5641
THUR	0.041856*	0.021881	1.912951	0.0558	-0.000428	0.125887	-0.003400	0.9973
FRI	0.074485*	0.022024	3.381913	0.0007	-0.184948	0.115064	-1.607345	0.1080
LOG(SIGMA)	-0.651754	0.019604	-33.24547	0.0000	0.623154	0.023604	26.39984	0.0000
	Regime 2 BULL				**Regime 2 BULL**			
MON	0.210841	0.110843	1.902158	0.0572	0.239956*	0.033715	7.117228	0.0000
TUE	0.182613	0.109984	1.660360	0.0968	0.022718	0.033205	0.684175	0.4939
WED	0.066527	0.108991	0.610387	0.5416	0.030983	0.033206	0.933052	0.3508
THUR	-0.008089	0.110714	-0.073058	0.9418	0.126136*	0.032982	3.824389	0.0001
FRI	0.138777	0.110761	1.252940	0.2102	0.078436*	0.032857	2.387215	0.0170
LOG(SIGMA)	0.541531	0.026000	20.82783	0.0000	-0.187243	0.016655	-11.24262	0.0000
	Transition Matrix Parameters				Transition Matrix Parameters			
P11-C	3.075188	0.123740	24.85196	0.0000	3.415571	0.206782	16.51771	0.0000
P21-C	-1.993319	0.137364	-14.51122	0.0000	-4.330752	0.201449	-21.49804	0.0000
	SEMDEX				**MOSENEW**			
	Regime 1 BEAR				**Regime 1 BULL**			
MON	0.006451	0.010732	0.601095	0.5478	0.189437*	0.089286	2.121688	0.0339
TUE	-0.000549	0.010736	-0.051109	0.9592	-0.047017	0.090879	-0.517361	0.6049
WED	0.032889	0.010893	3.019221	0.0025	0.202688*	0.091572	2.213430	0.0269
THUR	0.035747	0.010918	3.274109	0.0011	0.103449	0.089337	1.157967	0.2469
FRI	0.054689	0.010891	5.021446	0.0000	0.014334	0.089819	0.159593	0.8732
LOG(SIGMA)	-1.214262	0.015839	-76.66197	0.0000	0.275315	0.029200	9.428761	0.0000
	Regime 2 BULL				**Regime 2 BEAR**			
MON	0.162774	0.155238	1.048541	0.2944	-0.032332*	0.016487	-1.961027	0.0499
TUE	0.094545	0.155511	0.607963	0.5432	-0.007450	0.016415	-0.453849	0.6499
WED	0.007180	0.149062	0.048167	0.9616	0.012594	0.016484	0.763999	0.4449
THUR	0.267865	0.150165	1.783803	0.0745	0.019139	0.016939	1.129910	0.2585
FRI	0.259889	0.152590	1.703188	0.0885	0.040913*	0.017188	2.380372	0.0173
LOG(SIGMA)	0.601659	0.031716	18.97029	0.0000	-0.883001	0.020684	-42.68955	0.0000
	Transition Matrix Parameters				Transition Matrix Parameters			
P11-C	3.360878	0.113899	29.50763	0.0000	1.770955	0.129646	13.65988	0.0000
P21-C	-1.408197	0.132768	-10.60645	0.0000	-3.079257	0.126687	-24.30603	0.0000
	TUSISE							
	Regime 1 BULL							
MON	-0.042768	0.131530	-0.325156	0.7451				
TUE	0.258358*	0.133372	1.937125	0.0527				
WED	-0.117327	0.130261	-0.900702	0.3677				
THUR	0.103209	0.130218	0.792591	0.4280				
FRI	0.104296	0.135501	0.769704	0.4415				
LOG(SIGMA)	0.238085	0.046535	5.116222	0.0000				
	Regime 2 BEAR							
MON	0.016983	0.014413	1.178367	0.2387				
TUE	-0.026582	0.013958	-1.904452	0.0569				
WED	0.038692*	0.013918	2.779968	0.0054				
THUR	0.059279*	0.013982	4.239565	0.0000				
FRI	0.086259*	0.014006	6.158757	0.0000				
LOG(SIGMA)	-1.023128	0.018239	-56.09569	0.0000				
	Transition Matrix Parameters							
P11-C	1.379367	0.174644	7.898172	0.0000				
P21-C	-3.579583	0.155002	-23.09374	0.0000	NA			

P-values are symbolised as: Significance * of estimated coefficients is taken at *p*-value < 5%.

5.6.3 The MOY/January Effects

The regime switching results of the MOY effect is presented in Table 5.22. It can be seen that the popular January effect is absent in both the bull and bear periods in NGSEINDX returns. This reveals that the popular January effect is absent in NGSEINDX irrespective of the regime shift. Instead, the results reveal significant positive December effect in the bear period and positive May effects in the bull period, suggesting a shift from December effect to May effect. This implies that the December and May effects observed in two rolling GARCH windows could be in bear and bull periods respectively. Otherwise, both rolling GARCH and MSM show that February, March, July and November are not associated with any calendar anomaly.

The JALSH results in Table 5.22 reveal the presence of MOY effect in bullish market with all other months, other than May, June, September and November, having significant positive returns. The January effect is not dominant as December return is significantly higher than other months of the year. Thus, the December, October, April, July, August and October effects observed in JALSH rolling analyses can be linked with bull condition. The MOY effect, however, disappear in the bearish market since all the months of the year coefficients are not significant at 5 percent level of significance.

From the SEMDEX MOY regime switching results in Table 5.22, January calendar effect is present in bull regime because January return is positive, significant and higher than other months of the years. The January effect persists in bear regime in which January return remains significantly positive and higher than other months of the year, notably September and December months which are also significant and positive. It is noteworthy that the popular January effect remains in both bull and bear markets (though higher in the bull). However, it is right to infer that the September/December effects found in certain rolling windows in SEMDEX only appear in bear regime and disappear in bull regime in line with AMH.

Table 5.22: MOY MSM Result for NGSEINDX, JALSH, SEMDEX, MOSENEW and TUSISE

	NGSEINDX				**JALSH**			
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
Regime 1 BEAR					**Regime 1 BULL**			
JAN	0.025640	0.037326	0.686916	0.4921	0.096164	0.050348	1.909970	0.0561
FEB	-0.015667	0.038042	-0.411849	0.6805	0.097771	0.050414	1.939349	0.0525
MAR	-0.018695	0.033612	-0.556200	0.5781	0.146418	0.053385	2.742693	0.0061
APR	0.005751	0.031575	0.182144	0.8555	0.132386	0.052694	2.512358	0.0120
MAY	0.058823	0.034645	1.697869	0.0895	0.061754	0.049524	1.246956	0.2124
JUN	0.059908	0.039242	1.526604	0.1269	-0.014222	0.051967	-0.273682	0.7843
JUL	-0.006572	0.032559	-0.201848	0.8400	0.116961	0.050712	2.306372	0.0211
AUG	-0.037929	0.036211	-1.047447	0.2949	0.118969	0.051815	2.296052	0.0217
SEP	-0.024205	0.032982	-0.733893	0.4630	0.082304	0.053448	1.539905	0.1236
OCT	-0.035057	0.031756	-1.103974	0.2696	0.139252	0.052557	2.649535	0.0081
NOV	-0.029632	0.031434	-0.942668	0.3459	0.052320	0.048909	1.069731	0.2847
DEC	0.110708	0.034913	3.170947	0.0015	0.156241	0.054023	2.892113	0.0038
LOG(SIGMA)	-0.645776*	0.019665	-32.83909	0.0000	-0.188050	0.017326	-10.85339	0.0000
Regime 2 BULL					**Regime 2 BEAR**			
JAN	-0.014570	0.144391	-0.100909	0.9196	0.000446	0.169746	0.002630	0.9979
FEB	0.221692	0.151690	1.461481	0.1439	-0.082502	0.168058	-0.490917	0.6235
MAR	0.088883	0.180700	0.491882	0.6228	-0.043632	0.176065	-0.247817	0.8043
APR	0.571499	0.223947	2.551934	0.0107	0.058638	0.215175	0.272512	0.7852
MAY	0.575323	0.193206	2.977772	0.0029	0.029182	0.186146	0.156768	0.8754
JUN	0.111435	0.137042	0.813146	0.4161	-0.133229	0.178764	-0.745280	0.4561
JUL	-0.136954	0.178035	-0.769253	0.4417	-0.123349	0.186868	-0.660086	0.5092
AUG	-0.063371	0.147535	-0.429532	0.6675	-0.162767	0.164366	-0.990273	0.3220
SEP	0.164459	0.198999	0.826433	0.4086	-0.169476	0.197678	-0.857334	0.3913
OCT	0.156637	0.214978	0.728621	0.4662	0.158263	0.161734	0.978535	0.3278
NOV	-0.134496	0.204051	-0.659128	0.5098	0.083535	0.189969	0.439727	0.6601
DEC	0.141796	0.174937	0.810554	0.4176	0.083718	0.170462	0.491124	0.6233
LOG(SIGMA)	0.539131	0.026418	20.40784	0.0000	0.620247	0.024303	25.52110	0.0000
Transition Matrix Parameters								
P11-C	3.075188	0.123740	24.85196	0.0000	4.296596	0.200368	21.44352	0.0000
P21-C	-1.993319	0.137364	-14.51122	0.0000	-3.398328	0.207223	-16.39940	0.0000
SEMDEX					**MOSENEW**			
Regime 1 BULL					**Regime 1 BEAR**			
JAN	0.510345	0.228881	2.229745	0.0258	0.056469	0.028094	2.009972	0.0444
FEB	-0.061087	0.215229	-0.283823	0.7765	0.061588	0.027813	2.214337	0.0268
MAR	0.252769	0.237305	1.065166	0.2868	-0.023052	0.024755	-0.931174	0.3518
APR	0.276267	0.227109	1.216448	0.2238	0.042748	0.026020	1.642868	0.1004
MAY	0.150346	0.251087	0.598779	0.5493	0.028165	0.025484	1.105210	0.2691
JUN	0.480812	0.281970	1.705186	0.0882	-0.069427	0.023772	-2.920595	0.0035
JUL	0.137193	0.230372	0.595528	0.5515	-0.008854	0.024523	-0.361030	0.7181
AUG	0.005059	0.237237	0.021325	0.9830	0.080383	0.024436	3.289585	0.0010
SEP	0.176008	0.211779	0.831093	0.4059	-0.002165	0.027554	-0.078567	0.9374
OCT	0.132804	0.208058	0.638304	0.5233	0.007461	0.024578	0.303571	0.7615
NOV	0.243454	0.260837	0.933355	0.3506	-0.054002	0.027307	-1.977583	0.0480
DEC	0.182278	0.269353	0.676727	0.4986	-0.027133	0.027203	-0.997419	0.3186
LOG(SIGMA)	0.601832	0.032196	18.69252	0.0000	-0.889275	0.019316	-46.03725	0.0000
Regime 2 BEAR					**Regime 2 BULL**			
JAN	0.054430	0.017388	3.130311	0.0017	0.205683	0.111167	1.850223	0.0643
FEB	0.010052	0.019051	0.527668	0.5977	0.168270	0.125824	1.337344	0.1811
MAR	0.010462	0.017288	0.605140	0.5451	0.017911	0.140279	0.127684	0.8984
APR	0.000690	0.017099	0.040355	0.9678	0.113367	0.148150	0.765219	0.4441
MAY	0.024407	0.016166	1.509824	0.1311	-0.033686	0.140363	-0.239992	0.8103
JUN	0.031892	0.016437	1.940265	0.0523	0.315426	0.168397	1.873108	0.0611
JUL	0.011956	0.016966	0.704741	0.4810	-0.122529	0.170073	-0.720447	0.4713
AUG	0.006637	0.016139	0.411254	0.6809	0.317880	0.179499	1.770931	0.0766
SEP	0.052540	0.017934	2.929611	0.0034	-0.175433	0.142801	-1.228512	0.2193
OCT	0.006731	0.017435	0.386054	0.6995	-0.060675	0.144421	-0.420124	0.6744
NOV	0.017334	0.016724	1.036507	0.3000	0.144756	0.139678	1.036350	0.3000
DEC	0.044136	0.016689	2.644570	0.0082	0.186251	0.119595	1.557348	0.1194
LOG(SIGMA)	-1.227096	0.016153	-75.96907	0.0000	0.273782	0.028138	9.730039	0.0000
Transition Matrix Parameters					Transition Matrix Parameters			
P11-C	1.305325	0.130530	10.00022	0.0000	3.071841	0.121901	25.19956	0.0000
P21-C	-3.071624	0.099497	-30.87138	0.0000	-1.762424	0.127536	-13.81906	0.0000
TUSISE								
Regime 1 BULL								
JAN	0.231008	0.166677	1.385961	0.1658				
FEB	-0.217563	0.174312	-1.248127	0.2120				
MAR	0.522094	0.236688	2.205830	0.0274				
APR	0.446451	0.155672	2.867897	0.0041				
MAY	-0.017182	0.184082	-0.093337	0.9256				
JUN	-0.304921	0.228038	-1.337153	0.1812				
JUL	-0.071259	0.302248	-0.235764	0.8136				
AUG	0.215477	0.230201	0.936039	0.3493				
SEP	0.012979	0.176937	0.073355	0.9415				
OCT	-0.173853	0.162353	-1.070833	0.2842				
NOV	-0.118323	0.195855	-0.604137	0.5458				
DEC	0.112702	0.241219	0.467218	0.6403				
LOG(SIGMA)	0.200674	0.044589	4.500473	0.0000				
Regime 2 BEAR								
JAN	0.051030	0.023902	2.134916	0.0328				
FEB	0.039634	0.022365	1.772157	0.0764				
MAR	0.007529	0.021663	0.347549	0.7282				
APR	0.024369	0.023971	1.016631	0.3093				
MAY	0.037288	0.022210	1.678864	0.0932				
JUN	0.068265	0.021379	3.193112	0.0014				
JUL	0.067400	0.020047	3.362111	0.0008				
AUG	0.053152	0.019878	2.673946	0.0075				
SEP	0.022307	0.023614	0.944687	0.3448				
OCT	0.020459	0.022617	0.904613	0.3657				
NOV	0.013579	0.021919	0.619530	0.5356				
DEC	0.006190	0.021392	0.289371	0.7723				
LOG(SIGMA)	-1.029240	0.018092	-56.89071	0.0000				
	Transition Matrix Parameters							
P11-C	1.412827	0.170287	8.296753	0.0000				
P21-C	-3.537086	0.152282	-23.22720	0.0000	NA			

Significance of estimated coefficients is taken at *p*-value < 5%.

The regime switching result for MOSENEW in Table 5.22 shows that the MOY effect is significantly present in the bearish market. There is a significant positive January, February and August effect as well as negative June and November effect. The January effect is dominated by the August effect. The MOY anomalies identified during the bear condition disappear as the market transitions to the bull period. It implies that the January, February, August, June and November effect identified in certain rolling windows can be linked with bear market condition. It can be seen that bull period is not associated with significant MOY effect in MOSENEW as *p*-values reveal. Suffice to state that bear market condition favours MOY effects in MOSENEW while the effects vanish as the markets become bullish. From TUSISE switching regression results in Table 5.22, it can be seen that March and April effects are present in the bull market while January, June July, August are present in the bear market. Therefore, the popular January effect is not present in the bull market. Where it is found, the effect is not as strong as June and July effects. In essence, the effects observed in one regime disappear in the other regime and *vice versa*.

5.6.4 The HOM/Intra-month Effect

The intra-month MSM results are presented in Table 5.23 showing coefficient/average return of each half of the month. The NGSEINDX result indicates the absence of the HOM anomaly in stock return during the bear market. This is because the average returns in the first and second halves of the months are not significant at the 5 percent significant level. A look at the bull market result, on the other hand, shows the presence of HOM effect because the average return of the trading days in the first half of the month is significantly greater than the remaining days of the month. Thus, the four windows reflecting HOM effect in the rolling GARCH could be traced to bull market. The absence of HOM effect in the bear and its presence in the bull condition is in consonance with the AMH. The JALSH HOM MSM result is similar to the NGSEINDX result.

The coefficients of both halves of the months are not significant with large *p*-values during the bear period. This suggests the absence of the HOM effect in bear period in the JSE. When the bull result is taken into consideration, it can be seen that the return is positive, significant and larger in the first half of the month than the second half of the month in the JSE. Hence, the 11 windows of HOM effect picked in rolling GARCH analyses could be connected to the bull condition. The implication is that the profit opportunity in the bull regime disappears in the bear regime as AMH suggested.

The regime switching result for SEMDEX reveals that the intra-month calendar effect is found in the bearish market since the first half of the month return is positive, significant and higher than the second half of the months. Both first and second half coefficients are significant. In the same vein, the bullish market results show the persistence of intra-month effect in which returns for the first half of the months days are averagely and significantly greater than the remaining half of the month, albeit the insignificance of the latter. Nevertheless, the HOM effect is higher in bull (0.238189) than bear market (0.027591). The MOSENEW results in Table 5.23 reveal that the intra-month calendar effect is neither present in the bull nor the bear market. However, the first half returns are greater than second half returns in both bull and bear period, the insignificance of the coefficient estimates, however, undermine the significance of regime or market condition in informing the behaviour of the HOM calendar effect.

Lastly, the MSM results for TUSISE show that HOM effect cannot be found in the bull market where the coefficient estimates for the first and second half of the months are not statistically significant. However, the bearish market is associated with the intra-month effect in which the first half of the months' returns is significant and more positive relative to second half of the months. This suggests that the seven windows of HOM effect reported in rolling GARCH may not be unconnected to the bear market condition. This is in line with the AMH, which implies that profit opportunity changes, as does the market condition.

Table 5.23: HOM MSM Result for NGSEINDX, JALSH, SEMDEX, MOSENEW and TUSISE

	NGSEINDX				**JALSH**			
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
Regime 1 BEAR					**Regime 1 BEAR**			
FIRST	0.003605	0.014191	0.254054	0.7995	-0.087909	0.071229	-1.234177	0.2171
SECOND	0.005370	0.013686	0.392391	0.6948	0.045218	0.071086	0.636109	0.5247
LOG(SIGMA)	-0.647565	0.019973	-32.42241	0.0000	0.617653	0.024145	25.58081	0.0000
Regime 2 BULL					**Regime 2 BULL**			
FIRST	0.189467	0.069609	2.721863	0.0065	0.139377	0.021603	6.451663	0.0000
SECOND	0.046495	0.068970	0.674129	0.5002	0.058547	0.020766	2.819396	0.0048
LOG(SIGMA)	0.538955	0.026241	20.53851	0.0000	-0.189622	0.017228	-11.00656	0.0000
Transition Matrix Parameters								
P11-C	3.080279	0.125259	24.59123	0.0000	3.415453	0.205083	16.65401	0.0000
P21-C	-2.009900	0.138403	-14.52210	0.0000	-4.297264	0.197660	-21.74071	0.0000
SEMDEX					**MOSENEW**			
Regime 1 BEAR					**Regime 1BULL**			
FIRST	0.027591	0.007086	3.893752	0.0001	0.101241	0.058654	1.726059	0.0843
SECOND	0.023271	0.006973	3.337511	0.0008	0.093496	0.058513	1.597869	0.1101
LOG(SIGMA)	-1.214801	0.015945	-76.18881	0.0000	0.285302	0.029235	9.758830	0.0000
Regime 2 BULL					**Regime 2 BEAR**			
FIRST	0.238189	0.094985	2.507652	0.0122	0.006985	0.010811	0.646107	0.5182
SECOND	0.076493	0.097158	0.787303	0.4311	0.004642	0.010448	0.444340	0.6568
LOG(SIGMA)	0.598743	0.031647	18.91952	0.0000	-0.875212	0.020313	-43.08692	0.0000
Transition Matrix Parameters					Transition Matrix Parameters			
P11-C	3.348295	0.113497	29.50115	0.0000	1.765369	0.129834	13.59712	0.0000
P21-C	-1.404541	0.132517	-10.59893	0.0000	-3.102299	0.127587	-24.31510	0.0000
TUSISE								
Regime 1 BULL								
FIRST	0.077938	0.079857	0.975978	0.3291				
SECOND	0.042121	0.082131	0.512852	0.6081				
LOG(SIGMA)	0.230794	0.045844	5.034297	0.0000				
Regime 2 BEAR								
FIRST	0.038091	0.009279	4.105005	0.0000				
SECOND	0.031775	0.008692	3.655450	0.0003				
LOG(SIGMA)	-1.023321	0.018072	-56.62616	0.0000	NA			
Transition Matrix Parameters								
P11-C	1.403640	0.172496	8.137227	0.0000				
P21-C	-3.558932	0.154403	-23.04963	0.0000				

Significance of estimated coefficients is taken at *p*-value < 5%.

Having established that calendar anomalies vary over time, it is expedient to evaluate whether the observed variation is sparked by changes in market conditions. Switching model has been recognised as a potent tool capable of accounting for changing market cycles or regime switch in financial market. Hence, the study examines time-varying calendar anomaly in the selected African stock markets in the bull and bear market with the aid of Markov switching regression model. The study also estimates the probability of transitioning from one state to another and the probable time spent in a particular state. This helps in establishing how a changing calendar anomaly is in response to changing market conditions. Doing so, the study contributes to the growing knowledge on AMH by documenting how calendar anomalies have behaved under bull and bear market situations in selected African stock markets. Findings from the analyses as contained in Table 5.24 show that:

i. The weekend effect appears in the bear regime in NGSE, SEM, MOSE and TSE and disappear in bull regime;
ii. The weekend effect is found in the bull regime and it disappears in bear regime for MOSE and DOW effect is present in bull and absent in bear market for JSE.
iii. DOW effect appears in one regime and disappears in another regime in all the markets as rooted in AMH. Particularly, positive Monday effect is associated with bull periods in NGSEINDX, JALSH and MOSENEW while negative Monday effect is associated with Bear period in NGSEINDX and MOSENEW.
iv. The popular January effect is absent in both the bull and bear regimes in NGSE, JSE, MOSE and TSE, but present in the bull and bear in SEM though stronger in bull than bear. The January effect is nonexistent and where it exists, its behaviour conforms to the AMH.
v. The MOY effect appears in both regimes in NGSE, SEM and TSE; however, the specific effect observed in one regime disappeared in the other regime.
vi. The MOY effect appears in bull and disappears in bear in JSE as propounded by AMH;
vii. MOY effect in bear and disappear in bull in MOSE in line with the AMH.

viii. NGSE and JSE exhibit HOM effect in the bull regime and it disappear in bear regime; SEMDEX possesses HOM effect in both regimes but it is stronger in bull regime, TSE exhibits HOM effect in bear regime and it disappear in bull regime while MOSE does not exhibit HOM in both regime.

ix. All the markets except the JSE have higher tendency to be in the bearish state than otherwise. Hence, they are expected to stay in the bear market than bull market.

Table 5.24: Summary of Findings IV

Weekend effect					
Conditions	**NGSEINDX**	**JALSH**	**SEMDEX**	**MOSENEW**	**TUSISE**
UP/BULL	Absent	Opposite Present	Absent	Absent	Absent
DOWN/BEAR	Present	Absent	Present	Present	Present
REMARK	ADAPTIVE	ADAPTIVE	ADAPTIVE	ADAPTIVE	ADAPTIVE
DOW effect					
UP/BULL	Present: +Monday	Present	Absent	Present: +Monday	Present: +Tuesday
DOWN/BEAR	Present: -Monday	Absent	Present	Present: -Monday	Present: -Tuesday
REMARK	ADAPTIVE	ADAPTIVE	ADAPTIVE	ADAPTIVE	ADAPTIVE
January effect					
UP/BULL	Absent	Absent	Present: Stronger	Absent	Absent
DOWN/BEAR	Absent	Absent	Present	Absent	Absent
REMARK	EFFICIENT	EFFICIENT	ADAPTIVE	EFFICIENT	EFFICIENT
MOY effect					
UP/BULL	Present-May/April	Present	Present: stronger	Absent	Present: March/April
DOWN/BEAR	Present-December	Absent	Present	Present	Present: June/July
REMARK	ADAPTIVE	ADAPTIVE	ADAPTIVE	ADAPTIVE	ADAPTIVE
Intra-month or HOM effect					
UP/BULL	Present	Present	Higher	Absent	Absent
DOWN/BEAR	Absent	Absent	Lower	Absent	Present
REMARK	ADAPTIVE	ADAPTIVE	ADAPTIVE	EFFICIENT	ADAPTIVE

As indicated in Table 5.24, the findings for the majority of the markets show that they are adaptive since most of the calendar anomalies (except January effect) found in one regime tend to disappear when there is a shift in the market state. This cannot be observed when a single state model is employed, thereby, misleading market participants into believing that calendar anomaly is an all-or-nothing phenomenon or that a market remains efficient, or not, under any condition.

5.7 Summary of the Chapter

This chapter contains the empirical results and interpretations of the models that are estimated in this study. The purpose of the chapter is to present/show the results of the tests of the research hypotheses and by so doing, provide answers to the questions, which serve as the motivations for the study. The aims of the chapter are to achieve the empirical objectives of the study which are to:

- investigate whether market efficiency changes in cyclical version over time in African stock markets according to AMH;
- evaluate effect of market conditions (up, down, bull, bear, normal) on return predictability in African stock markets as propounded by AMH;
- analyse whether calendar anomalies disappear and reappear over time in African stock markets as postulated by AMH; and
- determine how calendar anomalies behave under different market conditions in African stock markets.

The chapter starts with the descriptive statistics results in order to provide information on the distributional properties of the indices return series of the selected African stock markets. The second segment (5.3) presents the results of the rolling window analyses for the linear and nonlinear tests with the aim of determining how market efficiency varies over time. The results of both sets of tests show that the market efficiency changes with time and the findings can be rationalised within the ambit of the new AMH, especially when the nonlinear BDS test is taken into consideration. The third segment (5.4) of the chapter presents the results of the regression with dummy variables, estimated to establish the effect of market conditions on the observed variations in market efficiency. The findings reveal that there are some evidences to support the assertions that efficiency changes as a results of changes in market conditions in all the selected African stock markets except the JSE. The results of the rolling GARCH estimations aimed at evaluating the behaviours of calendar anomalies are contained in the fourth subsection (5.5). The results show vividly that the behaviour of calendar anomalies does not remain the same over time. The last empirical results presented in the last segment are derived from the MSM estimated to show whether there is a relationship between changing behaviour of calendar anomalies and changing market conditions. The revelation from the empirical results provides strong substantiation for regime-dependent anomalies. The findings from the entire empirical results show that cycles of efficiency and inefficiency or anomaly is a reality in the behaviour of African stock market returns and that such cycles cannot by extricated from changing market regimes/states or conditions.

CHAPTER 6: DISCUSSION OF FINDINGS

6.1 Introduction

The hypotheses of time-changing efficiency and calendar anomalies, *vis-a-vis* market conditions, have been empirically tested in the previous chapter. The current chapter is devoted to the discussion of the main findings from the tests of hypotheses. The discussion is based on the linkage between the findings of this study and the findings of the existing studies as well as the proposition of the relevant theories. Specifically, the discussion of the findings is done with the aim of indicating the approach that best describes the behaviour of stock returns and calendar anomalies between the popular EMH and new AMH. In other words, the results are discussed in relation to the literature and previous studies. Therefore, the remaining parts of this chapter entail the discussion of time-varying efficiency results, discussion of return predictability and market condition results, discussion of the time-varying calendar anomalies results, discussion of results on calendar anomalies and market conditions and the summary of the chapter.

6.2 Discussion of Time-varying Efficiency Results

The first inference and the most-tested hypothesis from the AMH theory is that the market efficiency changes in a cyclical version over time; which is otherwise known as time-varying efficiency. This study examines the same hypothesis in the selected African stock markets using both linear and nonlinear dependency tests. Though most of the linear dependence tests (unit root, ACF and VR) support adaptive or time-varying behaviour, there are conflicting results based on the markets, with some tests showing that a market is efficient, some inefficient, as summarised in Table 5.9. Even where they are adaptive, the majority of the rolling linear tests still exhibit inefficiencies. This series of traditional linear tests, provided robustness to the study, but are not reliable for the adjudication of weak-form efficiency as elucidated in Chapter 4. For instance, unit root test is insufficient (Gilmore & McManus, 2003; Rahman & Saadi, 2008) and autocorrelation tests are biased, conflicting and unreliable (Hinich & Patterson, 1985; Amini *et al.,* 2010; Verheyden, *et al*., 2013). These observations require the tests of nonlinear dependence test of BDS, which shows that all the NGSE, JALSH, SEM, MOSE and TSE are time varying and adaptive. It is usually difficult to draw conclusion, when a series of tests yields conflicting results. Seetharam (2016), however, provides criteria for decision making in such situations, which is “to select one being an improvement over the other or argue the theoretical merits of each test before selecting the more appropriate one” (p. 307). Hence, in the face of conflict between linear and nonlinear results, the latter is preferred since the presence of nonlinear dependence implies market inefficiency irrespective of absence of linear dependence.

For the JSE and TSE, while VR tests show that the linear dependence is reported in returns throughout rolling windows, the BDS tests show that fluctuations in non-linear dependence occur. This finding is comparable to Hiremath and Kumari (2014) in which linear tests showed a switch between periods of efficiency and inefficiency, while nonlinear tests revealed presence of nonlinear dependence throughout the periods. With the growing literature (Amini *et al.,* 2010) on the inadequacy of linear estimation techniques (being a mere autocorrelation that does not capture nonlinearity) in establishing the efficiency or otherwise of financial markets, a combination of linear and nonlinear tools or a technique that captures both features will be satisfactory. Therefore, combining or exploring various types of the linear (unit root, ACF and VR) in conjunction with non-linear BDS testing tools, serves to ensure the avoidance of possible wrong inferences.

In essence, most of the tests that are employed in this study find periods of significant return dependence and independence in each of the five markets. These findings are contrary to the results of the absolute efficiency method observed for the full period, which had been the basis for the evaluation of the EMH prior to the emergence of the AMH. The rolling window estimation reveals that predictability and unpredictability occur in turn repeatedly, hence, according to Lo (2005), the idea that evolving markets must trend compulsorily toward some ideal equilibrium state is a mirage. Cycles of market efficiency and inefficiency are repeated in African stock markets. Thus, AMH appears to provide more appropriate description of the behaviour of market returns and the markets examined, therefore, are good examples of adaptive markets.

This finding of time-varying efficiency is in consonance with the findings of Todea *et al.* (2009) who reports changes in the degrees of dependence over time in Australia, Hong Kong, Singapore, Japan, India and Malaysia and Ito, Noda and Wada (2012) who concludes that stock market evolves through time and that there are cyclical movements in market efficiency in the US. The finding corroborates the findings of some of the earliest studies of cyclical efficiency in African stock markets conducted by Smith and Dyakova (2014), who disclosed successive periods of inefficiency and efficiency in South Africa, Tunisia and Nigeria although the study only applied linear VR tests. In addition, findings from nonlinear BDS tests employed in this study confirm the submission of Gyamfi *et al.* (2016) who studied Egypt, Botswana, Morocco, Kenya, Nigeria, Mauritius, South Africa, Tunisia stock markets and provided support for AMH as markets, which were found to be inefficient in the absolute forms, revealed periods of unpredictability in rolling window generalised spectra test results.

A significant revelation from nonlinear predictability tests is that JSE is only predictable in two of the 19 windows, hence, supporting the widely acclaimed view that the South African market is the most efficient in Africa (Smith *et al.,* 2002; Smith & Dyakova, 2014). Since JSE has fewer windows of inefficiencies relative to other markets, the study safely concluded that JSE is more efficient than the Nigeria, Mauritius and Morocco and Tunisian stock markets. Since the JSE sometimes portrays the behaviour of developed markets than developing ones, this finding is consistent with Niemczak and Smith (2013) who concluded that developed markets are more efficient than emerging markets. The NGSE and SEM have more windows of nonlinear predictability than other markets and this is in consonance with the body of existing findings that place the NGSE among the most inefficient markets (Smith *et. al.,* 2002; Smith & Dyakova, 2014). For SEM, larger periods of predictability are in line with the small size of this market. The few windows of nonlinear dependence in TSE equally comply with Smith and Dyakova (2014) which ranks TSE after the JSE in the order of relative efficiency. Ranking market efficiency in term of nonlinear predictability thus places JSE at the forefront, followed by TSE, MOSE, NGSE and SEM. This ranking is a reflection of the market liquidity (World Bank development Index appendix V) and market quality (Smith & Dyakova, 2014). In terms of the proportion of periods during which markets are inefficient, fluctuation in efficiency is more constant in Nigeria, Morocco and Mauritius stock markets than JSE and TSE. Thus, the three markets exhibit similar behaviour as far as changing market efficiency is concerned.

It must also be noted that NGSE, JALSH, SEM, MOSE and TSE undergo predictability or otherwise at different times. In other words, they adapt differently. Hence, different markets do not necessarily display the same return behaviour at the same time. This finding is similar to Urquhart and McGroarty (2016) who reported that different markets had significant predictability at different times, signifying that every market develops differently through time and the predictability among markets may be uncorrelated. Important implication for investors is that different markets should be treated or viewed differently even if such markets portray similar characteristics.

6.3 Discussion of Return Predictability and Market Condition Results

Study of efficiency and market condition relation is a rarity in the literature; even the few of them concentrate on the developed stock markets. This study examines the effect of market conditions on return predictability in the African stock markets and finds that, to an extent, the hypothesis of market efficiency being influenced by changing market conditions holds in selected African stock markets with the exception of JALSH. The lack of relationship between linear predictability and market conditions in the JSE, as noted in this study, is similar to findings of Urquhart and McGroarty (2016) for FTSE100 (UK) using Rank based VR. The lack of relationship between nonlinear predictability and market condition in JSE is also similar to the submission of Urquhart and McGroarty (2016) on EURO STOXX 50. This suggests that the market is not as reactive to changing conditions as NGSE, SEM, MOSE and further attests to the high level of efficiency of JSE.

The study finds that while there is high linear predictability in the NGSE and TSE throughout the bull/up and bear/down periods, returns are a little more predictable during the up than down market condition. We also find that though the up and down market conditions are associated with low nonlinear predictability, return is slightly less predictable during down than up market condition. This shows that the investors may benefit from abnormal profits in the up than the down condition. Up period in this case may be a period of economic boom, which is reflected in the stock market. This is in compliance with Lo (2005), who states that the degree of market efficiency is dependent on market conditions. The low nonlinear predictability reported in the up market condition is consistent with Urquhart and McGroarty (2016) in the US.

The significant presence of low linear predictability in the up and down conditions in NGSE and TSE and presence of high nonlinear predictability in the up and down markets in NGSE, SEM and TSE reveal that the up and down conditions have similar implications for return predictability in these markets. This differs from the findings of Urquhart and McGroarty (2016) who submitted that certain market conditions favour return predictability in the US, UK and Japan, while certain market conditions do not. For instance, the up and down market conditions have different implications for return predictability in the US as the bull, bear and normal conditions have in Japan. Specifically, Urquhart and McGroarty (2016) reported high nonlinear predictability during the bear and normal market conditions respectively in the US and Japanese markets; high linear predictability during normal condition in the US and UK and high linear predictability during bear condition in Japan. This suggests that the rate at which smaller stock market such as NGSE, SEM and TSE responds to the up and down conditions may not be as high as found in the developed market. In other words, one would not have expected similar behaviour in the up and the down market conditions as we have seen in the NGSE, SEM and TSE. The developed market of the US, UK, Japan differs from the African markets in terms of development indicators such as size, liquidity, sophistication and activities (WDI, 2017). In this case, the indicators may have a big role to play on the rate at which market/investors react to changing conditions, as investors in the developed market may be quicker in their reaction to events, news and happenings in the market ecology.

The high nonlinear predictability during the period of high volatility as found in the NGSE, SEM and TSE in this study is also consistent with Soteriou and Svenssion (2017) who documented the same in Sweden stock market as well as Urquhart and McGroarty (2016) in the US and UK markets. However, there is no relationship between volatility and predictability in JSE and MOSE. This study reports that the financial crisis does not have a noticeable relationship with return predictability (linear and nonlinear) in NGSE, JSE and TSE; the finding is similar to Zhou and Lee (2013), who submitted that there is no relationship between real estate sector return predictability and financial crisis in US. However, this study found high linear predictability during the financial crisis in SEM and MOSE, the finding that supports Kim *et al.,* (2011), who observed that there is high return predictability in the US stock market during the fundamental crisis. This suggests that the crisis may have different implications for return predictability in African stock markets, having no effect on GSE, JSE and TSE but significant effect in SEM and MOSE. High predictability during financial crisis may be caused by the panic and adverse reality of crisis, which may affect investors' ability to price stock efficiently.

Principally, the hypothesis of time-varying efficiency in line with changing market conditions is, to an extent, valid in the selected African stock markets except the JSE. It is noteworthy that return predictability behaviours of the NGSE, SEM and TSE markets are similar under different market conditions compared to the JSE and MOSE markets. It can be seen that the effect is similar in some markets than in the others, but the exact effect of market conditions on return predictability may not be generalised for all the five markets.

6.4 Discussion of the Time-varying Calendar Anomaly Results

Since the study of calendar anomalies is one of the ways of examining market efficiency in the literature, this study evaluates the behaviour of calendar anomalies using a rolling window GARCH approach. The findings also show that the DOW, MOY and HOM anomalies appear to conform to the time-varying behaviour initiated by the proponents of AMH. Alagidede and Panagiotidis (2009) is the only recognised African stock market calendar anomaly study where rolling window analysis was mentioned to examine the persistence of DOW effect. Unlike Alagidede and Panagiotidis (2009) who submitted that there is significant Friday effect in Ghana stock exchange, which vanishes with rolling windows, the current study shows a disappearance and reappearance of DOW effect in NGSE, JALSH, SEM, MOSE and TSE. This suggests the presence of time-varying calendar anomalies and confirms the appropriateness of AMH in describing stock return behaviour in the selected African stock markets.

The findings of the current study can also be compared with Zhang *et al.,* (2017) who established the presence of DOW effect in 25 countries, the anomalies that vanish with rolling windows in all except 6 countries. Bampinas *et al.*, (2016) have also established the reduction in the power of the DOW effect in two regional, six national indices through the application of rolling window estimation. Most of these studies mentioned, including Borges (2009), however, doubted the existence of the calendar anomalies due to the high instability in the behaviours of the anomalies over time. Consequently Ching (2015, p. 1) states, “the calendar effects may only be a ‘chimera’ delivered by intensive data mining as they are country-specific results and may not stable over time”.

Evanthia (2017) showed that the DOW is present in all sectors and general S&P500 indices using nonlinear models (EGARCH and TGARCH) in full sample but only one-fifth of the of the total number of regressions/windows is associated with anomaly. Hence, the study concluded that the anomalies are weak and time-variant as opposed to being persistent. Rather than considering the instability in the behaviour of the anomalies as a reflection of time-varying behaviour alluded by the proponents of AMH, virtually all these scholars (Alagidede & Panagiotidis, 2009; Borges, 2009; Bampinas *et al.*, 2016; Zhang *et al.,* 2017) imply that the presence of calendar effects in stock market could be as a result of data mining**.**

However, the findings from the current study are in line with the supporters of time-varying DOW, MOY and HOM calendar anomalies, inherent in the AMH. This is because DOW/weekend, MOY and HOM vary over time in NGSE, JSE, SEM, MOSE and TSE. Hence, the finding of this study is consistent with the submission of Urquhart and McGroarty (2014) who showed that the behaviour of Monday, January, Halloween and turn of the month calendar anomalies changes over time using similar rolling window estimation in of S&P 500 index in the US. This means that calendar anomaly is not an all or nothing phenomenon in the selected African stock market, just as it has been established in the US.

6.5 Discussion of Results on Calendar Anomalies and Market Conditions

In the application of MSM to the examination of calendar anomaly and market condition relations, the transition probabilities and constant expected durations are estimated. It is found that all the markets except the JSE have higher tendency to be in bearish state. Hence, they are expected to stay in the bear market than the bull market. This finding throws up a question on the performance of African stock markets. Higher duration of JALSH in bull regime has also been pointed out in a similar study by Rich (2018) for JSE market wide index and Top 40. Since JSE usually behaves like most developed markets, longer duration in bear regime (observed in remaining four African markets) could be an attribute of smaller or developing markets. Longer bearish trend may also be linked to illiquidity. The levels of liquidity of African stock markets have been very low, with South African being the only liquid market in the continent. Boako (2016) argued that illiquidity tends to cause serious retardation on the growth of markets. While JSE tends to enjoy investors' confidence due to longer duration in bull condition, level of confidence in NGSE, MOSE, SEM and TSE is likely to be low. Rising stock market trend is also a sign that the South African economy is stronger than the Nigeria, Morocco, Mauritius and Tunisia economies whose longer bearish condition is an indication of slows economy and possibly rising unemployment.

From the findings of calendar anomalies and market condition relation, weekend effect appears in the bear regime in NGSE, SEM and TSE and disappears in the bull regime. Conversely, weekend effect is found in the bull regime in MOSE and disappears in bear regime. DOW effect also exhibit changing behaviour where they are found. For instance, DOW is found in JSE in bull regime and disappears in bear regime. This regime switching behaviour of calendar anomalies has not been established previously, especially in the African stock markets and the only recognised studies, which considered market regime in African stock markets, were carried out by Atsin and Ocran (2015) and Rich (2018) on the JSE. While the former found reverse of weekend effect in bull regime as reported in the current study, Rich (2018) on the other hand, showed that there is no clear evidence of DOW effect under any market regime. It must be noted that the finding of positive Monday in JSE is not consistent with the international literature of negative Monday effect.

This study documents the Monday effect in NGSE, which is in consonance with Osazevbaru and Oboreh (2014) and a reverse of Monday effect in JSE and Nigeria in consonance with Chinzara and Slyper (2013), Du Toit *et al.* (2018) and Bhana (1985). This study also finds the presence of significant Friday effect in the SEM, which is consistent with Bundoo (2011). On the contrary, studies such as Chukwuogor (2007) concluded that DOW effect is absent in African countries, as the current study has also revealed during certain market condition. Therefore, some of the findings of this study have been documented by some of the previous studies (Chinzara & Slyper, 2013; Osazevbaru & Oboreh, 2014; Bhana, 1985; and Bundoo, 2011), but in absolute form. However, this study differs in that while the most of aforementioned study treated calendar anomaly as all or nothing, the current study shows how calendar effects are not always present in the markets where they have been documented and how they are not always absent where they are not found. This switching behaviour of calendar anomalies is not a universal constant but time-variant, varying with market condition in the selected African stock markets and in line with AMH.

This study also finds that the popular January effect is dominant in SEM and it is stronger in the bull market condition. The absence of January effect in other stock markets suggests that it is not prevalent in the African stock markets. The little evidence of January effect in all the markets is in conformity with Bundoo (2011) in Mauritius and Alagidede (2013) in the JSE who noted that the January effect that had been identified in many advanced markets are non-existent in African stock markets. This is corroborated by Rich (2018) who only observed negative January effect in the JSE. Insignificance of January effect may be connected to the peculiar features of the trading systems and market microstructure of the African markets. Alagidede (2013) notes that, tax arrangement in these African markets does not drive holders to sell shares at the tax year ending to generate a loss for tax purposes, the reason usually mentioned for January effect in the advanced markets. Moreover, lax regulation and undeveloped legal structure concerning the African stock markets could also account for the absence of proof for the tax-loss-selling hypothesis (Alagidede, 2013). The significant December effect during bull market is consistent with Atsin and Ocran (2015) who have similar finding in JSE. Further, this study supports Urquhart and McGroarty (2014) who submitted that market condition has no significant effect on behaviour of January effect in the US. Finding from the current study is not consistent with Oba (2014) who documented significant January effect in Nigeria, suggesting that Oba (2014) might have sampled a period when the effect appears.

Further, this study finds that the MOY effect changes with regime in the JSE and MOSE. The effect is associated with the bull and bear conditions respectively in the two markets. However, the MOY effect appears in both regimes in other stock markets; though, the specific effect observed in one regime disappears in the other regime. This study confirms that the MOY anomaly is prevalent in African markets as noted by Alagidede (2013) and Brishan (2012) but it must be noted that the particular effect is sensitive to regime. The sensitivity of MOY effect effects to market condition has not been documented in the selected African before, apart from Rich (2018) who reveals regime switching MOY in JSE. This study also establishes that the NGSE, the JSE, the SEM and the TSE exhibit intra-month effect in the bear regime and the effect disappears in bull regime or weakens as in the case of SEM. Conversely, the market regime has no relationship with intra-month in MOSE. In essence, the calendar anomalies considered in this study changes as markets condition changes as explained by AMH.

It must be noted that different market conditions favour different calendar anomalies in the selected markets except for the JSE where different anomalies are only found in the bull condition and TSE where most anomalies are found in the bear condition. For instance, the bear condition favours weekend effect in the NGSE and SEM while the Intra-month effect is favoured by bull condition in both markets. The presence of all identified anomalies in the bull condition in the JSE may be connected with the fact that, the JSE stays longer in the bull conditions (74 days) and the presence of most anomalies in bear condition in the TSE could also be due to the fact that the TSE stays longer in bear condition (37 days) than any other market. Since current study links calendar anomalies with different regimes in different markets (NGSE, SEM and MOSE) and same regime in some markets (JSE and TSE), it suggests that the market conditions could have different implications for calendar anomaly in these markets even when they belong to the same continent. Comparable study, carried out by Urquhart and McGroarty (2014) in the US discovered that calendar anomalies such as Monday and Hallowing effects are stronger in the down, bear, contraction and crashes compared to the up, bull, expansion and bubble just as the current study linked most calendar anomalies to bear market in TSE. This implies that market conditions could have similar implication for different markets whether the markets are developed or developing. More importantly, nonlinear models such as the MSM appears to bring out the salient type of stock return behaviour explained by the AMH, which cannot be adequately captured by single state model.

6.6 Summary of the Chapter

This chapter has presented extensive discussion of the main findings of the study. The study shows that time-variation is an essential feature of market efficiency and calendar anomalies in the selected African stock markets (NGSE, JSE, SEM, MOSE and TSE). The findings of the study show that some African stock markets exhibit similar behaviour than others. It has also been discussed how some findings in this study compare with findings from the developed stock markets where AMH has been investigated. The study submits that market efficiency and calendar anomaly are characteristics that vary under different regimes in the selected African stock markets and argues that the behaviour of calendar anomalies conforms to AMH than the EMH.

In terms of time-varying efficiency (rolling nonlinear dependence) and time-varying calendar anomalies (rolling GARCH), all the five markets are adaptive. Considering weak-form efficiency and market condition, all the markets (except JSE) are adaptive. For DOW/weekend/MOY effects and market condition, all the five markets are adaptive. In terms January effect and market conditions, all the market (except SEM), are efficient. In terms of HOM effect and market condition, all the markets (except MOSE) are adaptive. Taking all the models and tests into consideration, JSE is more efficient than others are (NGSE, SEM, MOSE, & TSE).

CHAPTER 7: SUMMARY AND CONCLUSION

7.1 Summary

It takes a theory to beat a theory (Lo, 2017). However, whether the AMH offers better explanations for stock return behaviour than the popular EMH remains a question of serious empirical investigation. This lacuna informs the analyses of efficiency and calendar anomalies in the selected African stock markets, namely the Nigerian Stock Exchange (NGSE), Johannesburg Stock Exchange (JSE), Stock Exchange of Mauritians (SEM), Casablancan (Morocco) Stock Exchange (MOSE) and Tunisian Stock Exchange (TSE). The study is made up of seven chapters, namely introduction, theoretical review, review of empirical studies, data and methodology, data analyses and interpretation, discussion of findings and summary and conclusion respectively.

The first chapter of this thesis provides the background and motivation for the study based on the need for broader evaluation of AMH in emerging markets such as the African stock markets. AMH presents a new opportunity for determining the appropriate description of African stock markets, whether it is inefficient or adaptive. Thus the chapter provides justification for the studies and also highlights the main objectives.

Chapter 2 lays the theoretical foundation for the current study through an extensive review of the major theories on the behaviour of stock returns over the year. The chapter provides a general review of the EMH, which holds that stock returns are independent and unpredictable resting on the assumptions of investors' rationality in respect of analysis of information and decision-making and of equal access to all information amongst others. The resistances to the assumptions of EMH by the proponents of BF who believe that investor biases and heuristics have important role to play in shaping the behaviour of financial markets are expounded. These contradictions have become the basis for many of the anomalies such as calendar anomalies. The chapter shows how AMH could provide a compromise for the unending debate between the EMH and BF. Lo (2005) new framework—AMH— shows that EMH and BF can be accommodated in an intellectually consistent manner. The arguments put up in the

AMH provide motivation for the examination of possibility of time-varying efficiency and anomalies and regime (market condition) switching in return behaviour.

Chapter 3 provides further detailed review of the empirical literature. The first aspect of the review focuses on the documentation of absolute efficiency/inefficiency in stock market under EMH. Similarly, the second segment of Chapter 3 traces the empirical studies on calendar anomalies in absolute form or using a single state model. The third segment focuses on the review of studies on AMH; hence, the content of the review is segregated into five, based on the objectives of the study. One important highlight from the review of empirical studies is the lack of consensus on the efficiency of stock market in absolute form. The review also reveals that there are little empirical studies of efficiency and anomalies within the AMH framework globally and particularly in emerging markets such as the African stock markets.

Chapter 4 contains a full description of the methodology and empirical models, which are employed to achieve the objectives of the study. AMH requires alternatives to fixed state models. Hence, the various tests of efficiency are implemented in rolling window approach. The dummy regression model is used to evaluate the market condition effect on return predictability. This study also explores several alternative variants of nonlinear GARCH model, especially the asymmetric TGARCH and EGARCH models that are able to capture the leverage effects. The GARCH family models are implemented using rolling window approach in order to track variation in the behaviour of day-of-the-week, MOY and intra-month effect. Lastly, this study models the switching behaviour of the calendar anomalies by using MSM, which is able to generate regime-specific regression results for the calendar anomalies under consideration.

In Chapter 5, the varying level of efficiency is tracked. Findings from the linear tests especially the VR, autocorrelation and KPSS tests show that there are periods of significant linear dependence and independence in each of the five markets. Result of the ordinary AR filtered returns shows significant nonlinear dependence throughout, indicating market inefficiency. However, the findings from the application of BDS to AR-

GARCH filtered returns reveal that nonlinear dependence is not an all or nothing event. This is contrary to the results of absolute efficiency method observed for the full period. In addition, the regression analyses of the monthly measures of return predictability against series of up, down, bull, bear, normal, volatile and financial crisis market conditions dummies are also performed. The analyses lead to the conclusion that market conditions do not affect return predictability in JSE and MOSE but for high linear predictability during financial crisis in the latter. Conversely, it is discovered that the effect of certain market conditions on predictability are similar in other markets. Rolling window GARCH estimations treat calendar anomalies as a feature that is dynamic as opposed to static. The finding shows that January effect is not present in NGSE and JSE but appears and disappears in other markets. Specifically, January effect appears in five, three and four windows out of possible 16 windows respectively in SEM, MOSE and TSE, meaning that the effect is weak. Other effects, namely weekend, DOW, MOY and HOM are time-variant. Lastly, the empirical analysis reveals that regime switching is an important feature of calendar anomalies. The study submits that a calendar anomaly that is found in bull regime disappears or weakens in bear regime and *vice versa*.

7.2 Concluding Remarks

Overall, the study reveals that predictability and unpredictability occur in turn repeatedly, hence, the idea that evolving markets must trend compulsorily toward some ideal equilibrium state is a mirage. The study concludes that, the selected African markets are good examples of the adaptive markets as cycles of market efficiency and inefficiency are repeated in the African markets. Further, the hypothesis of time-changing return predictability due to changing market condition is valid for NGSE, SEM and TSE but not strong enough in JSE and MOSE. Hence, the study concludes that, to an extent, the stock return behaviour changes in response to market condition. However, JSE seems to be less reactive to changing condition than other markets. In addition, January effect is not particularly strong in the African stock markets while other calendar effects are time-variant and adaptive. The study concludes that weekend, DOW, MOY and HOM effects behave in compliance with the AMH in African markets.

Similarly, reactions of investors to negative news in comparison to positive news also seem to change in SEM, MOSE and TSE as revealed by the varying leverage effect in these markets. This study also indicates that the JSE is stronger than NGSE, SEM, MOSE and TSE by considering longer duration in bull regime. Hence, this portrays South African economy as a stronger economy. Moreover, the power of calendar anomaly changes over time in response to changing market condition or regime. Therefore, the study concludes that calendar anomalies have nonlinear feature and that MSM and AMH provide a better description of the nonlinear feature than the single state models and EMH respectively.

7.3 Contributions and Implications of Findings

This study adds to the extant literature on the AMH in Africa and global markets. First, it shows that African stock markets are adaptive, as developed markets. Thus, it is more appropriate to describe African markets as adaptive markets rather than inefficient markets. Secondly, it provides empirical evidence of efficiency cum market condition in African stock markets. Thirdly, the study represents a timely contribution on calendar anomalies under AMH in African stock market. Fourthly, by evaluating DOW, MOY and HOM effects under AMH, this study extends the existing works by Urquhart (2013, 2014) on Monday and January effects in developed markets. Additionally, this study shows the usefulness of MSM in evaluating calendar anomalies under AMH, being able to accommodate efficiency and anomaly, as well as market conditions.

The findings from this study have some implications for investors, portfolio/fund managers and market regulators and academics in the field of finance. The study has documented time-varying efficiency; suggesting a repeated cycles of inefficiency and efficiency in selected African stock markets as postulated by the AMH. It also shows that various markets undergo predictability or otherwise at different time. It means that different markets do not necessarily display the same return behaviour at the same time. Important implication for market participants is that different markets should be treated or viewed differently. Similarly, the study establishes time-changing calendar anomalies in the selected markets. This implies that calendar anomalies are not always present where they have been documented in absolute form; and they are not always absent where they are not found in absolute form. Hence, market participants or investors should not be misled into believing that a market remains efficient or not at all time. In the same vein, market participants should not view market as being anomalous in absolute form. It would be prudent of investors to plan a flexible investment strategy to accommodate changes in market efficiency and calendar anomalies. Market regulators must also take market dynamic into consideration in the promulgation of stock exchange laws and regulations governing the exchanges.

This study finds similar behaviour for predictability in the up and down market conditions in the NGSE, SEM and TSE. This implies that the up and down conditions may not have strong influence on the trading strategy in these markets but volatility does. It implies that the rate at which smaller/developing stock market responds to up and down condition may not be as high as found in the developed market. Thus, market condition may have slightly different implications for developed and African stock markets and findings from developed markets may not always provide a good approximation of what is obtained in the African stock markets. The reaction of NGSE, SEM and TSE to change in market condition is similar. The similarity implies that diversification between the three stock markets may not yield significant synergistic effect for the investors when market condition is considered. Investors may however consider diversifying between these three markets and JSE or MOSE where predictability is not affected by market conditions. This findings equally has implication for local and international market participants, understanding of the effect of market conditions would assist both local and international investors in timing their investment in the stock markets.

Except JSE, all the selected African markets stay in the bearish than the bullish state. This has an implication for the performance of African stock markets. The sizes of the selected stock markets apart from the JSE are very small relative to economic growth. With many of the markets staying in the bear than the bull regime, this study suggests that the market regulators find a means of boosting market performance if the African markets would play a meaningful role in economic development. Since calendar anomalies are significantly influenced by market conditions, market participants and portfolio managers should pay attention to market conditions in the design and application of their investment strategy. For instance, active investment management may yield profits for investors and managers to exploit weekend effect when NGSE, SEM, MOSE and TSE are in the bear regime and JSE in bull regime. Conversely, investors may exploit the intra-month calendar anomaly when the NGSE, JSE and SEM are in the bull regime and TSE in bear regime. Investors, however, may become passive in the subsequent regime when the anomaly weakens and market become efficient. Unlike weak-form efficiency and market conditions, the examination of calendar anomaly under different regimes using MSM provides clearer picture of the cycles of efficiency and anomaly latent in AMH. This study reveals that calendar anomalies appear in certain market conditions and disappear/weaken in others, depending on the market and the particular anomaly; meaning that African stock markets undergo conditions of inefficiency and efficiency in support of the AMH. This submission is in contrast with the submission of single state models through which the majority of the African markets have been adjudged inefficient over the years. In particular, the model recommends the need for investors to adjust their investment strategy in the light of market regime or condition when making their asset location decisions.

7.4 Limitations

Despite the achievement of study objectives, this dissertation has some limitations, which are common to research of this nature. First, the study examines five African stock markets, dropping some markets, which could have provided some further information. However, the selected markets are still good enough to portray the behaviour of most African markets in terms of trading activities and MCAP. Secondly, the length of the full sample period is quite short when compared to similar studies from the developed markets (US, UK, Japan, etc.) where centuries of data are available. However, daily data over 1998-2018 are able to generate robust results and windows, sufficient to track cycles of efficiency and calendar anomaly over time. In addition, the sample size for TSE started from 1999:4 and hence, shorter than the remaining four markets, but it would have been impossible to observe the behaviours of other markets during1998-1999 windows, starting all markets from 1999. Third, the study adopts window sizes of 2 and 5 years respectively for time-varying efficiency and calendar anomaly. One could have considered different window size, which could generate different results. Nevertheless, the adequacy of the sizes employed in this study had been attested to by some of the earlier studies in the US. Lastly, there are many market conditions other than bull and bear condition that could not be incorporated in the current study which according to Lo (2017) could be social, cultural, political, economic and natural environments. Those external conditions/factors could provide further insight on the behaviour of efficiency/calendar anomaly since stock markets do not operate in isolation or vacuum.

7.5 Suggestions for Future Research

Being a relatively new theory, there is no limit to the adventure a researcher could seek or embark upon, as regards AMH. It is simply a question of where (be it broad market, sectoral or firm level) it has not been investigated and which model could be used. The AMH is gaining attention from researcher due to its recency but it obviously requires further exploration. The proponent of AMH has identified some market conditions to consider and presently little has been done. Researchers are now confronted with the task of determining framework or models that accommodate efficiency and anomaly, as well as market conditions, with a view to bringing out effect of changes in episode. As more and more data become available with time, this study suggests that similar studies be carried out in other African stock markets to aid generalisation of findings while other environmental conditions surrounding the markets are examined to ascertain their effects on stock return predictability. Since the stock market conditions cannot be dissociated from the general economic situation, the effect of economic conditions on market efficiency will make meaningful contributions. There are other types of calendar anomalies and other types of market anomalies, which have not been examined within the AMH point of view. There is room for firm-specific, sector-specific, region-specific and in fact comparative studies. Future researcher could also adopt MSM in the evaluation of other types of anomalies and higher number of regimes could be considered in doing so. Future study could make adjustment for possible thin-trading effect on the data. Except the JSE, all the selected African markets stay in the bearish than the bullish state. Since the reasons for this behaviour is outside the scope of the current study, searching for possible reasons for longer duration in the bearish state, provides motivation for further empirical investigations.

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List of Appendices

Appendix 1: Residual Diagnostic Results and Information Criteria for Table 5.11- Regression Results

NGSEINDX	**UP/DOWN**		**BULL/BEAR**		
	VRT	BDS (HAC)		**VRT**	**BDS (HAC)**
ARCH	Prob. F(1,200) = 0.918	Prob. F(1,200) = 0.00	**ARCH**	**Prob. F(1,200) = 0.877**	**Prob. F(1,215) = 0.000**
BG LM test	Prob. = 0.5171	Prob. = 0.0008	**BG LM test**	**Prob. = 0.5285**	**Prob. = 0.0014**
L-Jung box	Q-Stat Prob. = 0.338	Q-Stat Prob. = 0.000	**L-Jung box**	**Q-Stat Prob. = 0.296**	**Q-Stat Prob. = 0.006**
Adj. R^2	0.846168	0.676218	**Adj. R^2**	**0.848059**	**0.686815**
Information Criteria	AIC -3.781765 SBIC -3.688913 HQIC-3.744265	AIC -1.553274 SBIC-1.475648 HQIC-1.521920	**Information Criteria**	**AIC-3.798553*** **SBIC -3.705402*** **HQIC-3.760928***	**AIC -1.582083*** **SBIC -1.488932*** **HQIC -1.544458***
JALSH	**VRT**	**BDS**		**VRT**	**BDS**
ARCH	**Prob. F(1,200) = 0.9837**	**Prob. F(1,200) = 0.9474**	ARCH	Prob. F(1,200) = 0.996	Prob. F(1,215) = 0.948
BG LM test	**Prob. = 0.6594**	**Prob. = 0.9749**	BG LM test	Prob. = 0.7300	Prob. = 0.9937
L-Jung box	**Q-Stat Prob. = 0.352**	**Q-Stat Prob. = 0.874**	L-Jung box	Q-Stat Prob. = 0.424	Q-Stat Prob. = 0.914
Adj. R^2	**0.811654**	**0.008090**	Adj. R^2	0.810908	0.005905
Information Criteria	**AIC -13.48172*** **SBIC-13.40409*** **HQIC-13.45037***	**AIC 11.72307*** **SBIC11.78497*** **HQIC11.74807***	Information Criteria	AIC -13.47330 SBIC-13.38015 HQIC-13.43567	AIC 11.72537 SBIC 11.80274 HQIC 11.75662
SEMDEX	**VRT**	**BDS (HAC)**		**VRT**	**BDS (HAC)**
ARCH	**Prob. F(1,200) = 0.9321**	**Prob. F(1,200) = 0.1149**	ARCH	Prob. F(1,200) = 0.932	Prob. F(1,215) = 0.124
BG LM test	**Prob. = 0.7669**	**Prob. = 0.0000**	BG LM test	Prob. = 0.7873	Prob. = 0.0000
L-Jung box	**Q-Stat Prob. = 0.485**	**Q-Stat Prob. = 0.0000**	L-Jung box	Q-Stat Prob. = 0.507	Q-Stat Prob. = 0.0000
Adj. R^2	**0.924652**	**0.802027**	Adj. R^2	0.924190	0.797856
Information Criteria	**AIC -3.916452*** **SBIC-3.854352*** **HQIC-3.891369***	**AIC -1.343477*** **SBIC-1.265851*** **HQIC-1.312123***	Information Criteria	AIC -3.905849 SBIC-3.828223 HQIC-3.874495	AIC -1.318159 SBIC -1.225007 HQIC -1.280533
MOSENEW	**VRT (HAC)**	**BDS**		**VRT (HAC)**	**BDS**
ARCH	**Prob.F(1,200) = 0.0000**	**Prob.F(1,200) = 0.8646**	ARCH	Prob. F(4,213) = 0.558	Prob. F(1,215) = 0.866
BG LM test	**Prob. = 0.0000**	**Prob. = 0.8625**	BG LM test	Prob. (0.0000)	Prob. = 0.8472
L-Jung box	**Q-Stat Prob. = 0.0000**	**Q-Stat Prob. = 0.703**	L-Jung box	Q-Stat Prob. 0.0000	Q-Stat Prob. = 0.709
Adj. R^2	**0.491629**	**0.003028**	Adj. R^2	0.492367	0.686815
Information Criteria	**AIC -5.068407*** **SBIC-4.990781*** **HQIC-5.037053***	**AIC 19.48401*** **SBIC19.48401*** **HQIC19.50901***	Information Criteria	AIC-5.065391 SBIC -4.972240 HQIC-5.027766	AIC19.48616 SBIC 19.56353 HQIC19.517409
TUSISE	**VRT (HAC)**	**BDS**		**VRT (HAC)**	**BDS**
ARCH	**Prob.F(1,200).183**	**Prob.F(1,200).096**	ARCH	Prob.F(1,200).272	Prob.F(5,197).083
BG LM test	**0.0043**	**0.1274**	BG LM test	0.023	0.1213
L-Jung box	**Q-Stat Prob. 0.005**	**Q-StatProb.0.132**	L-Jung box	Q-Stat Prob..010	Q-Stat Prob..141
Jaque-Bera	**Prob.0.0000**	**Prob.0.005415**	Jaque Bera	Prob.0.0000	0.040258
Adj. R^2	**0.715137**	**0.670209**	Adj. R^2	0.715245	0.676709
Information Criteria	**AIC -7.614395*** **SBIC -7.532789*** **HQIC -7.581380***	**AIC -0.834497** **SBIC -0.752891*** **HQIC -0.801483**	Information Criteria	AIC -7.609984 SBIC -7.512057 HQIC -7.570366	AIC -0.849615* SBIC -0.751688 HQIC -0.80999*

Selected models are bolded. Model selection is based on the minimum AIC, SBIC & HQIC. HAC implies Heteroscedasticity and Autocorrelation Consistent.

Appendix II

Table 6.2: Rolling GARCH Information Criteria

		NGSEINDX			JALSH			SEMDEX			MOSENEW			TUSISE		
Model	**IC**	**DOW**	**MOY**	**HOM**	**DOW**	**MOY**	**HOM**	**DOW**	**MOY**	**HOM**	**DOW**	**MOY**	**HOM**	**DOW**	**MOY**	**HOM**
GARCH (1, 1)	AIC	2.288476	2.286724	2.283593	2.967068	3.572092	2.969738	1.029513	1.030588	1.030310	1.755388	1.756904	1.760260	1.195571	1.204818	1.202867
	SBIC	2.312593	2.297442	2.298331	2.978724	3.592814	2.978868	1.041173	1.051317	1.038083	1.769753	1.779104	1.769401	1.210284	1.229831	1.213167
	HQIC	2.296943	2.290487	2.288767	2.971151	3.579352	2.972938	1.033598	1.037851	1.033033	1.760423	1.764686	1.763464	1.200765	1.213649	1.206503
	Log Lik	-5520.113	-5525.871	-5515.295	-7465.043	-8982.100	-7411.405	-2583.315	-2579.022	-2588.320	-4367.816	-4365.597	-4383.969	-2579.607	-2592.637	-2598.411
TGARCH (1, 1)	AIC	2.288649	2.286834	2.283676	2.952394	2.957081	2.955130	1.029830	1.030918	1.030627	1.755518	1.757076	1.760425	**1.195231**	**1.204243**	**1.202400**
	SBIC	2.314105	2.298892	2.299754	2.965345	2.979097	2.965564	1.042786	1.052943	1.039696	1.771189	1.780582	1.770872	**1.211415**	**1.230726**	**1.214170**
	HQIC	2.297586	2.291067	2.289320	2.956931	2.964794	2.958787	1.034369	1.038635	1.033805	1.761011	1.765315	1.764087	**1.200944**	**1.213593**	**1.206555**
	Log Lik	-5519.531	-5525.137	-5514.496	-7427.079	-7431.886	-7373.914	-2583.112	-2578.853	-2588.120	-4367.140	-4365.026	-4383.380	**-2577.869**	**-2590.390**	**-2596.398**
EGARCH (1, 1)	AIC	**2.270044**	**2.268180**	**2.264765**	**2.949801**	**2.954519**	**2.952755**	**1.027598**	**1.028574**	**1.028031**	**1.751455**	**1.753734**	**1.756482**	1.195699	1.204914	1.203517
	SBIC	**2.295500**	**2.280238**	**2.280843**	**2.962752**	**2.976535**	**2.963189**	**1.040553**	**1.050599**	**1.037100**	**1.767126**	**1.777240**	**1.766929**	1.211884	1.231397	1.215288
	HQIC	**2.278980**	**2.272413**	**2.270409**	**2.954338**	**2.962232**	**2.956412**	**1.032137**	**1.036291**	**1.031209**	**1.756948**	**1.761973**	**1.760144**	1.201413	1.214263	1.207673
	Log Lik	**-5474.506**	**-5479.996**	**-5468.731**	**-7420.548**	**-7425.432**	**-7367.981**	**-2577.491**	**-2572.950**	**-2581.583**	**-4357.005**	**-4356.690**	**-4373.545**	-2578.885	-2591.843	-2598.819
1998-2002																
GARCH (1, 1)	AIC	1.465736	1.454586	1.450619	3.252707	3.261187	3.253544	0.691661	0.697912	0.691245	1.255615	1.277169	1.276205			
	SBIC	1.540537	1.487831	1.496331	3.293833	3.331103	3.282333	0.737403	0.772763	0.724512	1.300971	1.351389	1.309192			
	HQIC	1.493878	1.467093	1.467817	3.268169	3.287474	3.264368	0.708871	0.726074	0.703762	1.272670	1.305079	1.288609			
	Log Lik	-884.1606	-887.2974	-881.8561	-2018.063	-2016.350	-2021.585	-414.3718	-411.2162	-417.1160	-769.3645	-775.7607	-785.1615			
TGARCH (1, 1)	AIC	1.457672	1.446434	1.442815	3.242833	3.252035	**3.244502**	0.692518	0.698745	0.692030	1.256358	1.277792	1.277102			
	SBIC	1.536629	1.483834	1.492683	3.288073	3.326063	**3.277403**	0.742418	0.777754	0.729455	1.305837	1.356135	1.314212			
	HQIC	1.487377	1.460504	1.461576	3.259842	3.279868	**3.256872**	0.711292	0.728471	0.706111	1.274964	1.307252	1.291057			
	Log Lik	-878.1971	-881.2799	-876.0528	-2010.907	-2009.644	-2014.947	-413.8983	-410.7282	-416.5987	-768.8263	-775.1477	-784.7189			
EGARCH (1, 1)	AIC	**1.450361**	**1.439312**	**1.435412**	**3.242806**	**3.247495**	3.244763	**0.690225**	**0.695490**	**0.688739**	**1.242733**	**1.266813**	**1.266443**			
	SBIC	**1.529318**	**1.476713**	**1.485280**	**3.288045**	**3.321523**	3.277664	**0.740125**	**0.774498**	**0.726164**	**1.292213**	**1.345156**	**1.303553**			
	HQIC	**1.480066**	**1.453383**	**1.454173**	**3.259815**	**3.275328**	3.257133	**0.708999**	**0.725216**	**0.702819**	**1.261339**	**1.296273**	**1.280398**			
	Log Lik	**-873.6970**	**-876.8968**	**-871.4962**	**-2010.890**	**-2006.813**	-2015.110	**-412.4881**	**-408.7263**	**-414.5744**	**-760.3586**	**-768.3242**	**-778.0944**			
1999-2003																
GARCH (1, 1)	AIC	2.069060	2.064457	2.068009	3.104430	3.114789	3.100898	0.725694	0.733511	0.726090	1.361928	1.377993	1.370007	1.467096	1.470410	1.464748
	SBIC	2.145926	2.098620	2.114983	3.145556	3.184705	3.129687	0.771798	0.808954	0.759620	1.407256	1.452164	1.402973	1.524679	1.559403	1.501392
	HQIC	2.098027	2.077331	2.085711	3.119892	3.141076	3.111722	0.743049	0.761909	0.738712	1.378972	1.405883	1.382403	1.489067	1.504366	1.478730
	Log Lik	-1213.091	-1220.352	-1219.465	-1925.612	-1925.075	-1926.410	-430.9478	-428.7080	-434.1890	-836.1195	-839.1114	-844.1446	-665.3311	-660.8590	-668.2488
TGARCH (1, 1)	AIC	2.061447	2.057943	2.061717	**3.096033**	3.106666	**3.092210**	0.726260	0.734561	0.726694	1.363436	1.379584	1.571658	1.466777	1.471561	1.465305
	SBIC	2.142584	2.096376	2.112962	**3.141272**	3.180694	**3.125111**	0.776555	0.814195	0.764415	1.412884	1.457877	1.608744	1.529595	1.565789	1.507184
	HQIC	2.092023	2.072427	2.081029	**3.113042**	3.134499	**3.104580**	0.745192	0.764536	0.740893	1.382029	1.409024	1.585603	1.490746	1.507515	1.481285
	Log Lik	-1207.561	-1215.476	-1214.722	**-1919.377**	-1919.006	**-1919.993**	-430.2921	-428.3476	-433.5564	-836.0572	-839.1015	-968.5714	-664.1840	-660.3897	-667.5057
EGARCH (1, 1)	AIC	**2.054862**	**2.050566**	**2.054390**	3.097656	**3.106264**	3.093959	**0.724048**	**0.731333**	**0.724009**	**1.352103**	**1.371225**	**1.363171**	**1.460430**	**1.464767**	**1.458401**
	SBIC	**2.135999**	**2.088999**	**2.105634**	3.142896	**3.180292**	3.126861	**0.774344**	**0.810967**	**0.761730**	**1.401551**	**1.449518**	**1.400256**	**1.523249**	**1.558995**	**1.500280**
	HQIC	**2.085438**	**2.065049**	**2.073701**	3.114665	**3.134097**	3.106330	**0.742980**	**0.761308**	**0.738208**	**1.370696**	**1.400665**	**1.377116**	**1.484400**	**1.500721**	**1.474381**
	Log Lik	**-1203.643**	**-1211.087**	**-1210.362**	-1920.389	**-1918.755**	-1921.084	**-428.9454**	**-426.3817**	**-431.9214**	**-829.0080**	**-833.9021**	**-838.8921**	**-661.2584**	**-657.2577**	**-664.3230**
2000-2004																
GARCH (1, 1)	AIC	2.352412	2.348053	2.351825	3.063782	3.065484	3.060773	0.703021	0.725355	0.703952	1.568901	1.581251	1.571521	1.354906	1.364759	1.354214
	SBIC	2.430870	2.382923	2.399772	3.108963	3.139417	3.093632	0.749774	0.806164	0.737955	1.615005	1.656694	1.605051	1.403520	1.447402	1.388244
	HQIC	2.382016	2.361211	2.369917	3.080768	3.093279	3.073126	0.720635	0.755800	0.716762	1.586255	1.609649	1.584143	1.373372	1.396151	1.367140
	Log Lik	-1346.399	-1353.871	-1353.059	-1902.332	-1896.395	-1903.453	-409.7582	-414.7623	-413.3155	-944.4604	-944.9821	-949.0565	-675.5826	-673.5681	-678.2324
TGARCH (1, 1)	AIC	2.349325	2.345580	2.349468	3.047535	3.048227	3.043407	0.702908	0.725371	0.703808	1.570542	1.582890	1.573132	1.356717	1.365707	1.355846
	SBIC	2.432142	2.384808	2.401773	3.096824	3.126267	3.080373	0.753912	0.810433	0.742060	1.620838	1.662524	1.610853	1.410192	1.453211	1.394737
	HQIC	2.380573	2.360381	2.369204	3.066065	3.077566	3.057304	0.722123	0.757418	0.718219	1.589474	1.612866	1.587331	1.377030	1.398945	1.370619
	Log Lik	-1343.608	-1351.436	-1350.691	-1891.186	-1884.618	-1891.607	-408.6907	-413.7717	-412.2291	-944.4603	-944.9801	-949.0373	-675.4990	-673.0476	-678.0581
EGARCH (1, 1)	AIC	**2.345042**	**2.340243**	**2.344428**	**3.045645**	**3.042765**	**3.041379**	**0.696069**	**0.716450**	**0.696587**	**1.560676**	**1.573263**	**1.563179**	**1.351165**	**1.360256**	**1.350931**
	SBIC	**2.427858**	**2.379472**	**2.396733**	**3.094933**	**3.120805**	**3.078346**	**0.747072**	**0.801512**	**0.734839**	**1.610971**	**1.652897**	**1.600900**	**1.404640**	**1.447760**	**1.389822**
	HQIC	**2.376290**	**2.355045**	**2.364164**	**3.064175**	**3.072104**	**3.055277**	**0.715283**	**0.748497**	**0.710998**	**1.579608**	**1.603239**	**1.577378**	**1.371478**	**1.393494**	**1.365704**
	Log Lik	**-1341.124**	**-1348.341**	**-1347.768**	**-1890.005**	**-1881.207**	**-1890.341**	**-404.5970**	**-408.4370**	**-407.9074**	**-938.4517**	**-939.1173**	**-942.9760**	**-672.6897**	**-670.2893**	**-675.5710**
2001-2005																
GARCH (1, 1)	AIC	2.442720	2.431380	2.436685	2.916872	2.927099	2.918805	0.910681	0.929496	0.912737	1.604172	1.609413	1.601383	1.223483	1.234212	1.226732
	SBIC	2.523358	2.467219	2.436685	2.957866	2.996790	2.947501	0.957782	1.010907	0.946992	1.650398	1.685055	1.635002	1.272020	1.316725	1.260708
	HQIC	2.473198	2.444925	2.455310	2.932282	2.953296	2.929592	0.928434	0.960182	0.925648	1.621575	1.637890	1.614039	1.241918	1.265552	1.239636
	Log Lik	-1350.500	-1354.788	-1354.762	-1815.962	-1815.364	-1820.172	-529.0339	-531.7263	-533.2531	-962.7323	-958.9136	-964.0393	-610.3057	-608.7457	-614.9530
TGARCH (1, 1)	AIC	2.442886	2.430556	2.435731	2.903420	2.912661	**2.904492**	0.911822	0.930166	0.913956	1.771475	1.611020	1.602963	1.224300	1.232312	1.227014
	SBIC	2.532484	2.470875	2.489490	2.948514	2.986451	**2.937288**	0.963204	1.015862	0.952493	1.821903	1.690865	1.640785	1.277691	1.319679	1.265844
	HQIC	2.476750	2.445795	2.456049	2.920371	2.940399	**2.916820**	0.931188	0.962467	0.928481	1.790460	1.641080	1.617202	1.244579	1.265495	1.241762
	Log Lik	-1349.238	-1353.327	-1353.227	-1806.541	-1805.326	**-1810.212**	-528.7102	-531.1231	-532.9758	-1063.285	-958.8892	-963.9988	-609.7203	-606.7824	-614.0961
EGARCH (1, 1)	AIC	**2.437504**	**2.423858**	**2.430419**	**2.903163**	**2.911722**	2.905662	**0.906845**	**0.924611**	**0.909069**	**1.595712**	**1.600917**	**1.592362**	**1.217877**	**1.225125**	**1.222097**
	SBIC	**2.527102**	**2.464178**	**2.484178**	**2.948257**	**2.985512**	2.938458	**0.958228**	**1.010307**	**0.947606**	**1.646140**	**1.680762**	**1.630183**	**1.271267**	**1.312492**	**1.260927**
	HQIC	**2.471368**	**2.439097**	**2.450738**	**2.920114**	**2.939460**	2.917990	**0.926212**	**0.956912**	**0.923594**	**1.614697**	**1.630976**	**1.606600**	**1.238155**	**1.258308**	**1.236845**
	Log Lik	**-1346.221**	**-1349.573**	**-1350.250**	**-1806.380**	**-1804.738**	-1810.495	**-525.7591**	**-527.8319**	**-530.0781**	**-956.5971**	**-952.7564**	**-957.5635**	**-606.4634**	**-603.1385**	**-611.6033**
2002-2006																
GARCH (1, 1)	AIC	2.438823	2.423595	2.432118	2.903395	2.909954	2.902574	1.119184	1.121082	1.120252	1.846694	1.847348	1.841415	1.092029	1.108956	1.099935
	SBIC	2.524802	2.464321	2.486421	2.940337	2.975629	2.927203	1.166381	1.194022	1.154577	1.892828	1.922841	1.874968	1.143408	1.193031	1.137302
	HQIC	2.471339	2.438997	2.452655	2.917283	2.934644	2.911833	1.136975	1.148577	1.133191	1.864060	1.875766	1.854045	1.111498	1.140814	1.114095
	Log Lik	-1330.889	-1332.460	-1334.177	-1805.622	-1802.721	-1808.109	-650.9974	-646.1198	-654.6288	-1112.713	-1106.112	-1112.501	-569.9593	-571.9646	-577.1656
TGARCH (1, 1)	AIC	2.438850	2.423014	2.431853	2.887333	2.892240	2.885968	1.115445	1.115128	1.116670	1.846355	1.846723	1.840899	1.092702	1.107465	1.100097
	SBIC	2.529354	2.468266	2.490681	2.928381	2.962020	2.914701	1.166932	1.192359	1.155285	1.896684	1.926410	1.878645	1.148752	1.196211	1.142135
	HQIC	2.473078	2.440128	2.454101	2.902764	2.918472	2.896770	1.134853	1.144241	1.131226	1.865300	1.876719	1.855108	1.113941	1.141093	1.116026
	Log Lik	-1329.904	-1331.138	-1333.031	-1794.583	-1790.650	-1796.730	-647.7857	-641.5980	-651.5101	-1111.507	-1104.731	-1111.187	-569.3174	-570.1715	-576.2516
EGARCH (1, 1)	AIC	**2.431320**	**2.413508**	**2.422675**	**2.887209**	**2.893467**	**2.887243**	**1.107161**	**1.110959**	**1.108721**	**1.838397**	**1.839433**	**1.832720**	**1.088827**	**1.105143**	**1.097196**
	SBIC	**2.521825**	**2.458761**	**2.481503**	**2.928256**	**2.963247**	**2.915976**	**1.158649**	**1.188190**	**1.147337**	**1.888725**	**1.919120**	**1.870467**	**1.144877**	**1.193889**	**1.139234**
	HQIC	**2.465548**	**2.430622**	**2.444923**	**2.902640**	**2.919699**	**2.898045**	**1.126570**	**1.140072**	**1.123277**	**1.857342**	**1.869430**	**1.846929**	**1.110066**	**1.138771**	**1.113125**
	Log Lik	**-1325.736**	**-1325.877**	**-1327.951**	**-1794.506**	**-1791.417**	**-1797.527**	**-642.8859**	**-639.1320**	**-646.8084**	**-1106.664**	**-1100.295**	**-1106.210**	**-567.2560**	**-568.9358**	**-574.7082**
2003-2007																
GARCH (1, 1)	AIC	2.630708	2.416705	2.425583	2.886833	2.897807	2.890048	1.352771	1.339551	1.350105	2.024635	2.020565	2.019401	1.063528	1.080526	1.069407
	SBIC	2.707748	2.457491	2.479964	2.923775	2.963482	2.914677	1.395417	1.412049	1.379957	2.066576	2.091863	2.048759	1.113815	1.162814	1.105979
	HQIC	2.659846	2.432131	2.446151	2.900720	2.922496	2.899307	1.368840	1.366870	1.361354	2.040423	2.047404	2.030452	1.082558	1.111666	1.083247

	Log Lik	-1436.466	-1326.229	-1328.135	-1795.270	-1795.129	-1800.280	-796.2514	-781.3726	-797.6625	-1221.991	-1212.514	-1221.806	-570.2180	-572.5077	-576.4310
TGARCH (1, 1)	AIC	2.615832	2.414783	2.423818	2.875801	2.885115	2.878316	1.348883	1.335211	1.346184	2.024993	2.021225	2.019647	1.064965	1.081045	1.070560
	SBIC	2.697404	2.460101	2.482731	2.916848	2.954895	2.907049	1.395793	1.411974	1.380301	2.071127	2.096717	2.053199	1.119823	1.167904	1.111704
	HQIC	2.646685	2.431923	2.446100	2.891232	2.911347	2.889117	1.366560	1.364136	1.359040	2.042359	2.049643	2.032277	1.085725	1.113915	1.086130
	Log Lik	-1427.247	-1324.168	-1326.159	-1787.376	-1786.197	-1791.947	-792.9342	-777.7857	-794.3259	-1221.208	-1211.915	-1220.955	-570.0033	-571.7912	-576.0610
EGARCH (1, 1)	AIC	**2.597541**	**2.405078**	**2.415177**	**2.872911**	**2.883672**	**2.876606**	**1.339751**	**1.329260**	**1.338578**	**2.023373**	**2.019779**	**2.017113**	**1.063170**	**1.080900**	**1.070448**
	SBIC	**2.679113**	**2.450395**	**2.474089**	**2.913958**	**2.953452**	**2.905339**	**1.386661**	**1.406023**	**1.372695**	**2.069507**	**2.095271**	**2.050665**	**1.118028**	**1.167759**	**1.111591**
	HQIC	**2.628393**	**2.422218**	**2.437459**	**2.888342**	**2.909905**	**2.887408**	**1.357427**	**1.358185**	**1.351434**	**2.040739**	**2.048196**	**2.029743**	**1.083930**	**1.113769**	**1.086017**
	Log Lik	**-1417.141**	**-1318.805**	**-1321.385**	**-1785.569**	**-1785.295**	**-1790.879**	**-787.4914**	**-774.2390**	**-789.7924**	**-1220.222**	**-1211.035**	**-1219.413**	**-569.0223**	**-571.7117**	**-575.9996**
2004-2008																
GARCH (1, 1)	AIC	2.398958	2.388005	2.394561	3.128245	3.139558	3.130244	1.652938	1.643138	1.648816	2.289725	2.269146	2.261267	1.267704	1.296803	1.286972
	SBIC	2.482879	2.423341	2.443146	3.169266	3.209294	3.158958	1.695045	1.718931	1.682502	2.335951	2.340633	2.294908	1.316634	1.376927	1.318109
	HQIC	2.430649	2.401349	2.412908	3.143666	3.165773	3.141038	1.668792	1.671676	1.661499	2.307128	2.296060	2.273933	1.286189	1.327075	1.298736
	Log Lik	-1349.606	-1354.357	-1355.097	-1946.717	-1946.794	-1950.967	-990.8539	-976.9200	-990.3580	-1378.863	-1359.237	-1363.458	-705.8867	-714.6939	-720.7829
TGARCH (1, 1)	AIC	2.400684	2.389756	2.396306	3.112055	3.120345	3.113317	1.654561	**1.644775**	1.650407	2.291304	2.269664	2.260306	**1.266243**	**1.294045**	**1.285679**
	SBIC	2.489022	2.429508	2.449309	3.157178	3.194182	3.146134	1.700879	**1.724779**	1.688304	2.341732	2.345357	2.298153	**1.319621**	**1.378620**	**1.321264**
	HQIC	2.434043	2.404767	2.416321	3.129018	3.148101	3.125653	1.672000	**1.674898**	1.664676	2.310289	2.298162	2.274555	**1.286409**	**1.325998**	**1.299122**
	Log Lik	-1349.590	-1354.356	-1355.093	-1935.591	-1933.776	-1939.380	-990.8365	**-976.9110**	-990.3217	-1378.821	-1358.551	-1361.876	**-704.0606**	**-712.1354**	**-719.0513**
EGARCH (1, 1)	AIC	**2.390122**	**2.381259**	**2.389224**	**3.107618**	**3.117279**	**3.110291**	**1.653518**	1.647294	**1.650259**	**2.288969**	**2.262650**	**2.252646**	1.266803	1.296608	1.287771
	SBIC	**2.478459**	**2.421011**	**2.442226**	**3.152741**	**3.191117**	**3.143107**	**1.699836**	1.727298	**1.688156**	**2.339398**	**2.338343**	**2.290492**	1.320181	1.381182	1.323356
	HQIC	**2.423480**	**2.396270**	**2.409239**	**3.124580**	**3.145036**	**3.122627**	**1.670958**	1.677417	**1.664528**	**2.307954**	**2.291148**	**2.266895**	1.286969	1.328561	1.301214
	Log Lik	**-1343.564**	**-1349.508**	**-1351.052**	**-1932.815**	**-1931.858**	**-1937.437**	**-990.2053**	-978.4364	**-990.2321**	**-1377.404**	**-1354.297**	**-1357.230**	-704.3772	-713.5833	-720.2343
2005-2009																
GARCH (1, 1)	AIC	2.539308	2.530319	2.529450	3.313810	3.330475	3.318528	2.145188	2.115417	2.143582	2.381457	2.379458	2.379951	1.310271	1.343786	1.334750
	SBIC	2.617603	2.565117	2.577297	3.354857	3.400255	3.347261	2.182202	2.181219	2.168258	2.422824	2.453919	2.408908	1.357213	1.420600	1.364622
	HQIC	2.568846	2.543447	2.547501	3.329241	3.356708	3.329329	2.159104	2.140157	2.152859	2.397016	2.407463	2.390842	1.327960	1.372732	1.346007
	Log Lik	-1458.607	-1463.380	-1459.875	-2061.131	-2064.547	-2067.080	-1328.525	-1302.962	-1330.523	-1464.122	-1454.884	-1466.190	-769.2664	-782.2244	-787.8435
TGARCH (1, 1)	AIC	2.540578	2.531779	2.531110	3.300691	3.316577	3.306168	2.146785	2.117013	2.145178	2.383067	2.381031	2.381566	**1.309923**	**1.342324**	**1.334249**
	SBIC	2.623224	2.570927	2.583307	3.345843	3.390462	3.339006	2.187912	2.186929	2.173967	2.428571	2.459629	2.414660	**1.361133**	**1.423406**	**1.368388**
	HQIC	2.571758	2.546549	2.550803	3.317665	3.344353	3.318513	2.162248	2.143300	2.156002	2.400182	2.410593	2.394013	**1.329221**	**1.372878**	**1.347114**
	Log Lik	-1458.346	-1463.230	-1459.841	-2051.932	-2054.861	-2058.355	-1328.521	-1302.958	-1330.519	-1464.119	-1454.858	-1466.190	**-768.0593**	**-780.3538**	**-786.5451**
EGARCH (1, 1)	AIC	**2.524804**	**2.517067**	**2.518684**	**3.293645**	**3.311111**	**3.301545**	**2.139446**	**2.116260**	**2.138488**	**2.382038**	**2.378509**	**2.380483**	1.310032	1.344363	1.336661
	SBIC	**2.607449**	**2.556215**	**2.570881**	**3.338796**	**3.384996**	**3.334383**	**2.180572**	**2.186176**	**2.167277**	**2.427541**	**2.457106**	**2.413576**	1.361242	1.425445	1.370801
	HQIC	**2.555984**	**2.531837**	**2.538376**	**3.310619**	**3.338887**	**3.313890**	**2.154908**	**2.142547**	**2.149312**	**2.399152**	**2.408070**	**2.392930**	1.329329	1.374917	1.349526
	Log Lik	**-1449.174**	**-1454.675**	**-1452.615**	**-2047.528**	**-2051.444**	**-2055.466**	**-1323.944**	**-1302.488**	**-1326.347**	**-1463.481**	**-1453.297**	**-1465.519**	-768.1241	-781.5680	-787.9816
2006-2010																
GARCH (1, 1)	AIC	2.637449	2.636471	2.633211	3.401404	3.416004	3.406440	2.234032	2.229633	2.229228	2.421998	**2.417367**	2.419848	1.357607	1.369914	1.377998
	SBIC	2.709558	2.666164	2.679870	3.442451	3.485784	3.435173	2.270738	2.294889	2.253699	2.463151	**2.487328**	2.448655	1.399218	1.444813	1.407125
	HQIC	2.664612	2.647656	2.650787	3.416835	3.442237	3.417241	2.247826	2.254155	2.238423	2.437471	**2.443672**	2.430679	1.373263	1.398095	1.388957
	Log Lik	-1565.469	-1574.883	-1568.926	-2115.877	-2118.002	-2122.025	-1398.440	-1388.669	-1398.413	-1498.904	**-1489.020**	-1500.565	-824.2496	-823.8122	-839.7795
TGARCH (1, 1)	AIC	2.637449	2.637758	2.634799	3.383905	3.398459	3.388981	2.235478	2.231124	2.230605	**2.423367**	3.056141	**2.421281**	**1.355914**	**1.368318**	**1.376149**
	SBIC	2.709558	2.671692	2.685699	3.429057	3.472344	3.421819	2.276262	2.300458	2.259154	**2.468636**	3.130217	**2.454204**	**1.401685**	**1.447378**	**1.409438**
	HQIC	2.664612	2.650541	2.653973	3.400879	3.426235	3.401326	2.250804	2.257179	2.241333	**2.440388**	3.083993	**2.433660**	**1.373135**	**1.398064**	**1.388674**
	Log Lik	-1565.469	-1574.655	-1568.879	-2103.940	-2106.037	-2110.113	-1398.351	-1388.608	-1398.281	**-1498.758**	-1885.976	**-1500.458**	**-822.2089**	**-821.8313**	**-837.6438**
EGARCH (1, 1)	AIC	**2.621043**	**2.621217**	**2.620029**	**3.378158**	**3.392129**	**3.385965**	**2.229878**	**2.230682**	**2.227347**	2.424085	2.420118	2.422453	1.360006	1.374417	1.382050
	SBIC	**2.697394**	**2.655151**	**2.670929**	**3.423310**	**3.466014**	**3.418803**	**2.270663**	**2.300016**	**2.255897**	2.469353	2.494194	2.455376	1.405777	1.453477	1.415339
	HQIC	**2.649804**	**2.633999**	**2.639202**	**3.395132**	**3.419904**	**3.398310**	**2.245204**	**2.256737**	**2.238076**	2.441105	2.447970	2.434832	1.377227	1.404163	1.394575
	Log Lik	**-1554.626**	**-1564.730**	**-1560.017**	**-2100.349**	**-2102.080**	**-2108.228**	**-1394.823**	**-1388.330**	**-1396.229**	-1499.205	-1489.733	-1501.189	-824.7234	-825.5793	-841.2699
2007-2011																
GARCH (1, 1)	AIC	2.648387	2.648554	2.642003	3.382877	3.389641	3.379918	1.985303	2.003284	1.993126	2.251076	2.235985	2.246833	1.460749	1.476317	1.477584
	SBIC	2.719922	2.678010	2.688290	3.423898	3.459376	3.404531	2.025880	2.072265	2.021530	2.292149	2.305810	2.275585	1.502387	1.547102	1.506730
	HQIC	2.675320	2.659645	2.659430	3.398297	3.415856	3.389170	2.000546	2.029198	2.003797	2.266517	2.262236	2.257643	1.476416	1.502951	1.488550
	Log Lik	-1587.922	-1598.024	-1590.054	-2105.990	-2103.221	-2108.139	-1248.682	-1253.082	-1256.642	-1395.797	-1379.373	-1396.147	-886.8998	-889.4589	-900.2364
TGARCH (1, 1)	AIC	2.648447	2.648716	2.642113	3.349755	3.353587	3.348057	1.985013	2.002442	1.992114	**2.250593**	**2.234630**	**2.246332**	**1.458631**	**1.472024**	**1.475798**
	SBIC	2.724190	2.682379	2.692608	3.394878	3.427424	3.376772	2.029648	2.075481	2.024575	**2.295774**	**2.308562**	**2.279191**	**1.504433**	**1.546973**	**1.509109**
	HQIC	2.676964	2.661390	2.661124	3.366718	3.381344	3.358852	2.001781	2.029880	2.004308	**2.267579**	**2.262425**	**2.258686**	**1.475865**	**1.500225**	**1.488332**
	Log Lik	-1586.959	-1597.122	-1589.120	-2084.272	-2079.669	-2087.210	-1247.498	-1251.548	-1255.000	**-1394.496**	**-1377.526**	**-1394.835**	**-884.5995**	**-885.8229**	**-898.1402**
EGARCH (1, 1)	AIC	**2.634761**	**2.635279**	**2.628922**	**3.346345**	**3.347272**	**3.345326**	**1.980350**	**1.998002**	**1.988791**	2.255493	2.237873	2.251514	1.464427	1.478258	1.479675
	SBIC	**2.710504**	**2.668943**	**2.679417**	**3.391468**	**3.421109**	**3.374041**	**2.024985**	**2.071041**	**2.021253**	2.300674	2.311806	2.284373	1.510229	1.553206	1.512986
	HQIC	**2.663278**	**2.647954**	**2.647934**	**3.363308**	**3.375029**	**3.356121**	**1.997118**	**2.025440**	**2.000986**	2.272479	2.265668	2.263868	1.481660	1.506458	1.492209
	Log Lik	**-1578.665**	**-1588.979**	**-1581.127**	**-2082.139**	**-2075.719**	**-2085.502**	**-1244.542**	**-1248.733**	**-1252.893**	-1397.556	-1379.552	-1398.071	-888.1581	-889.6501	-900.5208
2008-2012																
GARCH (1, 1)	AIC	2.627796	2.618795	2.614777	3.198328	3.205305	3.195318	1.635749	1.641014	1.636842	2.103738	2.091757	2.098270	1.446327	1.464469	1.463731
	SBIC	2.698767	2.648018	2.656525	3.239348	3.279143	3.219931	1.676045	1.713546	1.669079	2.148919	2.161582	2.127022	1.487775	1.534931	1.492745
	HQIC	2.654504	2.629792	2.630488	3.213748	3.233062	3.204570	1.650880	1.668250	1.648947	2.120724	2.118007	2.109079	1.461918	1.490974	1.474645
	Log Lik	-1591.211	-1595.702	-1590.244	-1990.554	-1986.918	-1992.671	-1036.061	-1031.428	-1038.760	-1302.784	-1289.302	-1303.370	-883.1070	-887.3097	-896.8540
TGARCH (1, 1)	AIC	2.626730	2.617342	2.614272	3.164284	3.164332	3.159880	1.634785	1.639794	1.635393	**2.093963**	**2.082883**	**2.088859**	**1.442490**	**1.460208**	**1.460843**
	SBIC	2.701875	2.650740	2.660194	3.209407	3.242271	3.188595	1.679110	1.716356	1.671659	**2.143251**	**2.156815**	**2.121718**	**1.488083**	**1.534814**	**1.494001**
	HQIC	2.655009	2.629911	2.631553	3.181247	3.193631	3.170675	1.651429	1.668543	1.649011	**2.112493**	**2.110677**	**2.101212**	**1.459640**	**1.488271**	**1.473316**
	Log Lik	-1589.559	-1593.813	-1588.934	-1968.260	-1960.289	-1969.505	-1034.445	-1029.648	-1036.834	**-1295.680**	**-1282.760**	**-1296.493**	**-879.7374**	**-883.6782**	**-894.0705**
EGARCH (1, 1)	AIC	**2.618450**	**2.609023**	**2.604465**	**3.157740**	**3.156376**	**3.155814**	**1.630559**	**1.636691**	**1.631008**	2.099577	2.087711	2.094062	1.447492	1.464757	1.464095
	SBIC	**2.693596**	**2.642421**	**2.650387**	**3.202863**	**3.234316**	**3.184529**	**1.674884**	**1.713253**	**1.667274**	2.148865	2.161644	2.126921	1.493085	1.539363	1.497254
	HQIC	**2.646729**	**2.621592**	**2.621746**	**3.174703**	**3.185675**	**3.166608**	**1.647204**	**1.665441**	**1.644626**	2.118107	2.115506	2.106415	1.464642	1.492821	1.476568
	Log Lik	**-1584.492**	**-1588.722**	**-1582.932**	**-1964.166**	**-1955.313**	**-1966.962**	**-1031.743**	**-1027.664**	**-1034.030**	-1299.186	-1285.776	-1299.742	-882.8263	-886.4874	-896.0788
2009-2013																
GARCH (1, 1)	AIC	2.584520	2.580188	2.573090	2.859876	2.865865	2.860001	1.110299	1.117588	1.109896	**1.907220**	1.898398	1.903841	1.229545	1.242192	1.238439
	SBIC	2.655258	2.609315	2.614701	2.905028	2.939750	2.884629	1.154347	1.189666	1.141931	**1.952401**	1.972331	1.932593	1.270939	1.312562	1.267415
	HQIC	2.611135	2.591147	2.588746	2.876850	2.893641	2.869259	1.126833	1.144643	1.121921	**1.924206**	1.926193	1.914650	1.245114	1.268660	1.249338
	Log Lik	-1571.188	-1578.525	-1571.164	-1776.422	-1773.166	-1781.500	-704.5875	-702.2852	-707.3280	**-1180.059**	-1167.550	-1181.949	-750.4734	-751.2960	-758.9747
TGARCH (1, 1)	AIC	2.585232	2.581160	2.574381	2.831818	2.834132	2.828576	**1.111837**	**1.119131**	**1.111421**	-10.36779	**1.898398**	**1.903977**	**1.224340**	**1.236271**	**1.233124**
	SBIC	2.660132	2.614448	2.620153	2.881074	2.912121	2.865518	**1.159889**	**1.195213**	**1.147460**	-10.31851	**1.976438**	**1.936836**	**1.269873**	**1.310781**	**1.266240**
	HQIC	2.613413	2.593684	2.591603	2.850335	2.863451	2.842464	**1.129874**	**1.147689**	**1.124948**	-10.34926	**1.927737**	**1.916331**	**1.241466**	**1.264296**	**1.245580**
	Log Lik	-1570.625	-1578.123	-1570.957	-1757.886	-1752.332	-1758.860	**-704.5787**	**-702.2797**	**-707.3105**	6486.687	**-1166.549**	**-1181.034**	**-746.2543**	**-746.6338**	**-754.6875**
EGARCH (1, 1)	AIC	**2.581276**	**2.576882**	**2.567045**	**2.830919**	**2.833608**	**2.828660**	1.119587	1.126269	1.118443	1.910881	1.902576	1.906758	1.235084	1.244352	1.241911
	SBIC	**2.656175**	**2.610170**	**2.608655**	**2.880175**	**2.911598**	**2.865602**	1.167640	1.202352	1.154482	1.960169	1.980616	1.939617	1.280617	1.318861	1.275026
	HQIC	**2.609457**	**2.589406**	**2.582701**	**2.849436**	**2.862927**	**2.842548**	1.137624	1.154828	1.131970	1.929410	1.931915	1.919112	1.252210	1.272377	1.254367
	Log Lik	**-1568.194**	**-1575.494**	**-1567.449**	**-1757.324**	**-1752.005**	**-1758.912**	-709.5741	-706.8804	-711.8362	-1181.345	-1169.158	-1182.771	-752.8994	-751.6318	-760.1220
2010-2014																

GARCH (1, 1)	AIC	**2.343069**	2.337323	**2.332691**	2.609008	2.614573	2.607952	0.530683	0.543655	0.533350	1.702400	1.701180	1.700068	1.119412	1.121182	1.123831
	SBIC	**2.413439**	2.366299	**2.374085**	2.654189	2.688506	2.640811	0.574786	0.615823	0.565425	1.743474	1.771005	1.728819	1.160860	1.191644	1.152845
	HQIC	**2.369537**	2.348222	**2.348260**	2.625994	2.642368	2.620305	0.547239	0.570746	0.545391	1.717842	1.727431	1.710877	1.135003	1.147687	1.134745
	Log Lik	**-1432.188**	-1438.634	**-1432.769**	-1618.326	-1614.801	-1620.666	-330.4946	-331.8417	-335.2109	-1053.149	-1045.387	-1054.692	-681.2370	-675.3300	-686.9656
TGARCH (1, 1)	AIC	2.342429	**2.337309**	2.332739	**2.565912**	**2.580650**	**2.563635**	**0.531438**	**0.544511**	**0.534298**	**1.703768**	**1.702625**	**1.701472**	**1.116940**	**1.118812**	**1.121269**
	SBIC	2.416938	**2.370425**	2.378272	**2.615201**	**2.658690**	**2.600602**	**0.579550**	**0.620689**	**0.570382**	**1.748949**	**1.776558**	**1.734331**	**1.162533**	**1.193419**	**1.154428**
	HQIC	2.370454	**2.349765**	2.349865	**2.584442**	**2.609989**	**2.577533**	**0.549499**	**0.573108**	**0.547843**	**1.720754**	**1.730420**	**1.713825**	**1.134090**	**1.146876**	**1.133742**
	Log Lik	-1430.792	**-1437.626**	-1431.799	**-1590.412**	**-1592.616**	**-1591.990**	**-329.9802**	**-331.3930**	**-334.8205**	**-1053.003**	**-1045.289**	**-1054.569**	**-678.7106**	**-672.8667**	**-684.3838**
EGARCH (1, 1)	AIC	2.344773	2.340633	2.334447	2.567377	2.581482	2.564038	0.538967	0.551349	0.541381	1.705823	1.704997	1.703110	1.126540	1.126473	1.130909
	SBIC	2.419282	2.373748	2.379980	2.616665	2.659522	2.596897	0.587079	0.627527	0.577466	1.751004	1.778929	1.735969	1.172132	1.201079	1.164068
	HQIC	2.372798	2.353088	2.351573	2.585906	2.610821	2.576392	0.557028	0.579945	0.554927	1.722809	1.732792	1.715463	1.143690	1.154536	1.143382
	Log Lik	-1432.242	-1439.681	-1432.855	-1591.327	-1593.135	-1593.242	-334.8252	-335.7930	-339.3789	-1054.287	-1046.770	-1055.592	-684.6382	-677.5968	-690.3365
2011-2015																
GARCH (1, 1)	AIC	**2.345375**	2.340928	**2.340057**	2.608266	2.618885	2.608767	0.278754	0.289877	0.278647	1.673009	1.718161	1.671879	1.086404	1.096644	1.100644
	SBIC	**2.415699**	2.369885	**2.381424**	2.653447	2.692817	2.641626	0.322857	0.362045	0.310722	1.714269	1.784177	1.700761	1.132056	1.167197	1.129695
	HQIC	**2.371824**	2.351819	**2.355615**	2.625251	2.646679	2.621121	0.295310	0.316968	0.290688	1.688525	1.742987	1.682740	1.103578	1.123185	1.111572
	Log Lik	**-1434.787**	-1442.034	**-1438.495**	-1617.862	-1617.419	-1621.175	-168.3782	-168.5356	-171.3093	-1028.939	-1050.978	-1031.237	-658.7679	-659.0808	-671.5468
TGARCH (1, 1)	AIC	2.343672	**2.339435**	2.338795	2.566436	2.575484	2.564106	**0.278614**	**0.290152**	**0.278817**	**1.672754**	**1.716638**	**1.671776**	**1.085779**	**1.095976**	**1.100439**
	SBIC	2.418133	**2.372529**	2.384299	2.615724	2.653524	2.601073	**0.326727**	**0.366331**	**0.314902**	**1.718140**	**1.786780**	**1.704784**	**1.135582**	**1.170680**	**1.133641**
	HQIC	2.371678	**2.351882**	2.355909	2.584966	2.604823	2.578004	**0.296675**	**0.318749**	**0.292363**	**1.689822**	**1.743015**	**1.684189**	**1.104515**	**1.124079**	**1.112929**
	Log Lik	-1432.733	**-1440.111**	-1436.714	-1590.739	-1589.390	-1592.284	**-167.2883**	**-167.7130**	**-170.4189**	**-1027.780**	**-1049.032**	**-1030.173**	**-657.3830**	**-657.6694**	**-670.4208**
EGARCH (1, 1)	AIC	2.345603	2.343238	2.341237	**2.563336**	**2.567468**	**2.556527**	0.285677	0.297025	0.285568	1.674532	1.718805	1.673754	1.095617	1.104193	1.109688
	SBIC	2.420064	2.376332	2.386741	**2.612624**	**2.645508**	**2.593493**	0.333789	0.373203	0.321652	1.719918	1.788946	1.706762	1.145420	1.178896	1.142890
	HQIC	2.373609	2.355685	2.358352	**2.581866**	**2.596807**	**2.570424**	0.303738	0.325622	0.299114	1.691600	1.745182	1.686166	1.114352	1.132295	1.122178
	Log Lik	-1433.928	-1442.464	-1438.226	**-1588.803**	**-1584.384**	**-1587.551**	-171.8330	-172.1356	-174.7630	-1028.885	-1050.378	-1031.401	-663.4480	-662.7348	-676.1226
2012-2016																
GARCH (1, 1)	AIC	**2.438705**	**2.436835**	**2.437386**	2.565752	2.576396	2.564195	**0.094884**	**0.104780**	**0.093149**	1.521825	1.524352	1.518346	0.913267	0.915175	0.921579
	SBIC	**2.508983**	**2.465773**	**2.478727**	2.610933	2.650329	2.597054	**0.138822**	**0.176679**	**0.125104**	1.563138	1.594584	1.547266	0.958536	0.985136	0.950387
	HQIC	**2.465136**	**2.447719**	**2.452934**	2.582738	2.604191	2.576548	**0.111374**	**0.131764**	**0.105142**	1.537362	1.550765	1.529222	0.930288	0.941480	0.932411
	Log Lik	**-1493.777**	**-1502.619**	**-1499.961**	-1591.312	-1590.959	-1593.340	**-50.34219**	**-49.74030**	**-52.22083**	-933.5314	-928.0980	-934.3747	-557.9656	-553.1543	-567.1439
TGARCH (1, 1)	AIC	2.439878	2.438034	2.438583	2.532616	2.544039	2.530460	0.239000	0.621809	0.229547	1.523436	1.525962	1.519957	0.914829	0.916491	0.923093
	SBIC	2.514291	2.471107	2.484057	2.581904	2.622079	2.567426	0.286933	0.697702	0.257507	1.568881	1.600326	1.553008	0.964213	0.990567	0.956016
	HQIC	2.467864	2.450473	2.455685	2.551146	2.573378	2.544358	0.256990	0.650292	0.240041	1.540527	1.553929	1.532387	0.933397	0.944343	0.935472
	Log Lik	-1493.504	-1502.362	-1499.702	-1569.619	-1569.753	-1571.272	-142.5138	-382.9998	-141.4020	-933.5305	-928.0962	-934.3734	-557.9387	-552.9739	-567.0871
EGARCH (1, 1)	AIC	2.442749	2.441103	2.441208	**2.521964**	**2.530827**	**2.519064**	0.097669	0.105863	0.170366	**1.523267**	**1.525786**	**1.519597**	**0.912488**	**0.913413**	**0.921626**
	SBIC	2.517161	2.474176	2.486682	**2.571252**	**2.608867**	**2.556031**	0.145601	0.181756	0.198327	**1.568711**	**1.600150**	**1.552648**	**0.961872**	**0.987489**	**0.954549**
	HQIC	2.470735	2.453542	2.458310	**2.540493**	**2.560166**	**2.532962**	0.115658	0.134346	0.180860	**1.540358**	**1.553753**	**1.532027**	**0.931056**	**0.941265**	**0.934005**
	Log Lik	-1495.283	-1504.264	-1501.328	**-1562.966**	**-1561.501**	**-1564.156**	-51.14298	-49.44031	-103.1419	**-933.4252**	**-927.9872**	**-934.1502**	**-556.4801**	**-551.0563**	**-566.1732**
2013-2017																
GARCH (1, 1)	AIC	**2.532568**	**2.533052**	**2.530372**	2.526039	2.536350	2.525716	0.096255	0.108505	0.096013	1.516027	1.520593	1.513960	0.804100	0.797538	0.804167
	SBIC	**2.602892**	**2.562009**	**2.571739**	2.571249	2.610330	2.550376	0.140139	0.180314	0.127928	1.557368	1.590872	1.542899	0.849340	0.867453	0.832956
	HQIC	**2.559018**	**2.543943**	**2.545931**	2.543036	2.564164	2.534987	0.112724	0.135453	0.107990	1.531575	1.547025	1.524844	0.821109	0.823825	0.814991
	Log Lik	**-1550.659**	**-1560.959**	**-1556.300**	-1565.248	-1564.682	-1570.047	-51.32536	-52.25691	-54.16839	-929.1789	-925.0075	-930.8984	-490.3565	-480.2649	-494.3982
TGARCH (1, 1)	AIC	2.534141	2.534627	2.534202	2.494269	2.507111	2.493902	0.206704	**0.101931**	0.414612	**1.516317**	1.520875	**1.514230**	**0.805493**	0.799126	**0.805621**
	SBIC	2.608602	2.567721	2.579706	2.543589	2.585201	2.522672	0.254576	**0.177730**	0.450517	**1.561791**	1.595287	**1.547303**	**0.854845**	0.873154	**0.838523**
	HQIC	2.562147	2.547074	2.551316	2.512812	2.536470	2.504719	0.224669	**0.130377**	0.428086	**1.533420**	1.548861	**1.526669**	**0.824048**	0.826958	**0.817991**
	Log Lik	-1550.634	-1560.934	-1557.671	-1544.424	-1545.437	-1549.195	-121.8405	**-47.00050**	-259.4612	**-928.3584**	-924.1819	**-930.0657**	**-490.2249**	-480.2548	**-494.3048**
EGARCH (1, 1)	AIC	2.537448	2.536488	2.533562	**2.489576**	**2.500015**	**2.488478**	**0.093269**	0.104288	**0.092057**	1.517188	**1.520855**	1.514586	0.806011	**0.798530**	0.806598
	SBIC	2.611908	2.569582	2.579066	**2.538896**	**2.578105**	**2.517248**	**0.141142**	0.180086	**0.127962**	1.562663	**1.595268**	1.547658	0.855363	**0.872558**	0.839499
	HQIC	2.565453	2.548935	2.550676	**2.508119**	**2.529374**	**2.499294**	**0.111235**	0.132733	**0.105531**	1.534291	**1.548841**	1.527024	0.824566	**0.826363**	0.818968
	Log Lik	-1552.680	-1562.086	-1557.275	**-1541.495**	**-1541.009**	**-1545.810**	**-48.39182**	-48.52616	**-50.60711**	-928.8982	**-924.1697**	-930.2858	-490.5477	**-479.8834**	-494.9138

Appendix IIIA: Probability of the Ljung-Box Q statistics for Rolling GARCH

Period	DOW	MOY	HOM	DOW	MOY	HOM	DOW	MOY	HOM
	NGSE			JALSH			SEMDEX		
1998-2002	0.503	0.452	0.523	0.192	0.138	0.185	0.186	0.191	0.185
1999-2003	0.484	0.150	0.521	0.137	0.290	0.255	0.466	0.425	0.414
2000-2004	0.255	0.087	0.244	0.312	0.230	0.347	0.205	0.120	0.170
2001-2005	0.167	0.104	0.245	0.218	0.613	0.183	0.145	0.105	0.178
2002-2006	0.118	0.277	0.136	0.551	0.733	0.772	0.547	0.399	0.536
2003-2007	0.146	0.244	0.147	0.746	0.995	0.838	0.169	0.129	0.169
2004-2008	0.149	0.318	0.206	0.997	0.745	0.997	0.116	0.184	0.136
2005-2009	0.238	0.108	0.107	0.798	0.721	0.830	0.207	0.162	0.103
2006-2010	0.148	0.555	0.556	0.840	0.872	0.789	0.477	0.623	0.462
2007-2011	0.108	0.612	0.129	0.947	0.926	0.942	0.317	0.266	0.236
2008-2012	0.212	0.699	0.249	0.769	0.935	0.795	0.550	0.141	0.190
2009-2013	0.222	0.384	0.181	0.749	0.574	0.695	0.116	0.102	0.135
2010-2014	0.457	0.512	0.307	0.391	0.410	0.594	0.116	0.121	0.147
2011-2015	0.101	0.093	0.043	0.646	0.724	0.874	0.226	0.273	0.303
2012-2016	0.199	0.168	0.254	0.927	0.923	0.929	0.240	0.262	0.116
2013-2017	0.132	0.173	0.123	0.230	0.396	0.296	0.313	0.418	0.405
	MOSENEW			TUSISE					
1998-2002	0.168	0.330	0.445	NA	NA	NA			
1999-2003	0.129	0.149	0.131	0.558	0.457	0.481			
2000-2004	0.158	0.217	0.180	0.373	0.272	0.363			
2001-2005	0.101	0.115	0.102	0.279	0.187	0.288			
2002-2006	0.293	0.487	0.311	0.745	0.687	0.664			
2003-2007	0.329	0.481	0.314	0.637	0.548	0.511			
2004-2008	0.433	0.591	0.452	0.490	0.338	0.195			
2005-2009	0.473	0.369	0.462	0.229	0.258	0.143			
2006-2010	0.692	0.600	0.708	0.057	0.072	0.037			
2007-2011	0.479	0.232	0.463	0.427	0.365	0.329			
2008-2012	0.175	0.147	0.231	0.291	0.424	0.270			
2009-2013	0.122	0.316	0.153	0.086	0.104	0.081			
2010-2014	0.076	0.061	0.100	0.167	0.160	0.184			
2011-2015	0.146	0.219	0.149	0.125	0.208	0.126			
2012-2016	0.242	0.344	0.260	0.103	0.316	0.164			
2013-2017	0.338	0.537	0.371	0.541	0.550	0.429			

Appendix IIIB: Probability of Arch Heteroscedasticity Test for Rolling GARCH

Period	DOW	MOY	HOM	DOW	MOY	HOM	DOW	MOY	HOM
	NGSE			JALSH			SEMDEX		
1998-2002	0.503	0.452	0.523	0.192	0.138	0.185	0.186	0.191	0.185
1999-2003	0.484	0.150	0.521	0.137	0.290	0.255	0.466	0.425	0.414
2000-2004	0.255	0.087	0.244	0.312	0.230	0.347	0.205	0.120	0.170
2001-2005	0.167	0.104	0.245	0.218	0.613	0.183	0.145	0.105	0.178
2002-2006	0.118	0.277	0.136	0.551	0.733	0.772	0.547	0.399	0.536
2003-2007	0.146	0.244	0.147	0.746	0.995	0.838	0.169	0.129	0.169
2004-2008	0.149	0.318	0.206	0.997	0.745	0.997	0.116	0.184	0.136
2005-2009	0.238	0.108	0.107	0.798	0.721	0.830	0.207	0.162	0.103
2006-2010	0.148	0.555	0.556	0.840	0.872	0.789	0.477	0.623	0.462
2007-2011	0.108	0.612	0.129	0.947	0.926	0.942	0.317	0.266	0.236
2008-2012	0.212	0.699	0.249	0.769	0.935	0.795	0.550	0.141	0.190
2009-2013	0.222	0.384	0.181	0.749	0.574	0.695	0.116	0.102	0.135
2010-2014	0.457	0.512	0.307	0.391	0.410	0.594	0.116	0.121	0.147
2011-2015	0.101	0.093	0.043	0.646	0.724	0.874	0.226	0.273	0.303
2012-2016	0.199	0.168	0.254	0.927	0.923	0.929	0.240	0.262	0.116
2013-2017	0.132	0.173	0.123	0.230	0.396	0.296	0.313	0.418	0.405
	MOSENEW			TUSISE					
1998-2002	0.168	0.330	0.445	NA	NA	NA			
1999-2003	0.129	0.149	0.131	0.558	0.457	0.481			
2000-2004	0.158	0.217	0.180	0.373	0.272	0.363			
2001-2005	0.101	0.115	0.102	0.279	0.187	0.288			
2002-2006	0.293	0.487	0.311	0.745	0.687	0.664			
2003-2007	0.329	0.481	0.314	0.637	0.548	0.511			
2004-2008	0.433	0.591	0.452	0.490	0.338	0.195			
2005-2009	0.473	0.369	0.462	0.229	0.258	0.143			
2006-2010	0.692	0.600	0.708	0.057	0.072	0.037			
2007-2011	0.479	0.232	0.463	0.427	0.365	0.329			
2008-2012	0.175	0.147	0.231	0.291	0.424	0.270			
2009-2013	0.122	0.316	0.153	0.086	0.104	0.081			
2010-2014	0.076	0.061	0.100	0.167	0.160	0.184			
2011-2015	0.146	0.219	0.149	0.125	0.208	0.126			
2012-2016	0.242	0.344	0.260	0.103	0.316	0.164			
2013-2017	0.338	0.537	0.371	0.541	0.550	0.429			

Appendix IV: MSMs Information Criteria

		NGSEINDX			JALSH			SEMDEX		
Model	**IC**	**DOW**	**MOY**	**HOM**	**DOW**	**MOY**	**HOM**	**DOW**	**MOY**	**HOM**
2 REGIMES	AIC	**2.391494**	**2.396410**	**2.395627**	**3.014321**	**3.023280**	**3.016505**	**1.182336**	**1.188793**	**1.183678**
	SBIC	**2.411595**	**2.435272**	**2.407687**	**3.033751**	**3.060844**	**3.028163**	**1.200474**	**1.225068**	**1.194042**
	HQIC	**2.398551**	**2.410053**	**2.399861**	**3.021129**	**3.036440**	**3.020589**	**1.188691**	**1.201502**	**1.187309**
	Log Lik	**-5771.220**	**-5769.115**	**-5787.218**	**-7576.568**	**-7585.130**	**-7588.068**	**-2963.122**	**-2965.380**	**-2972.502**
3 REGIMES	AIC	NA	NA	NA	NA	NA	NA	NA	NA	NA
	SBIC	NA	NA	NA	NA	NA	NA	NA	NA	NA
	HQIC	NA	NA	NA	NA	NA	NA	NA	NA	NA
	Log Lik	NA	NA	NA	NA	NA	NA	NA	NA	NA
		MOSENEW			**TUSISE**					
Model	**IC**	**DOW**	**MOY**	**HOM**	**DOW**	**MOY**	**HOM**			
2 REGIMES	AIC	1.821341	1.820056	1.822218	1.252840	1.261854	1.259684			
	SBIC	1.840932	1.857932	1.833973	1.274914	1.304531	1.272929			
	HQIC	1.828208	1.833332	1.826338	1.260633	1.276921	1.264360			
	Log Lik	-4527.424	-4510.219	-4535.612	-2698.024	-2703.545	-2718.846			
3 REGIMES	AIC	**1.766373**	**1.768748**	**1.769831**	**1.196136**	**1.209235**	**1.204468**			
	SBIC	**1.799025**	**1.828828**	**1.790729**	**1.232927**	**1.276929**	**1.228013**			
	HQIC	**1.777818**	**1.789808**	**1.777156**	**1.209125**	**1.233134**	**1.212780**			
	Log Lik	**-4380.333**	**-4365.257**	**-4397.959**	**-2565.233**	**-2572.599**	**-2592.275**			

Appendix V: MCAP Liquidity Turnover Ratio and Listed Companies

	Market Capitalisation				Market Liquidity		Turnover Ratio		Listed Company	
	$ million		% of GDP		Value of share traded (% . GDP)		Value of share traded (% of MCAP)		Number	
	2010	2017	2010	2017	2010	2017	2010	2017	2010	2017
SSA										
South Africa	925,007	1,230,977	**246.5**	**352.3**	**73.9**	**117.3**	30.0	25.7	352	294
Nigeria	50,546	37,218	**13.7**	**9.9**	**1.4**	**0.6**	10.1	5.9	215	166
Mauritius	7,753	9,743	**77.5**	**73.0**	**3.6**	**3.4**	4.7	4.6	62	74
Morocco	69,152	67,048	**74.2**	**61.4**	**6.5**	**3.9**	8.8	6.3	73	73
Tunisia	10,652	8,923	**24.2**	**22.2**	**4.2**		17.2		56	81
East Asia & Pacific	15,935,646	26,458,884	95.0	111.5	111.5	124.9	118.5	112.1	13,784	18,145
Europe & Central Asia	9,549,591	11,065,344	56.7	75.9	56.7		82.8		11,111	7,066
Latin America & Caribbean	2,733,571	2,017,232	61.7	42.3	25.1	17.6	41.5	40.9	1,283	1,197
Middle East & North Africa	1,061,817	1,371,105	51.5	52.0	19.8	14.9	41.1	28.5	2,119	1,952
North America	19,456,181	34,490,481	117.3	163.9	225.7	195.1	193.1	111.8	8,064	7,627
South Asia	1,731,377	2,436,705	86.3	83.0	55.0	44.2	64.0	50.4	6,111	6,483

http://wdi.worldbank.org/table/5.4

UNIVERSITY OF KWAZULU-NATAL ™
INYUVESI YAKWAZULU-NATALI

03 May 2019

Mr Adefemi Obalade (217080495)
School of Accounting, Economics & Finance
Westville Campus

Dear Mr Obalade,

Protocol reference number: HSS/0303/019D
Project title: Adaptive Market Hypothesis and Calendar Anomalies in selected African Stock Markets

Full Approval – No Risk / Exempt Application

In response to your application received on 20 March 2019, the Humanities & Social Sciences Research Ethics Committee has considered the abovementioned application and the protocol has been granted **FULL APPROVAL.**

Any alteration/s to the approved research protocol i.e. Title of the Project, Research Approach and Methods must be reviewed and approved through the amendment/modification prior to its implementation. In case you have further queries, please quote the above reference number.

PLEASE NOTE: Research data should be securely stored in the discipline/department for a period of 5 years.

The ethical clearance certificate is only valid for a period of 1 year from the date of issue. Thereafter Recertification must be applied for on an annual basis.

I take this opportunity of wishing you everything of the best with your study.

Yours faithfully

....
Dr Rosemary Sibanda (Chair)

/ms

Cc Supervisor: Dr Paul-Francois Muzindutsi
cc Dean & Head of School: Professor Josue Mbonigaba
cc School Administrator: Ms Seshni Naidoo

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