An analysis of the Random Walk Hypothesis: Evidence from the Lusaka Stock Exchange

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ABSTRACT

The paper evaluates whether the Lusaka Stock Exchange (LuSE) is weak form efficient, and whether stock price movements conform to the random walk hypothesis of non-predictability in future price movements based on past price information. The methods employed are the parametric and non-parametric individual as well as multiple variance ratio tests. In addition, the study incorporates the Runs Test. The study further examines seasonality in Zambian stock returns of the day of the week effect as well as monthly related effects. The period of analysis is from 3rd January, 2006 to 17th February, 2014. The study incorporates daily data as well as monthly data of the LuSE All share Index in order to investigate the random walk hypothesis as well as seasonality effects of the Zambian market. The period of analysis is broken down into two sub periods after accounting for multiple structural breaks in the data.

The results of the study are mixed, the results of the Runs test finds the Zambian stock market price series to be mutually independent and conform to a random sequence, and are as such unpredictable. While the variance ratio tests reject the random walk hypothesis for the Zambian market, and as such, support the view of the use of technical trading strategies in order to outperform buy-and-hold strategies. The study finds no evidence of any seasonality in the data, either for daily data as well as monthly data. As such there is evidence that investors may acquire returns greater than those of the market, however, transaction costs and commissions would have to be minimal in order to exploit any patterns in the stock price series of the Lusaka stock exchange.

DECLARATION

I, Taniya Kabaye declare that this project report is my own, unless otherwise as specified in the references and acknowledgments. It is submitted in partial fulfilment of the requirements for the degree of Master of Management in Finance and Investment at the University of the Witwatersrand, Johannesburg. It has not been submitted before any degree or examination in this or any other university.

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Taniya Kabaye

Signed at_________________________

On the ______________________ day of ___________________ 20__

DEDICATION

To my supervisor Professor Paul Alagidede, my mum Miriam Msuku, family, friends and all those who gave me support, encouragement and guidance during my studies, words cannot adequately explain the gratitude I have for you. Without all the support you rendered to me, I would have not been able to complete my Masters Research report. My gratitude will forever be with you. To my dear Dad Joseph Kabaghe, for the all the love and support you rendered to me, may your soul rest in peace.

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CHAPTER 1: INTRODUCTION

1.1. BACKGROUND

There has been considerable world economic attention on ways to generate wealth, more so on the times-series properties of stocks, and whether there is an effortless strategy to create wealth by predicting stock price movements. Jordan and Miller (2009: 211) argue 'that market efficiency is one of the most controversial and intriguing issues in investments, with the debate raging on for several decades and showing few signs of abating'. Basic intuition would entail that the best trading strategy, whether one is a professional investor or the common Joe on the street trying to make an extra buck, basically involves acquiring those stocks that are on the upward trend 'bullish market', and getting rid of those that are on the downward trend 'the bearish market' (Black, 1971). However, stock prices do not move about in predictable manners, and the prediction of stock prices by investors tend not to be as straight forward as this. Several different strategies for making money in the stock market have been tried and tested, continue to be tried, and are likely to be tried for many years to come. However, the usefulness of these trading strategies largely depends on how efficient the stock market is viewed by the investor (Jordan & Miller, 2009).

Particular attention on the properties of stock prices has been paid to investigate whether they can be described as unit root which entails that that stock price series follow a random walk, which essentially means that they are unpredictable. On the other hand, they may be described as mean reverting which entails that stock price movements follow a trend stationary process and revert to some process, and are as such predictable (Chaudhuri, & Wu, 2003). Such Studies include Zhang, (2001) who analysed the China free shares market, Smith, Jefferis and Ryoo (2002) who analysed the Botswana, Egyptian, Kenyan, Moroccan, Nigerian, Mauritius, South African and Zimbabwean markets.

1.2. EFFICIENCT MARKET HYPOTHESIS

It is largely argued that an indication of an efficient stock market is one in which investors cannot consistently earn above normal returns from their respective investment strategies because current prices already reflect all available information in the market (Lo & Mackinlay, 1999). As such, the returns from speculative trading activity in an efficient stock market should be zero. If the stock market is efficient then it is a waste of time to research and find mispriced stocks as the market will provide the best estimate of risk and reward at that particular time to provide a fair price for the given asset (Westerlund & Narayan, 2013). As such, stock prices in the market will be appropriately priced offering the appropriate reward for risk. However, if stock market is inefficient, then an investor may attempt to spot out the overpriced and underpriced equities in the market in order to gain maximum returns from their portfolio, and earn returns greater than those of the market (Jordan and Miller, 2009).

Given that investors are constantly seeking for ways to outperform the market, easy profits (arbitrage) should not last in a competitive market environment (Maghyerech, 2003). However, there are certain market anomalies that have been persisting for numerous years for various stock markets around the world, and this phenomenon has fascinated many investors given the arguments of market efficiency. Given that these anomalies tend to repeat themselves overtime, investors may therefore time these anomalies and gain from the price movements (Jordan and Miller, 2009). Some of the anomalies in the market for instance include, the day of the week effect and the January effect. The day of the week effect shows that certain days tend to have significantly higher or lower returns than other days. For instance, Monday has been found to have on average a negative return relative to other week days. In addition, the January effect refers to the tendency for returns in January to be significantly higher than returns in other months (Kim & Shamsuddin, 2008).

1.3. CONTEXT OF THE STUDY

The study seeks to examine the efficiency of the Lusaka Stock Exchange (LuSE), and tests the validity of the random walk hypothesis in Zambia. The study further examines seasonality in Zambian stock returns. The study builds on the work of Tembo and Mlambo (2009) who examines solutions to the challenges being faced in the capital markets in Zambia. The few notable studies on the market efficiency of the LuSE have analysed it using the Augmented Dickey Fuller (ADF) test. Such studies include Tembo and Mlambo (2009) for the period May 1995 to October 2008 using individual stocks to determine whether the LuSE is weak form efficient or not, for which it is found to be weak form efficient. However, as Zhang (2001) argues, the ADF tests have proven to be not powerful enough and structurally incentive to predictability by a number of studies such as Fama and French (1988), Campbell, Lo and Mackinlay (1997), and Dockery (2000). It is for this reason that the study will incorporate more stringent tests such as the variance ratio tests of Lo and MacKinlay (1988), Chow and Denning (1993), as well as Wright's (2000) test based on ranks and signs. In addition, the use of the Runs test is incorporated into the study. Furthermore, the study incorporates the Bai-Perron (2003) structural break model that accounts for unexpected shifts in the economic environment of time series data. Furthermore, the study analyses the presence of seasonality effects of the day of the week and January effect.

1.4. STATEMENT OF THE PROBLEM

In a competitive market, stock prices must follow a random walk for them to be fairly priced and for them to be able to incorporate past information. This is essential in the workings of any capital market (Magnusson and Wydick, 2002). However, If past price information can be used to predict future price changes then investors may take advantage of this information and make superior profits in the future by studying past trends (Jordan and Miller, 2009). However, in a competitive market, easy profits do not last. In addition, patterns in prices should not exist as price changes in one period should be independent of prices changes in other periods. In an efficient market the analysis of past price information should not be able to consistently earn investors superior profits, and as such stock prices series must follow a random walk process (Jordan and Miller, 2009). The purpose of this study is to evaluate whether the Lusaka Stock Exchange (LuSE) is weak form efficient, and whether stock price movements conform to the random walk characteristics of non-predictability in future price movements based on past prices. In addition, the study seeks to investigate the seasonal effects of the day of the week and monthly related effects such as the January effect. This analysis is of immerse importance as it will enable investors to come up with more appropriate mechanisms in order to effectively manage their portfolio's that contain stocks listed on the LuSE, and how best to maximize returns from them. In addition, stock market efficiency is of particular importance for emerging nations to prove that they are at least efficient in the weak form so as to gain investor confidence.

This importance stems from the fact that an efficient market is one which reflects available information to the market participants at any given time (Smith, Jefferis & Ryoo, 2002).

1.5. OBJECTIVES

1.5.1. GENERAL OBJECTIVE

The purpose of this study is to evaluate whether the Lusaka Stock Exchange (LuSE) is weak form efficient.

1.5.2. SPECIFIC OBJECTIVES

- To determine whether stock returns are mean reverting or random walk.
- To determine whether there is a seasonal effect in stock returns.
- To determine which investment strategy may be most appropriate for LuSE stocks.

1.5.3 HYPOTHESIS FORMULATION

Hypothesis one

Lusaka Stock Exchange returns follow a random walk.

H_0: Lusaka Stock Exchange returns are random walk.
H_1: Lusaka Stock Exchange share returns are mean reverting.

Hypothesis two

The arithmetic daily returns on Monday are no different from the daily returns of the other weekdays.

$H_{0:}\ R_iMon = R_iTue = R_iWed = R_iThur = R_IFri$
$H_{1:}\ R_iMon \neq R_iTue \neq R_iWed \neq R_iThur \neq R_IFri$

Hypothesis three

The monthly returns in January are not different from the arithmetic monthly returns of other months.

$H_{0:}\ R_iJanuary = R_iFebuary = R_iMarch = \cdots = R_iDecember$
$H_{0:}\ R_iJanuary \neq R_iFebuary \neq R_iMarch \neq \cdots \neq R_iDecember$

1.6. SIGNIFICANCE OF THE STUDY

The study will provide analysis on a market for which studies lag behind those of not only developed markets, but also other developing markets stock markets, and as such may provide particularly interesting insights and information. In addition, the study will complement the existing studies on stock markets. Furthermore, the study is important in that it will add to the literature on the efficiency of the LuSE in order to provide a more conclusive answer of whether the LuSE is weak form efficient as studies tend to be few and inconclusive. Moreover, the study will analyse stock returns for market anomalies of the day of the week effect and the January effect. Lastly, the study takes into account the most recent happenings in the operations of the LuSE relative to other older studies. The findings of this study will therefore go a long way in improving the functioning of the Zambian capital market. As such, it is therefore essential to assess the efficiency of the Zambian stock exchange and whether it is attaining its aspiration as one of the major drivers of economic development.

1.7. ORGANISATION OF THE STUDY

The study is divided into six chapters. Chapter one contains the introduction about the random walk hypothesis and market efficiency, the problem statement and significance of the study. Chapter two provides an overview of the Lusaka Stock Exchange. Chapter three provides the literature review. Chapter four provides the research methodology and design, which describes how the study is to be carried out. Chapter five provides the analysis and presentation of results. Finally chapter six is the conclusion as well as recommendations of the study.

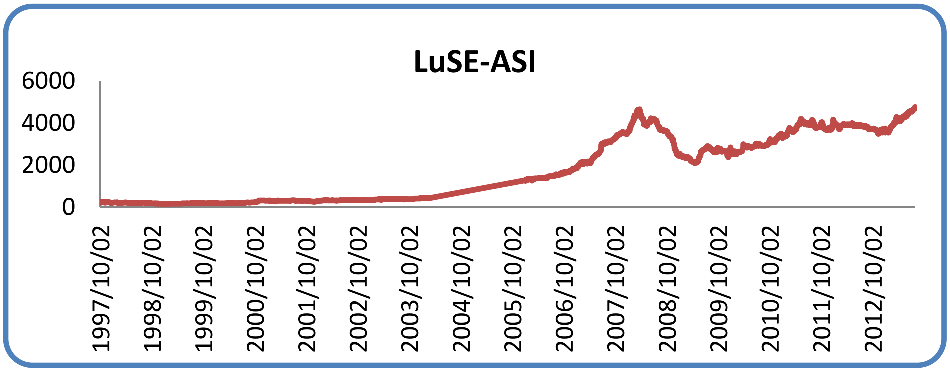
CHAPTER 2: OVERVIEW OF THE ZAMBIAN MARKET

2.1. OVERVIEW OF THE LUSE

The Lusaka Stock Exchange (LuSE) was established in 1993 through the Securities Act Chapter 354 of the Laws of Zambia, which was enacted to allow for the setting up of a formal capital market. This was done under the assistance of the World Bank and the International Finance Corporation (IFC). This came about due to the privatization programme that the Zambian government adopted in order for the general populous to be able to own a stake in some of the firms that where being privatized (Tembo & Mlambo, 2009). The Securities and Exchange Commission (SEC) which oversees the market is particularly concerned with the governing of the exchange in terms of full disclosure of material information, and does not in any way attempt to determine whether a security is fairly priced or not (Republic of Zambia, 2004). The capital market has developed since its establishment in 1993, from 1995 the number of listed companies has grown from 2 to 21 companies. The market capitalisation has grown from US$19 million in 1995 to $3,004 billion in 2012 (The World Bank, 2014). The LuSE All Share Index which was started in 1997 at 100 was recorded at 5,300.1 points as of 31st December 2013 (Bloomberg, 2014).

The LuSE is categorised by a two tier market structure for which the top tier consists of listed companies which tend to meet the criteria of full listing on the stock exchange. Whilst the second tier consists of firms quoted on the stock exchange, and these firms tend not to meet the full criterion of listing on the stock exchange. However, for the purpose of this study only listed firms will be considered for this study (Marone, 2003).

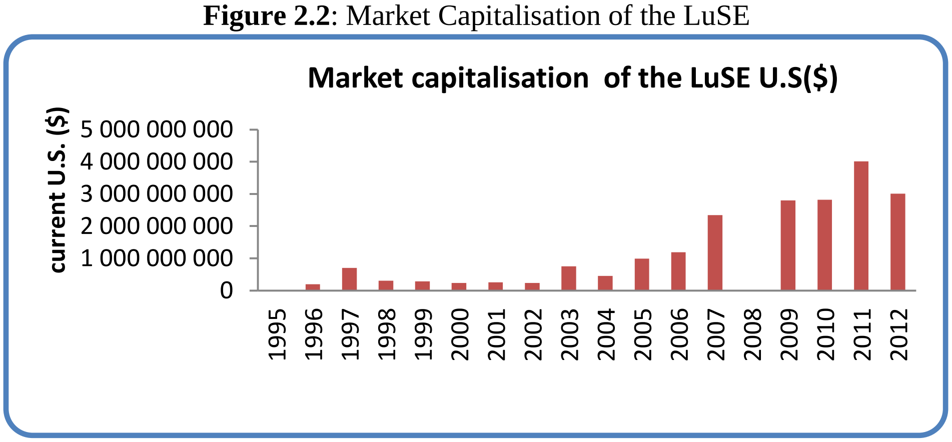
Figure 2.1: LuSE Index



Source: Bloomberg, 2014

Figure 2.1 above depicts the time series value of the daily stock movement of the LuSE All Share Index (ASI) from 10th February, 1997 till 1st August, 2013. It can be observed that there is very minimal upward growth in the LuSE index from 1997 till 2003. However, after 2003 onwards, the index value picked up drastically from 2003 onwards till 2006. Thereafter there is exponential growth in the LuSE index that steadily grew due to increased activity and growth in share prices of most stocks on the LuSE index till 2008, this coincides with the onset of the global financial crisis of 2008 which lead to a reduction in the LuSE-ASI as global growth slowed down (Tembo & Mlambo, 2009). After 2010 the index starts to pick up, with levels similar to those prior the crisis.

Figure 2.2: Market Capitalisation of the LuSE



Source: The World Bank, 2014

The figure 2.2 depicts the market capitalisation of the LuSE in United States of America Dollar (U.S.$) from 1995 to 2012, this refers to the total market value of the listed firms. In 1995 the market capitalisation was US$ 19 million consisting of two firms, which grew to $195 million in 1996, and as of 2012 the market capitalisation was at $3,004 billion (The World Bank, 2014)[1].

2.2 OTHER MARKET DEVELOPMENTS

In addition, Zambia debuted its $750-million (U.S.) 10 year Euro Bond in September of 2012 which was oversubscribed 15 times, and was issued with a 5.625-per-cent yield delivering an order book of US $11.9-billion for the B+ rated country, which was a rear feet for first time emerging African market (Rintoul, 2013). For instance, Other African countries to issue bond at that time included the higher rated Namibia which issued a $500 million bond in October 2011 which was oversubscribed five times generating an order book of $2.5 billion. Whilst Nigeria issued a $500 million which was oversubscribed 3 times generating an order book worth $1.5 billion in January 2011[2].

In addition, the Bank of New York Mellon (BNY) began selling American Depositary Receipts (ADRs) for three Zambian companies of Copperbelt Energy, Zambia National Commercial Bank (ZANACO) and Zambeef Products which are the first ADR deposits in Southern Africa outside South Africa the bank has issued, which is amongst the leading issuer of receipts worldwide (Hill, 2013)[3].

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[1] The World Bank (2014). Market capitalization of listed companies (% of GDP),2014, 14, January, from, http://data.worldbank.org/indicator/CM.MKT.LCAP.GD.ZS

[2] Zambia euro bond could be African tipping point (2012). The Globe and Mail, 2012, 5 October, from, http://www.theglobeandmail.com/report-on-business/international-business/african-and-mideast-business/zambia-euro-bond-could-be-african-tipping-point/article4592068/

[3] Hill, M. (2013, 8 October).Bank of New York Mellon issues ADRs to Zambian companies. Mail & Guardian. Retrieved 21 November, 2013, from, http://mg.co.za/article/2013-10-08-bank-of-new-york-mellon-issues-first-adrs-in-africa-outside-sa-to-zambian-companies

2.3. SUMMARY

Despite the LuSE showing some promise, it is characterised by low turnover ratios with a small number of investors trading in the market which has an effect of excess volatility on the stock prices. In addition, the Zambian stock market has had a limited number of firms being listed on the stock exchange, whilst in its first ten years, the LuSE only had 10 firms listed on the exchange, today the total number of firms listed stands at 21. One would have thought that the exchange would be able to have a listing of at least two firms each year on the exchange. In addition, because the wealth of the nation is relatively small, the country tends to have insufficient number of people with sufficient income/savings to invest in the stock market, with a Gross National Income (GNI) per capita of $1,350 in 2012 (The Word Bank, 2014)[4]. In addition, even those with disposable income tend not to be involved in the operations of the stock market. There is therefore, a need for greater awareness and participation in the market from domestic inventors.

[4]The World Bank. (2014). Zambia country Statistics. Retrieved 4th January 2014, from, http://data.worldbank.org/country/zambia

CHAPTER 3: LITERATURE REVIEW

INTRODUCTION

In this chapter, literature that is relevant to random walks and market efficiency is discussed.

3.1. ORIGINS OF THE EFFICIENT MARKET HYPOTHESIS

The origins of the efficient market hypothesis can be traced as far back as the studies of Bachelier in the 1900s who identified that that future returns where independent of past returns. His analysis involved the study of the returns of government bonds from the Paris Stock Exchange for his PhD in Mathematics. Unfortunately the findings of Bachelier were largely overlooked until his findings were later on looked at by economists' Paul Samuelson and Paul Cootner (1964) who later on circulated his work, and made his work better known (Dimson and Mussavian, 1998). Today, there is much more literature and focus on the efficient market hypothesis. Of the numerous authors that have covered this topic, Eugene Fama is one of the outstanding candidates. His research on the summary of the efficient hypothesis has appeared in a number of the world's leading financial journals (Fama, 1965, Fama, 1991). In additional, Malkiel's (1973) study of the 'Random Walk on Wall Street' figures out prominently.

3.2. EFFICIENT MARKET HYPOTHESIS AND THE RANDOM WALK THEORY

3.2.1 EFFICIENT MARKET HYPOTHESIS

The Efficient Markets Hypothesis (EMH) which is a historical compilation of works states that an efficient market is one in which prices fully reflect all valuable information correctly and instantaneously (Fama, 1970). In addition, stock price changes are independent of one another, and the best estimate of future prices should be current prices and not those of the past (Lee, Tsong and Lee, 2013). The EMH has therefore been used to analyse the way stock markets function, which ultimately has implications on one's investment decisions and how they approach the market. If the market is efficient, then an astute investor may perform no better than a common layman in predicting stock price movements (Lo and MacKinley, 1999). As such, if the market is efficient then it is a waste of time to research and find miss-priced assets as the market will provide the best estimate of risk-return trade-off at that particular time to provide a fair price for the given asset (Brealey and Myers, 2003). However, if the market is inefficient, then an investor may attempt to spot out the overpriced and underpriced equities in the market in order to maximise the return of their portfolio (Brealey and Myers, 2003).

3.2.2 INTUITION BEHIND THE EFFICIENT MARKET HYPOTHESIS

The basic intuition behind the efficient markets hypothesis may be related to the economic principles of supply and demand. For instance, given that the stock market price is lower than what available information in the market would suggest, investors may profit by buying the asset, as its price is lower than its market value. However, as more and more investors foresee the price of the stock as being underpriced by the market, this leads to greater demand for that particular stock or equity, leading to a push in its price until it is no longer underpriced (Malkiel, 2003). On the other hand, if the stock market price is greater than what available information in the market would suggest, this entails that the stock price is greater than its market value. Investors may profit by selling the stock immediately or by short selling the stock that they do not currently own. The increase in the supply of the asset would lead to a reduction in the price of the stock until it was no longer overpriced. The profit motive of investors is what leads to the 'correcting' of prices such that no other investor may consistently earn excess profits, as the market tends to correct itself (Malkiel, 2003).

3.2.3. RANDOM WALK HYPOTHESIS AND THE EFFICIENT MARKET HYPOTHESIS

The random walk hypothesis refers to the fact that consecutive stock price changes in a stock are unrelated to one another other, that is, the stock price today has no relation to the stock price tomorrow. In addition, the stock markets are described as efficient in the weak form if the current stock price is able to incorporate all its past prices information. This therefore entails that studying the past price behaviour of stock prices cannot earn investors abnormal returns (Chen, 2011). The term 'random walk' may be traced to Kendall (1953) who examined 22 UK stock and commodity prices. Through his findings, he discovered the returns of the price changes of the 22 times series to be fairly random from one time period to the next (Dimson and Mussavian, 1998). The non-existence of any visible correlation for price changes form one time period to the next came as a surprise to Kendall, and was against most of the sentiments of those times, for which it was perceived that stock prices movements were fairly correlated with each other. It is essentially through the work of these findings that the term Random Walk Model was coined (Dimson and Mussavian, 1998). The theory of random walks essentially argues that if stock prices are wandering randomly, then it poses a major challenge to investors who attempt to predict stock market movements (Zhang, 2001).

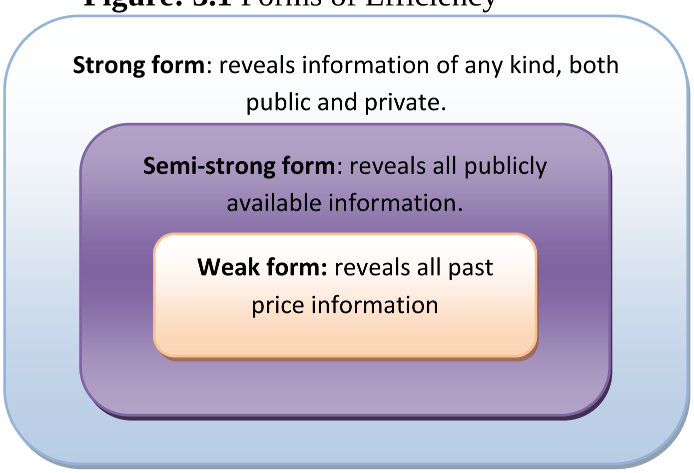
3.2.4. RWH AND THE MARTINGALE PROCESS

The test for market efficiency based on the random walk hypothesis examines whether stock price changes from one period to the next are independent and identically distributed (I.I.D) (Smith, 2009). However, stock market returns tend not to be I.I.D since they tend to be characterised by conditional heteroscedasticity for successive price changes. As such a more appropriate procedure for testing the unpredictability in stock price movements characterised by heteroscedasticy is the martingale process. As such, the martingale process which is less restrictive than the conventional random walk model is deemed more appropriate when stock price returns have general form of heteroscedastsicty. As such, if stock price returns are martingale they are unpredictable, however they are not I.I.D in the purest sense (Smith, 2009).

3.3. LEVELS OF MARKET EFFICIENCY

The different forms of market efficiency are categoriesd depending on the information available to the market (Jordan &Miller, 2009). The levels of market efficiency are: the weak form; semi-strong form, and strong form efficient. The Figure below shows the relationships among the information sets.

Figure: 3.1 Forms of Efficiency



Source: Jordan and Miller, 2009:210

Weak Form Efficiency: This form of efficiency states that prices fully reflect all historical information. This information includes the history of past stock prices, company characteristics and market characteristics. In addition, this form of efficiency states that it is not possible to beat the market through trading strategies that incorporate past prices or technical trading techniques such as the Dow Theory and Price Volume Systems (Jordan and Miller, 2009).

Semi-Strong Efficiency: This form of efficacy states that stock prices fully reflect all available public information. If a market is semi-strong form efficient, it is also weak-form efficient (Magnusson and Wydick, 2002). As Jordan and Miller (2009) argue, if a market is semi strong efficient, then the use of a firm's financial statement in beating the market are rendered inadequate.

Strong-Form Efficient: This form of efficiency reflects all available information. In addition, no information of any kind whether public or private is useful acquiring above normal returns. If a market is strong-form efficient, it is necessarily weak and semi-strong-form efficient as well (Jordan and Miller, 2009). However, ignoring the issue of legality, the possession of non-public inside information may enable an investor earn excess returns relative to the market (Jordan and Miller, 2009).

3.4. SEASONALITY AND THE EFFICIENT MARKET HYPOTHESIS

A number of market anomalies have been discovered in financial literature for which various studies have shown that there has been a predictable pattern in stock price returns over a period of time. These include return seasonality studies such as the January effect and day of the week effect. These studies that have been carried out provide evidence of market inefficiencies that contradict the Random Walk Hypothesis. For instance a study by Robins, Sandler and Durand (1999) provide evidence of the January Effect on the Johannesburg Stock Exchange (JSE), where stock returns are significantly higher during the month of January relative to any other months of the year. In addition, Sullivan and Liano (2003) provide evidence of the Monday effect on the New York Stock Exchange (NYSE), where average returns are negative from the close of Friday to the close of Monday, particularly for small firms. However, this is not to say that those particular days or months are the only ones to have experienced significantly different returns relative to other days or months, as other days and months have been found to have significantly different returns relative to other periods, for instance, studies on countries in the Pacific Rim such as Korea and Japan have shown the lowest mean return occurring on a Tuesday, these studies include Dubious and Louvet (1996) as well as Brooks and Persand (2001). However, Monday effect and the January Effect are amongst the most common seasonality effects (Dupernex, 2007).

3.4.1. DAY OF THE WEEK EFFECT

Studies on the financial literature of the day of the week effect have shown Monday to have significantly lower returns, whilst the other week days tend to higher returns relative to Monday, most notably that of Friday. The Monday effect has been attributed to the tendency of firms to release unfavourable information over the weekend, as such the stock prices tend to be discounted in the coming week therefore resulting in low returns on Monday (Dalina, Duy, Tri, Hau, & Nghiem, 2012). Such studies include Keim and Stambaugh (1984) who analyse daily returns of the Standard and Poor's Composite Stock Index from 1928 to 1982. In addition, a study by Chusanachoti and Kamath (2002) analyse the Thai stock market for which Monday and Thursday are found to have negative returns whilst the other week days had positive returns for the period 1990-1998 (Dalina, *et al*, 2012).

3.4.2. THE JANUARY EFFECT

The January Effect states that stocks that tend to underperform in the fourth quarter of the prior year tend to outperform the market leading to considerably high returns in the month of January (Gultekin & Gultekin, 1983). The reason for the January Effect is that investors tend to sell equities that are performing badly towards the end of the year. In addition, investors sell equities that are performing badly so that they may off-set losses on those stocks against the taxes they would otherwise have paid if they still kept those loss making stocks on their books, which leads to downward pressure on the prices. Then in January when many buyers are now willing to buy up these stocks, it tends to create upward pressure on stock prices therefore leading to the January Effect, whereby returns are higher in the month of January than in December (Gultekin & Gultekin, 1983).

3.5. ARE SHARE PRICES CORRECT

the objective of the EMH more so in the weak form is not to determine whether stock prices are 'correct' but to demonstrate that stock prices are able to incorporate all past price information. As such, this provides the investor with an unbiased estimate of the expected returns from holding the asset. The share price is an evaluation of expected future discounted cash flows, however, as new information is always entering the market this changes investors' expectations of the future profitability of the firm as well as its share price (Maghyerech, 2003).

3.6. IMPLICATIONS OF RANDOM WALK THEORY TO STOCK PRICE PREDICTION

As Assaf (2006) argues the random walk properties of stock price returns have an significant bearing on the determination of security return dynamics which then affects how investors approach the market, and the potential trading strategies they adopt. According to Jordan and Miller (2009) market practitioners in general have two based approaches when predicting stock market movements; these include technical analysis and fundamental analysis techniques. Technical analysis is based on the premise that that it is possible to predict future stock trends through the use of past price information, however, this collides with the teaching of the EMH which argue that analysing past information cannot result in investors acquiring abnormal returns. On the other hand, fundamental value analysis depends on a security's earnings potential. If actual prices inclines towards its intrinsic value, then estimating the intrinsic value helps predict security price movements. Fundamental analysis is essentially done in order to gain an insight on a company's future performance (Jordan and Miller, 2009).

3.7. INVESTMENT PHILOSOPHIES AND STRATEGIES

3.7.1 FUNDAMENTAL INVESTING

Fundamental analysis involves identifying firms with strong prospected future earnings. This is done by analysing a firms accounting and economic information through the use of its financial statements in order to obtain a depiction of the economic value of the business. In addition, fundamental analysis involves the analysis of non-financial aspects of the firms, such as the quality of its management as well as the quality of products in order to get a better understanding and insight into the value of the business as well as its future prospects, relative to its competitors in the industry (Jordan & Miller, 2009).

Investors analyse the books of firms in order to determine whether there may be a discrepancy between the businesses future intrinsic value and its market value. As such fundamental analysts tend to buy shares of firms that they feel are currently undervalued in the market, and that eventually the market participants will realise the true value of the firm. As such, analysts tend to have a long term view on the stocks they buy, adopting buy and hold strategies. Therefore, analysts wait till such a time in the future when the market price of the stock reflects its actual value, this is will result in the investor realising a profit from their original investment (Jordan & Miller, 2009).

3.7.2. RANDOM WALK STRATEGIES

Random walk strategies are based on the premise that stock prices move about in wandering patterns, and that investors who may not have financial relationships in the market, or have no financial prowess in terms of analysing stock markets are not likely to outperform market indexes. It is argued that the most optimal investment strategy is for an investor to hold a portfolio of stocks that best resembles the market. In addition, is more optimal for investors to adopt a buy and hold strategy, meaning that they should keep to their portfolio for a substantial period of time, rather than actively being involved in the market (Jordan & Miller, 2009).

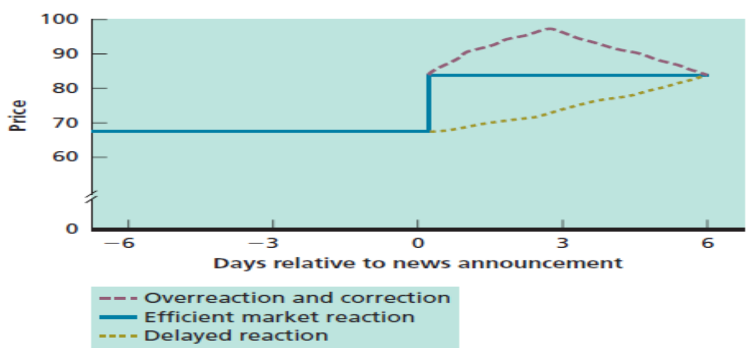
3.7.3. TECHNICAL ANALYSIS

Technical analysis is an investment evaluation method whereby investors forecast future stock price movements, based on its past price information (Jordan & Miller, 2009). Technical analysts are traders who attempt to exploit short-lived market movements in order to acquire returns greater than those of the market. They tend to hold trading positions for short lived time periods, and therefore their trading positions are largely due to immediate market movements and forecasts. This sort of trading tends to constantly require the active participation of the investor with good insight of market movements in order to be able to take advantage of price movements, these sort of traders are usually referred to as ‘active traders’ (Jordan and Miller, 2009). Technical analysts usually adopt different techniques in order to analyse stock market movements, such techniques include the Dow Theory. The Dow Theory is aimed at signaling to investors where the general trend of the stock price movement is likely to be, that is whether the stock price is likely to be in the upward trend or downward trend for a particular period of time (Jordan and Miller, 2009).

3.7.4. REASON FOR THE BELIEF OF TECHNICAL ANALYSIS

Technical analysis is based on the premise that information does not enter the market instantaneously, but over a period of time. Therefore, by observing the past and current trends in the market, investors may be able to depict the beginning and end of major/primary shifts in market movements. Figure 3.2 below describes how information enters the market, and because market reactions are not instantaneous, investors may be able to profit from this (Jordan and Miller, 2009).

Figure 3.2: Market Reactions to Information



Source: Jordan and Miller, 2009:213

3.8. IMPORTANCE OF AN EFFICIENT STOCK MARKET

The importance of an efficient stock exchange stems from the fact an efficient capital market is one that is able to adequately perform the roles that it has been assigned to it Smith *et al* (2002). For instance, an efficient market is able to more adequately allocate the appropriate price of risk and return in the market. As such finances will flow to the more efficient sectors of the economy rather than those that may be less efficient (Magnusson & Wydick, 2002). It has been argued by various authors that emerging markets play an important role in the functioning of markets and in the economy in general. For instance, (Dockery, 2000; Fama 1991; Magnusson and Wydick, 2002) argue that a fully functioning and efficient market effectively transfers capital from savings to a productive environment, allowing for efficient allocation of resources. In addition, it is further argued that an efficient capital market mitigates the cost of lending and trade, which ultimately results in a more productive economy (Dockery, 2000). Furthermore, the capital markets improve the available capital for domestic firms to further expand their business operations. Likewise, the Zambian Government sees the capital markets aiding to provide the missing link in the nation's quest for sustainable economic growth and poverty reduction (Republic of Zambia, 2004).

3.9. TESTS FOR MARKET EFFICIENCY

There are various tests and techniques that have been developed in order to determine the levels of market efficiency. These tests can broadly be classified into three different components depending on the form of efficiency that is being analysed, these include;

1. **Test for Weak Form Efficiency**: Tests for return predictability are used to analyse weak form efficiency, these include serial correlation tests as well as variance ratio tests (Jordan and Miller, 2009).
2. **Tests for Semi-Strong Efficiency**: Event Studies are used to analyse the semi-strong form efficiency. These tests analyse how public information about the firm is readily incorporated into stock prices (Jordan and Miller, 2009).
3. **Tests for Strong Form Efficiency**: These tests are used to analyse for private information and whether investors have information relevant to the firm that is not known by the market (Jordan and Miller, 2009).

3.10. DIFFERENT FORMS OF RANDOM WALK

In addition to Fama's classification of market efficiency in terms of weak, semi-strong and strong, Campbell, Lo and Mackinlay (1997) classified random walk test returns into three distinct categories; these include Random Walk one (RW1), Random Walk two (RW2), and Random Walk three (RW3). For which RW1 is the most restrictive version of the random walk.

Random Walk 3: This is the most relaxed version of the random walk and implies that price movements are uncorrelated although they may be dependent. Tests for RW3 involve checking for the presence of serial correlation of the observations over time. Tests for RW3 include, Autocorrelation coefficients tests (Campbell *et al*, 1997).

Random Walk 2: This is a stronger test of weak form efficiency than RW1. It imposes an additional conditionality, that is price movements are uncorrelated and independent, but do not have to be identically distributed (I.N.I.D) which allows for the heteroscedasticity assumption. The condition of independence implies that future stock prices are independent of past price information, and as such it is not foreseeable to predict the future based on past price information. Tests for RW2 include: Filter rules and Technical analysis (Campbell *et al*, 1997).

Random Walk 1: This is the most restrictive form of RW. In RW1 price movements are Independent and Identically Distributed (I.I.D). In addition, Campbell *et al* (1997) argue that if the error terms of a stock price series are I.I.D then this would be equivalent to a brownian motion in terms of stock price movements. In order to account for the presence of RW1, Campbell *et al* (1997) classified the following test; Sequences and reversal, and the Runs test. It is argued that tests for RW1 fall under non parametric models (Campbell *et al*, 1997).

3.11. DIFFERENT CLASSIFICATIONS OF TESTS

3.11.1. RUNS TESTS

The runs test is a non-parametric test, which implies that it does not rely on the assumptions of normality in the time series properties of stocks. This test accounts for whether consecutive stock price changes are independent of one another (Borges, 2010). For instance positive returns could have a label of 1, whilst negative returns have a label of 0. Therefore the sequence in share price movements may be as follows using the Runs Test: 1001110100 or ($+ - - + + + - + - -$) where they are 6 runs, 3 runs of 1 (1,3,1) and 3 runs of 0 (2,1,2). Likewise, we could encounter a series of runs with a sequence such as 0000011111, which has the same number of 1's and 0s, however only 2 runs (one of five 0s, and one of five 1s).

3.11.2. AUTOCORRELATION

The tests for autocorrelation examine the similarity between successive stock price changes and its lags over a given period of time of its error term. Coefficients may either be positively, negatively or have zero correlation. Positive serial correlated states that successive price changes move in the same direction. Negatively serial correlated entails that successive price changes move in opposite directions. Whilst zero correlation entails that successive price changes are not related. In terms of market efficiency, the autocorrelation coefficient between successive variables should be zero. Tests for Autocorrelation include the Ljung-box and Box-Pierce among others (Brooks, 2002).

3.11.3. UNIT ROOT TEST

The unit root test which is one of the traditional tests for market efficiency is used to test whether a time-series is stationary or contains a unit root, for which the null hypothesis is that there is a unit root. If the time-series is stationary then it may be implied as random walk, which is an indication of weak form efficiency. However, if the time series properties of the stock is not stationary or does contain the unit root, then it is not weak form efficient (Ojdanic, 2006). However, it should be noted that unit roots tests have proven not to be powerful enough by a number of studies such as Summers (1986) Poterba and Summers (1988) and Fama and French (1988), and Karemera *et al* (1999) for which it is argued that is biased to accepting the RWH when this may in fact not be the case. In addition, Dockery (2000) argues that these tests are structurally insensitive to predictability (Ojdanic, 2006).

3.11.4. VARIANCE RATIO TESTS

Variance ratio (VR) tests consists of testing the null hypothesis that a univariate time series is random walk against stationary alternatives by exploiting the fact that the variance of random walk increments is linear in all sampling intervals (Charles & Darné, 2009). The null hypothesis is that the variance ratio is one, which implies that the given time series is Random Walk, otherwise it is not. A VR of less than one implies that negative serial correlation is present in stock returns, whilst a VR greater than one implies positive serial correlation (Darrat and Zhong, 2000). For instance, a VR greater than one this implies that errors in one time period are positively correlated with errors in the next time period, whilst a VR of less than one implies that errors in one time period are inversely correlated with errors in the next time period (Ojdanic, 2006). VR tests are typically divided into distinct categories of single and multiple tests. In addition, the variance ratio tests have been found to be more powerful than unit root tests when testing the random walks hypothesis, and as such they are more often being used by both academics and practitioners in order to test for market efficiency (Lam, 2006).

3.11.4. A. INDIVIDUAL VARIANCE RATIO TESTS BY LO AND MACKINLAY (1988)

The individual variance-ratio tests introduced by Lo and MacKinlay (1988) and Poterba and Summers (1988) is often used to test the hypothesis that a given time series or its first difference is a collection of independent and identically distributed observations. This test uses the fact that the variance for an I.I.D series increases linearly in each observation interval. The test by Lo and MacKinlay (1988) is an individual test for unity for each lag, and requires all given lags to be equal to one in order for the stock price series to be deemed random walk, otherwise they are not. In addition, if the variance ratio is greater than one, this implies positive serial correlation in the returns, whilst a variance ratio of less than one implies negative serial correlation (Charles & Darné, 2009).

3.11.4. B. MULTIPLE VARIANCE RATIO TESTS BY CHOW AND DENNING (1993)

The Multiple variance ratio (MVR) test is a modification of individual variance ratio tests, it jointly test the null hypothesis of random walk that the variance ratio equals one. This is done through controlling the size of the test by forming a studentized maximum modulus (SMM) statistic. In addition, the Chow and Denning test reduces type I errors, which refers to rejecting the null when it is in fact correct. The decision to accept or reject the null hypothesis is based on the maximum absolute value of the variance ratio test statistics. (Smith *et al*, 2002).

3.11.4.C. NON PARAMETRIC VARIANCE RATIO TESTS BY WRIGHT (2000)

The ranks and signs test is a non-parametric variance ratio tests. Wright (2000) argues that the potential benefits of ranks test over the other variance ratio test is that, the test is more powerful than other variance ratio tests if the data is highly non normally distributed in testing to determine whether time series data is random walk. Wright's variance ratio test based on ranks and signs are a modification of the Lo and Mackinlay tests which incorporates the use of signs and ranks instead of differences as proposed by Lo and Mackinlay.

3.11.4.D. BOOTSTRAPPING VARIANCE RATIO TESTS BY KIM (2006)

Boot strapping is a resampling method which is used to approximate the variance ratio test statistic. In addition, it is also a means of improving small sample properties of variance ratio tests. The Kim (2006) test uses a wild bootstrap method to the VR statistic, and is applicable to data with unknown forms of conditional and unconditional heteroscedasticty. The test is conducted in three stages, but essentially involves repeating a random sequence several times in order to form a bootstrap distribution of the test statistic (Charles & Darné , 2009).

3.12. TESTS FOR SEASONALITY

The tests for seasonality are generally categorised into two forms, these include parametric tests which are based on the assumption of normality in the data, and non-parametric tests which does not rely on normally distributed returns for the data. In addition, in order to test for the day-of-the-week effect, and the January effect, similar procedure may be used, whilst only changing the use of input variables be it daily data or monthly, in order to examine each effect (Zhang, 2001).

3.12.1. DAY OF THE WEEK EFFECT ANALYSIS

Dummy Variable Analysis

In order to analyse whether any day of the week is present, a regression analysis may be carried out. For instance, the null hypothesis tests that all returns for each day are all statistically alike. Whilst a rejection of the null implies that at least one of the days has significantly higher or lower returns relative to the other week days. The day of the week analysis may be calculated with the use of dummy variables, whereby you calculate average return for each day of the week and run a dummy variable regression.

$$Y_t = \alpha + \beta_1 Tue + \beta_2 Wed + \beta_3 Thur + \beta_4 Fri + \varepsilon_t$$

Where Y_t is the stock price return on day *t*, and $\beta_1, \beta_2, \beta_3, \beta_4$ are the coefficient of the dummy variables for each weekday except Monday. Whilst α would be the average returns of Monday, and $\beta_i (i = 1,2,3,4)$ shows the excess return relative to Monday, be it positive or negative (Dupernex, 2007).

Parametric and Non-Parametric Tests

In addition, the analysis of variance (ANOVA) as well as the Kruskal-Wallis test is used to determine the whether the day of the week effect is present in stock market returns. The vast majority of seasonality tests tend to adopt the ANOVA which is a parametric test, and as such relies on the assumptions of normality, independence and stationarity in the data. However, if the data does not confer to these assumptions then Kruskal-Wallis test which is a non-parametric test tends to be utilised. However, for the most part both tests tend to be used for comparability of the results (Zhang, 2001).

In addition, in order to determine which exact day is significantly different from the other, the parametric Duncan test which is a multiple comparison test is usually utilised. Likewise if the conditionality's of normality are not met then a nonparametric test of the Mann-Whitney U is adopted which is a rank test (Zhang, 2001).

3.13. JANUARY EFFECT

Dummy Variable Analysis

Subsequently, Monthly returns may be modeled through the use of dummy variables, for instance by specifying a model with eleven variables, you may then estimate the difference in the returns of the eleven months relative to the remaining months (Dupernex, 2007).

$$Y_i = \alpha + \beta_1 Feb + \beta_2 Mar + \beta_3 Apr +, \dots, + \beta_{11} Dec + \varepsilon_t$$

Where Y_t is the mean stock price return for month *t.* $\beta_1, \beta_2, \beta_3, \dots, \beta_{11}$ are the coefficients of the dummy variables for each month of the year. Whilst α would be the average returns of January, and $\beta_i (i = 1,2,3,4)$ shows the excess return of January relative to the other months, be it positive or negative (Dupernex, 2007).

Parametric and Non-Parametric Tests

Likewise, in order to determine whether the mean return of each particular month is statistically different from the other, a parametric and non-parametric test of the ANOVA or the Kruskal-Wallis may be adopted. For which the null hypothesis tests for equal average returns for each month. Whilst a rejection of the hypothesis implies that at least one of the returns is not equal to the other returns (Zhang, 2001). In addition, in order to determine which particular month is different from the other months, the Duncan test which is a parametric test and /or the Mann-Whitney U test which is a non-parametric test may be utilized (Zhang, 2001).

3.14. EMPIRICAL REVIEW ON MARKET EFFICIENCY

Most empirical work on market efficiency has focused on more established markets. However, an increasing body of work is slowly expanding to smaller developing markets. A number of researchers tend to use a combination of tests in order to analyse market efficiency.

Studies on the Random Walk Hypothesis

For instance, a study by Karamera *et al* (1999) which analysed the weak from efficiency of 15 emerging countries stock markets incorporated the use of the multiple variance-ratio test of Chow and Denning (1993) to examine the random walk properties of these markets. In addition, the equity markets were analysed with equity prices based in local currency, as well as U.S. Dollar denominated stock market returns. Their results of the study indicate that the returns of most of the markets analyse conform to the properties of the RWH, more so when the equities are analysed based on local currency rather than U.S Dollar denominations. For which it may be argued that this is an indication that local investors have more information of their domestic markets relative to international investors. In addition, they incorporate the runs test that suggests that most of the emerging markets are weak-form efficient. In addition, Karamera *et al* (1999) recommend that investors are unlikely to consistently outperform the market through the use of past price information in many of the examined markets, and therefore recommends investors should set-up their investment strategies on the assumption of random walks.

In addition, a study by Smith *et al* (2002) analysed four categories of stock markets in Africa in order to determine whether these stock markets price formation process was random walk. The categories were divided by the relative sizes of the respective markets in Africa. These consisted of South Africa as a large market; thereafter, they were five medium sized markets consisting of Egypt, Kenya, Morocco, Nigeria and Zimbabwe; as well as two small new markets which had experienced significant growth in their stock markets which consisted of Botswana and Mauritius. Of all the markets analysed, only the Johannesburg Stock Exchange (JSE) of South Africa was the market found to be weak form efficient, whilst the seven other markets did not follow a random walk process. This therefore provides evidence for the use of technical trading strategies for the other stock markets which were found not to be random walk. The distinguishing factor between the South African and the other African markets was the sophisticated nature of the South African financial market relative to the other African countries.

Other notable studies include Malkiel's (1973) 'A Random Walk Down Wall Street' who analyses the American markets, and for which his analysis favours that of the efficient market hypothesis, and argues that the best trading strategy involves a buy-and-hold strategy of an index rather constantly seeking to make short term gains in the market by constantly analysing prices, and this tends to be far more costly and time consuming than undertaking the buy and hold strategy.

In terms of trading strategies and predictability, studies by Fama (1965) and Malkiel (2003) have supported the view that that there is no long term profitability by adopting trading strategies such as those based on technical trading. They provide evidence that traders are unable to do better than the market, or benchmark indices. For instance, Malkiel (2003) shows that benchmark indices outperform actively managed funds for a period of ten years from 1991 to 2001.

However, since most investors tend to have sophisticated trading tools, it is argued that investors are rational individuals and would not be willing to invest in trading strategies at a great expense, both in terms of their time as well as financially if they were unable to beat the market or get considerable returns by doing so, as such studies by Lo, Mamaysky and Wang (2000) have found that analysts may be able to have predictive power of future returns by using sophisticated nonparametric statistical tools in order to predict future returns, although it is argued to be modest (Dupernex, 2007).

In addition, a study by Tembo and Mlambo (2009) which examines the efficiency of the LuSE, and how best to solves its problem, analysed all individual stock prices time-series returns using fortnightly data for the period May 1995 to October 2008 for which 18 securities were tested for random walk. The method of analysis involved the Augmented Dickey Fuller (ADF), for which the study found 17 security stock prices to follow a random walk. The results therefore show the LuSE to be weak form efficient as only one of the security prices analysed was not consistent with the random walk properties.

In addition, a study by Bley (2011) analyses the weak form efficiency of stock markets in the Gulf region over a 10 year period from 2000-2009. The study incorporates daily, weekly as well as monthly data. The study incorporates the use of the ADF tests, Lo and MacKinlay (1988) variance ratio test, as well as Wrights (2000) variance ratio test. The markets analysed include Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and United Arab Emirates. The study rejects the null hypothesis that the markets are weak form efficient for daily data for all markets. However, the weekly as well as monthly data are consistent with the operations of the RWH and are therefore weak form efficient for Bahrain, Qatar and Saudi Arabia. The meaning of these results may entail that as more time is given to allow for various price formations processes to occur, this may led to the acceptance of the RWH as shown by the weekly and monthly data, however, if the price formation period of analysis is short such as that of daily data this may lead to a rejection of the RWH for markets which may be not be characterised by high turnovers.

Studies on Market Anomalies

A study by Zhang (2001) conducts the random walk and seasonality effects of the China free share market using risk adjusted returns. The results of the study show that the stock returns do not follow a random walk, for which there is significant first order correlation in the returns. The results do not show any weekend effect, however, there is a considerable difference between Friday returns (0.1 percent) and Tuesday returns (-0.21 percent), for which Zhnag (2001) recommends a strategy of buying on Tuesday and Selling on Friday. In addition, there is no significant January effect. Tests conducted include the autocorrelation and partial autocorrelation to account for the random walk, as well as the ANOVA, and other non-parametric test such as the Kruskal-Wallis to account for seasonality (Zhang, 2001).

Furthermore, a study by Kohers, Kohers, Pandey and Kohers (2004) argues that during the 1980s, the day of the week effect was significantly present in developed markets, whilst this phenomenon tended to disappear in the 1990s. They therefore argue that the improvements in the efficiency of these markets have diminished the effect of the market anomalies.

Likewise a study by Bourman and Jacobsen (2002) has found evidence of lower market returns in the months of May and October compared to the other months of the year. In addition, Keim and Stambaugh (1984) investigate the size effect in relation to the day of the week effect, for which their results show that aggregate returns tend to increase as the week goes along, and they tend to do so more quickly for smaller firms relative to the bigger firms they observed.

However, despite there being findings of seasonality effects being present in time-series data which goes against the teachings of EMH such that investors may be able to time the markets and make easy profits from benefiting from these seasonal patterns. It is often argued that when transaction costs are taken into account, investors may not necessarily be able to make easy profits by developing strategies based on these seasonal patterns as the transaction costs tend to wipe out any premiums and as such this stock market predictability does not necessary translate into inefficiency (Kohers, Kohers, Pandey and Kohers, 2004).

CHAPTER 4: RESEARCH METHODOLOGY AND DESIGN

4.1 DATA SELECTION

The data used in the study consists of daily time series data as well as monthly data of the LuSE-ASI, which is a market capitalisation weight based index of all listed firms calculated in local currency Zambian Kwacha (ZMW). The information is obtained from Bloomberg. The period of analysis ranges from period 3rd January 2006 to 17th February 2014. This period of analysis is chosen because before 2006, the data for the LuSE index is inconsistent. The use of the index to analyse markets is similar to various studies such as (Smith, 2009) who analyse Greek, Hungarian, Polish and Turkish markets among others.

Table 4.1: description of data

Variable	Start date	End date	Frequency	Source
LuSE-ASI	03-01-2006	17-02-2014	Daily	Bloomberg
LuSE-ASI	01:2006	02:2014	Monthly	Bloomberg

4.2. RESEARCH DESIGN

4.2.1. DATA AND METHODOLOGY

The daily as well as monthly returns are calculated by the first difference of natural logarithm of the LuSE-ASI as depicted below,

$$R_{j,t} = \left[\ln\left(\frac{P_{j,t}}{P_{j,t-1}}\right)\right] * 100$$

Where, $R_{j,t}$ refers to the return of the index at period t. P refers to the value of the index at period j. And, $P_{j,t-1}$: refers to the value of the index.

4.2.2. STRUCTURAL BREAKS AND TIMES-SERIES DATA

A structural break refers to unexpected shift or break that appears in time series data. Structural breaks come about due to economic crisis and change in policy among other factors. This can lead to huge forecasting errors and unreliability of the model in general if not taken into account

(Chancharat and Valadkani, 2007). As such, the study takes into account the Bia-Perron (2003) structural break procedure that takes into account up to five structural breaks in a time series. Given a regression with an unidentified number of breaks, say *m*:

$$y_t = x_t^{'}\beta + z_t^{'}\delta_j + \mu_t \qquad t = T_{j-1} + 1, \dots, T_j$$

In the above model, y_t is the observed dependant variable at time t. The null hypothesis is concerned with testing that the regression coefficients remain constant over time

$$H_0: \beta_i = \beta_0 (i = 1, \dots., n),$$

Against the alternative that at least one of the coefficients varies over time. For which it may be assumed that they are m possible break points. The indices $(T_{1,\dots,}T_m)$ refer to the break points which are explicitly treated as unknown (Bai & Perron, 2003).

4.3. STATISTICAL TESTS

4.3.1. RUNS TEST

As described above, the Runs test which is a non-parametric is test used to test the hypothesis that stock price series returns are mutually independent. The actual returns $r_{j,t}$ are counted and compared to the expected number of runs (μ) (Borges, 2010).

$$\mu = \frac{[N(N+1) - \sum_{I=1}^{3} n_i^2}{N}$$

Where N refers to the number of returns and $n_i$is a count of price change in each category (Borges, 2010):

$$\sigma_m = \sqrt{\left(\frac{\sum_{i=1}^{3} n_i^2 \{\sum n_{i=1}^{3} n_i^2 + N(N-1)\} - 2N \sum n_{i=1}^{3} n_i^3 - N^3}{N^2(N-1)} \right)}$$

In addition, the Z statistic is used to test the hypothesis that the returns are mutually independent. The Z statistic is shown as follows (Borges, 2010):

$$Z = \frac{R - \mu}{\sigma_m}$$

4.3.2. INDIVIDUAL VARIANCE RATIO TESTS OF LO AND MACKINLAY (1988)

Given that P_t is the log of the price level at time *t*. The variance ratio is depicted by the following:

$$VR_q = \frac{\frac{1}{q}\, Var(P_t - P_{t-q})}{Var(P_t - P_{t-1})} = \frac{\sigma^2(q)}{\sigma^2(1)}$$

Where$Z(q_i)$ and $Z^*(q_i)$ are the test statistics used to test the null hypothesis of random walk under the assumption of homoscedasticity and heteroscedasticity, respectively. Where;

$$Z(q) = \frac{(VR(q) - 1)}{\sqrt{\theta(q)}} \sim N(0,1)$$

$$Z^*(q) = \frac{(VR(q) - 1)}{\sqrt{\theta^*(q)}} \sim N(0,1)$$

Where $Z^*(q)$is the test that is applicable for a martingale process. The random walk hypothesis requires that $VR(q) = 1$, for all lags of q. This is analogous to studies by Smith (2009). However, one of the drawbacks of the single variance ratio tests, such as that of Lo and MacKinlay test is that it ignores the joint nature of testing the RWH, and this may lead to a rejection of the null hypothesis when it is otherwise correct (Charles & Darné , 2009).

4.3.3. MULTIPLE VARIANCE RATIO TEST

The Multiple Variance Ratio (MVR) test jointly tests the null hypothesis for random walk. For instance, consider a set of variance ratio estimates such that $\{VR(q_i)|i = 1,2,3, \ldots, L\}$,which corresponds to a predefined lags set of lags $\{(q_i)|i = 1,2,3, \ldots, L\}$. Under the null hypothesis, the multiple variance ratio test follows a random walk and requires the variance ratio to be equal to one. If the variance ratio is equal to one, then it may be concluded that the market is weak form efficient, otherwise it is not. For which the null is given as, $H_o: VR(q_i)$ =1 for $i = 1,2,3, \ldots, L$. In addition, the rejection of the null will lead to a rejection of RWH, for which the absolute values of the test statistic is given below:

$$Z_1(q) = \underset{1\le i\le L}{\text{Max}} |Z(q_i)|$$

$$Z_2(q) = \underset{1\le i\le L}{\text{Max}} |Z^*(q_i)|$$

Where $Z(q_i)$ and $Z^*(q_i)$ are defined above

The decision of whether to accept or reject the null hypothesis under the Chow and Denning test is based on the results of the maximum absolute value of the variance ratio test as well as the SMM critical values for $Z(q)$ under the homoscedastic assumption, as well as $Z^*(q)$ under the heteroscedasticity assumption . If the absolute Z statistics are greater than the SMM critical value, then the RWH is rejected for the stock price series, otherwise it is not. For large samples the SMM critical values are 2.23, 2.49 as well as 3.03 at 1, 5 and 10 percent level of significance respectively (Smith *et al*, 2002).

4.3.4. WRIGHTS (2000) VARIANCE RATIO TEST BASED ON RANKS AND SIGNS

Given T is the number of observations of asset returns, Wright (2000) proposed R_1 and R_2 to be defined as the rank and S_1 and S_2 to be the sign.

$$R_1(k) = \left(\frac{(Tk)^{-1}\sum_{t=k}^{T}(r_{1,t} + \cdots . + r_{1,t-k+1})^2}{T^{-1}\sum_{t=k}^{T} r_{1.t}^2} - 1\right) \text{x}\ \phi(k)^{-1/2}$$

$$R_2(k) = \left(\frac{(Tk)^{-1}\sum_{t=k}^{T}(r_{2,t} + \cdots . + r_{2,t-k+1})^2}{T^{-1}\sum_{t=k}^{T} r_{2.t}^2} - 1\right) \text{x}\ \phi(k)^{-1/2}$$

And where the standardized ranks $r_{1,t}$ and $r_{2,t}$are defined as:

$$r_{1,t} = \frac{r(x_t) - (T+1)/2}{\sqrt{\frac{(T-1)(T+1)}{12}}}$$

$$r_{2,t} = \phi^{-1}\frac{r(x)}{T+1}$$

And for which $\phi(k)$ refers

$$\phi(k) = \frac{2(2-1)(k-1)}{3kT}$$

For which the critical values of $R_1$and R_2 are obtained by simulating their exact distributions. In addition, the tests based on the signs of first difference are given by the following:

$$S_1(k) = \left(\frac{(Tk)^{-1} \sum_{t=k}^{T} (s_t + \cdots . + s_{t-k+1})^2}{T^{-1} \sum_{t=k}^{T} s_t^2} - 1 \right) \text{x } \phi(k)^{-1/2}$$

$$S_2(k) = \left(\frac{(Tk)^{-1} \sum_{t=k}^{T} (s_t(\hat{\mathrm{U}}) + \cdots . + s_{t-k+1}(\hat{\mathrm{U}}))^2}{T^{-1} \sum_{t=k}^{T} s_t(\hat{\mathrm{U}})^2} - 1 \right) \text{x } \phi(k)^{-1/2}$$

Where x $\phi(k)$ refers to and $s_t = 2u(x_t, 0), s_t\left(\hat{U}\right) = 2u(x_t, U)$ and

$$u(x_t, q) = \begin{cases} 0.5 & if\ x_t > q \\ -0.5 & otherwise \end{cases}$$

The critical values of S_1 and S_2 are obtained by simulating their exact sampling distribution. In addition, S_1 assumes a zero drift value. In this study, S_2 is not computed, because according to Wright (2000) it is deemed to have weak statistical properties and as such is not computed. This is similar to other studies by Chen (2011). In addition, the rank and signs test is computed using permutation bootstrap, with 5000 replications, and a seed of 1000.

4.4. SEASONALITY TESTS

4.4.1. DAY OF THE WEEK EFFECT ANALYSIS

The day of the week analysis is conducted through the use of dummy variables, whereby the average return for each day of the week is calculated and run as a dummy variable regression.

$Y_t = \alpha + \beta_1 Tue + \beta_2 Wed + \beta_3 Thur + \beta_4 Fri + \varepsilon_t$

Where Y_t is the stock price return on day *t*, and $\beta_1, \beta_2, \beta_3, \beta_4$ are the coefficient of the dummy variables for each day of the week. The main null and alternative hypotheses are stated below:

$H_{0:}\ R_i Mon = R_i Tue = R_i Wed = R_i Thur = R_I Fri$

$H_{1:}\ R_i Mon \neq R_i Tue \neq R_i Wed \neq R_i Thur \neq R_I Fri$

4.4.2. MONTLY EFFECT ANALYSIS

Subsequently, monthly effects are modelled through the use of dummy variables. Whereby, the average return for each month is run by dummy variable regression as depicted below (Dupernex, 2007).

$$Y_i = \alpha + \beta_1 Feb + \beta_2 Mar + \beta_3 Apr +, \dots, + \beta_{11} Dec + \varepsilon_t$$

Where Y_t is the mean stock price return for month *t*. $\beta_1, \beta_2, \beta_3, \dots, \beta_{11}$ are the coefficients of the dummy variables for each month of the year. Whilst α would be the average returns of January, and $\beta_i (i = 1,2,3,4)$ shows the excess return of January relative to the other months, be it positive or negative (Dupernex, 2007). The main null and alternative hypotheses are stated below:

$H_{0:}\ R_i January = R_i Febuary = R_i March = \cdots R_i December$

$H_{1:}\ R_i January \neq R_i Febuary \neq R_i March \neq \cdots R_i December$

4.5. ESTIMATION TECHNIQUES

The study incorporates the use of Ordinary Least Squares (OLS) method in order to depict the findings of the study for which E-views is the primary statistical package of use.

4.6. LIMITATIONS OF THE STUDY

The study focuses on the market efficiency, but given the extensive literature on this topic, the study only provides a discussion on the central teachings of the RWH hypothesis and market efficiency relating to weak form efficiency. In addition, the study does not take into account all equities listed on the LuSE but rather adopts the use of Indexes, by analysing daily as well as monthly returns.

CHAPTER 5: PRESENTATION OF RESULTS

The study incorporates daily market prices for the period 3rd January 2006 to 17th February 2014, as well as monthly data for the period January 2006 to February 2014 collected from Bloomberg. Monthly data is incorporated in order to account for thin trading that may be associated with the LuSE, and thereby avoid an empirical bias of concluding positive serial correlation in the results (Lo and MacKinlay, 1990). In addition, a, b and c refer to the levels of significance at 1, 5 and 10 percent where stated, respectively.

5.1. STRUCTURAL BREAKS RESULTS

The Bai-Perron (2003) structural breaks model which endogenously searches for multiple break points rejects the null that there are no structural breaks in the time-series of both daily as well as monthly data. In addition, it determines the most important break dates as 3/11/2008 for daily data as well as 2008:04 for the monthly data. Furthermore, the dates coincides with the onset of the global financial crisis, as such, there is a justification to incorporate these results. The results of the structural breaks are depicted in table 5.1.A and 5.1.B for daily as well as monthly results respectively.

Table 5.1.A: description of daily breaks in trend

Daily Break dates:	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical Value
1: 3/11/2008	21.38263	21.38263	21.38263	8.58
2: 2/20/2008, 5/06/2009	23.48921	23.48921	27.91378	7.22
3: 2/20/2008, 5/06/2009, 5/16/2011	16.54089	16.54089	23.81221	5.96
4: 2/20/2008, 5/06/2009, 5/16/2011, 11/14/2012	15.0119	15.0119	25.81205	4.99
5: 3/30/2007, 6/16/2008, 12/15/2009, 5/16/2011, 11/14/2012	8.354855	8.354855	18.33367	3.91

The table 5.1A above shows the individual test statistics for the daily time series returns, which are the F-statistic, the scaled F-statistic, and weighted F-statistic along with the critical values for the scaled statistics. In each case, the statistics far exceed the critical value so the study rejects the null of no breaks. In addition the results show the order of different specified structural dates from one break to a maximum of five beaks in the series.

Table 5.1.B: description of monthly breaks in trend

Monthly Break dates	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical Value
1: 2008M04	12.66501	12.66501	12.66501	8.58
2: 2008M03, 2009M05	11.27595	11.27595	13.39995	7.22
3: 2008M03, 2009M05, 2011M06	8.583764	8.583764	12.35716	5.96
4: 2008M03, 2009M05, 2011M06, 2012M12	10.75905	10.75905	18.49953	4.99
5: 2008M03, 2009M05, 2010M07, 2011M10, 2012M12	6.665353	6.665353	14.62627	3.91

The table 5.1.B above shows the individual test statistics for the monthly returns time series, which are the F-statistic, the scaled F-statistic, and weighted F-statistic along with the critical values for the scaled statistics. In each case, the statistics far exceed the critical value so that the study rejects the null of no breaks. In addition the results show the order of different specified structural dates from one break to a maximum of five beaks in the series.

5.2. SUMMARY OF RESULTS

In conjunction with the use of structural breaks, the results of the summary statistics are broken down into three categories based on daily returns as well as monthly returns. Firstly the results show the entire period of analysis, sub period 1 analysis (before the break in trend) and sub period 2 analysis (after the break in tend). Table 5.2.A depicts the daily results, whilst table 5.2.B depicts the monthly results. The returns are computed as: $R_t = lnP_t - lnP_{t-1}$. Where P_t is the LuSE index.

Table 5.2.A Summary of descriptive Statistics for daily data

	Observations	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ARCH(10)
Entire period: 03/01/2006-17/02/2014	2013	0.072004	1.051129	0.276762	10.77377	5094.388[a] (0.0000)	13.89955[a] (0.0000)
Sub-period 1: 0/01/2006-11/03/2008	549	0.233344	1.05913	0.363124	8.445214	690.3169[a] (0.0000)	3.195945[a] (0.0006)
Sub-period 2: 13/03/2008-17/02/2014	1463	0.012369	1.41879	0.24023	11.87572	4816.275[a] (0.0000)	12.723297[a] (0.0000)

p-value in the parenthesis

Table 5.2.A depicts the basic statistics for the daily returns for the LuSE-ASI. The mean of 0.072% for the whole period of analysis, refers to the daily compounded average return for the period 2008 to 2014, this entails on average investors acquired a compounded return of 0.07% for each day they invested in the LuSE index over that period of time. Whilst sub period 1 has the highest daily average returns of 0.23%, sub-period 2 has the lowest returns of 0.012% per day. If the data were to be exactly normally distributed, the values of skewness and kurtosis would be zero and three respectively (Brooks, 2002). However, in the above case, the returns have high kurtosis values of 10.77, 8.45 and 11.88 for the entire period of study, sub-period 1 and sub-period 2 respectively, implying that they are leptokurtic, which entails that most returns are centred around the mean. In addition, the LuSE returns are slightly positively skewed to the right as shown by the skewness values all greater than zero, this means that most returns are to the right of the mean. In addition, all returns for each period analysis are not normally distributed at any level of significance as shown by the Jarque-Bera test for normality. In addition the ARCH test for 10 lags shows that the residuals have a strong presence of conditional heteroscedasticity.

Table 5.2.B Summary of descriptive Statistics for monthly data

	Observations	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ARCH(10)
LuSE-ASI monthly returns: Entire period	97	1.437638	5.655485	0.132485	4.197311	6.077486[b] (0.04789)	1.330038 (0.2660)
Sub-period 1:01/2006-04/2008	27	4.096191	5.569278	0.210712	4.183165	1.774662 (0.41175)	0.481096 (0.6712)
Sub-period 2: 05/2008-02/2014	69	0.395937	5.421033	-0.35638	4.021002	4.457631 (0.10766)	3.48144[a] (0.0057)

p-value in the parenthesis

Table 5.2.B depicts the basic statistics for the monthly returns for the LuSE-ASI. The mean of 1.44% for the whole period of analysis, refers to the average monthly compounded return over the entire period of study, this entails that one would have earned an average compounded return of 1.44% per month they invested in the LuSE index over the period of analysis. In addition, sub period 1 has the highest average return of 4.1%, whilst sub period 2 has the lowest return of 0.4% per month. If the data were to be exactly normally distributed, the values of skewness and kurtosis would be zero and three respectively (Brooks, 2002). However, in the above case, the returns have high kurtosis values, implying that they are leptokurtic, implying that most returns

are centred around the mean. In addition, the LuSE returns are negatively skewed in sub-period 2, meaning that most returns are to the left of the mean, whilst the other periods of analysis have positively skewed returns. Given a level of significance of 5 percent, sub-period 1 and 2 have returns that are normally distributed, whilst the entire period of analysis has returns that are not normally distributed as shown by the Jarque-Bera test for normality. In addition the ARCH test for 10 lags shows that the residuals for sub period 2 may have a strong presence of conditional heteroscedasticity, whilst the other periods may not.

5.3. RUNS TEST RESULTS

The non-parametric runs test investigations whether successive stock movements are independent of one another as should be the case under EMH (Borges, 2010). This is done for the daily and monthly returns of the LuSE All Share Index. The runs test does not require normality of the distributions, for which the null and alternative hypothesis may be expressed as:

$H_{0:}$ the prices do not follow a pattern $H_{1:}$ the prices follow a pattern

The null hypothesis (H_0) is accepted if the value of Z lies in the region of -1.96 to +1.96 at 5 percent level of significance, otherwise, it is rejected if the Z value is outside that region. Table 5.3A and 5.3B below depict the daily and monthly results, all Z statistics lie within the region of acceptance for all periods, and as such the study fails to reject the null that stock price returns follow a random pattern.

Table 5.3.A: Daily LuSE-ASI returns: Runs Test Results

	Entire period	sub period 1	sub period 2
Average return	0.072004	0.233344	0.012369
Actual Number of runs [R]	970	243	731
Negative returns (N-)	1198	355	804
Positive returns (N+)	815	194	659
Total observations (n)	2013	549	1463
Expected number of runs E(R)	971.0646	251.8925	725.3144
Variance(R)	467.2243	114.4091	358.3496
Standard Deviation	21.61537	10.69622	18.93012
Z statistic	-0.04925	-0.83137	0.300346
p-value	0.48036	0.202802	0.618043

Table 5.3.A depicts the runs test results for daily returns. According to the Runs statistics, the null hypothesis cannot be rejected at 5 percent level of significance for all periods of analysis. Since the calculated Z values lies within the critical Z value range at 5 percent level of significance. Therefore, the study fails to reject the null that the LuSE index follows a random pattern, and is therefore weak form efficient according to the runs test.

Table 5.3.B: Monthly LuSE-ASI returns: Runs Test Results

	Entire period	sub period 1	sub period 2
Mean return	1.437638	4.096191	0.395937
Actual Number of runs [R]	44	13	34
Negative returns (N-)	49	16	35
Positive returns (N+)	48	11	34
Total observations (n)	97	27	69
Expected number of runs E(R)	49.49485	14.03704	35.49275
Variance(R)	23.99224	6.035665	16.98908
Standard Deviation	4.898188	2.456759	4.121781
Z statistic	-1.12181	-0.42212	-0.36216
p-value	0.130971	0.33647	0.358615

Table 5.3.B above, depicts the Z statistics of the LuSE-ASI for monthly stock price returns. According to the Runs statistics, the null cannot be rejected at 5 percent level of significance. Since the calculated Z values lies within the critical Z value range at 5 percent level of significance. Therefore, the study fails to reject the null hypothesis that the LuSE follows a random pattern, and therefore weak form efficient according to the runs test.

However, as noted by Handoker, Siddik and Azam (2011) the runs test is amongst the least restrictive methods for testing the random walk hypothesis and market efficiency. As such the study further seeks the use of more stringent tests such as the variance ratio tests.

5.4. PARAMETIC VARIANCE RATIO TESTS RESULTS

The parametric variance ratio tests of Lo and McKinley (1988) as well as that of Chow and Denning (1993) are utilized in order to determine whether the LuSE is weak form efficient under the assumption of homoscedastic $Z(q)$ as well as heteroskedastic $Z^{*}(q)$ exponential random walks.

5.4.1. DAILY VARIANCE RATIO TESTS RESULTS: LO AND MACKINLAY

The Lo and McKinley individual variance ratio results are depicted below. The results are depicted for intervals 2,4,6,8 and 16. As argued by Smith *et al* (2002) the random walk hypothesis requires that $VR(q) = 1$, for all q values.

Table 5.4.A Lo and Mackinlay Variance ratio estimates and test statistics of RWH for daily returns: whole period: 3/01/2006 ~ 17/02/2014

	Number of lags(q)			
	q=2	**q=4**	**q=8**	**q=16**
VR(q)	0.929667	0.926432	1.042135	1.274656
Z(q)	-3.1556[a]	-1.76431[c]	0.639089	2.799565[a]
	(0.0016)	(0.0777)	(0.5228)	(0.0051)
Z*(q)	-2.3773[b]	-1.19381	0.442860	2.088823[b]
	(0.0174)	(0.2326)	(0.6579)	(0.0367)

Z(q), refers to the test statistic assuming homoscedasticity. Whilst Z*(q) refers to the variance ratio statistic assuming the heteroscedasticity assumption. p-value in the parenthesis

The test statistics based on the individual variance ratio test of Lo and Mackinlay (1988) are reported in table 5.4.A. Given a significance level of 5 percent, the tests statistics show that only the lags at q = 4 and 8 are not significant either assuming homoscedasticity Z(q) or heteroscedasticity-consistent Z*(q), while the other lags are significant. Therefore, the study rejects the null hypothesis that the variance ratio is equal to one. Therefore, the random walk hypothesis may be rejected for the Lusaka Stock Exchange stock price series.

Table 5.4.B Lo and Mackinlay (1988) Variance ratio test for sub period 1 and 2: daily returns.

		Number of lags(q)			
Time period		**q=2**	**q=4**	**q=8**	**q=16**
Sub-period 1:	***VR(q)***	0.917095	0.738800	0.707442	0.743100
04/01/2006-	***Z(q)***	-1.94253[c]	-3.27134[a]	-2.31736[b]	-1.36751
11/03/2008		(0.0521)	(0.0011)	(0.0205)	(0.1715)
	Z*(q)	-1.39569	-2.37857[b]	-1.74503[c]	-1.07629
		(0.1628)	(0.0174)	(0.0810)	(0.2818)
Sub-period 2:	***VR(q)***	0.921130	0.962807	1.091679	1.316450
13/03/2008-	***Z(q)***	-3.0167[a]	-0.76042	1.185464	2.749834[a]
17/02/2014		(0.0026)	(0.4470)	(0.2358)	(0.0060)
	Z*(q)	-2.31755[b]	-0.4989	0.796411	2.016919[b]
		(0.0205)	(0.6179)	(0.4258)	(0.0437)

The test statistics based on the individual variance ratio test of Lo and Mackinlay for sub period 1 and 2 are reported in table 5.4.B. Given a significance level of 5 percent, all lags are insignificant except for the 4^{th} and 8^{th} assuming homoscedasticity Z(q). Whilst assuming heteroscedasticity-consistent Z*(q) the 4^{th} lag is significant, as such the study rejects the null that the variance ratio is equal to one for sub period 1. For sub period 2, Z(q) and Z*(q) for q =2, and 16 are all statistically significant, therefore the study rejects the null that the variance is equal to one. As such, the RWH may be rejected for the LuSE stock price series for sub period 2.

5.4.2. MONTHLY VARIANCE RATIO TESTS: LO AND MACKINLAY

Table 5.4.C Lo and Mackinlay Variance ratio estimates and test statistics of RWH for Monthly returns: whole period: 01/2006 ~ 02/2014

	Number of lags(q)			
	q=2	**q=4**	**q=8**	**q=16**
VR(q)	1.268313	1.725899	2.601014	3.398665
Z(q)	2.642581^{a}	3.821448^{a}	5.330611^{a}	5.367037^{a}
	(0.0082)	(0.0001)	(0.0000)	(0.0000)
Z*(q)	2.086183^{b}	3.145246^{a}	4.478293^{a}	4.549956^{a}
	(0.0370)	(0.0017)	(0.0000)	(0.0000)

Z(q), refers to the test statistic assuming homoscedasticity. Whilst Z*(q) refers to the variance ratio statistic assuming the heteroscedasticity assumption. p-value in the parenthesis

Table 5.4.C shows the test statistics based on the individual variance ratio test of Lo and Mackinlay (1988) for the entire period based on the monthly index. The variance ratio test statistics assuming homoscedasticity Z(q) are all statistically significant at all lags, thus the study rejects the null that the variance ratio is equal to one. In addition the variance ratio results assuming heteroscedasticity-consistent Z*(q) is only significant for the 1^{st} lag at 1% level of significance, whilst all other lags are significant. Therefore the study rejects the null hypothesis that the variance ratio is equal to one. Therefore, the random walk hypothesis may be rejected for the LuSE index series.

Table 5.4.D Lo and Mackinlay (1988) Variance ratio test for monthly returns: sub period 1 and 2

		Number of lag(q)			
Time period		q=2	q=4	q=8	q=16
Sub-period 1:	***VR(q)***	0.949812	0.721932	0.989893	1.901438
01/2006-04/2008	***Z(q)***	-0.26079	-0.77232	-0.01775	1.064135
		(0.7943)	(0.4399)	(0.9858)	(0.2873)
	Z*(q)	-0.37865	-0.97279	-0.02129	1.285120
		(0.7049)	(0.3307)	(0.9830)	(0.1988)
Sub-period 2:	***VR(q)***	1.252164	1.706216	1.972813	1.360117
05/2008-02/2014	***Z(q)***	2.094631[b]	3.135655[a]	2.731807[a]	0.679590
		(0.0362)	(0.0017)	(0.0063)	(0.4968)
	Z*(q)	1.517653	2.469704[b]	2.266998[b]	0.588437
		(0.1291)	(0.0135)	(0.0234)	(0.5562)

Z(q), refers to the test statistic assuming homoscedasticity. Whilst Z*(q) refers to the variance ratio statistic assuming the heteroscedasticity assumption. *p-value in the parenthesis*

Table 5.4.D shows the variance ratios and test statistic for sub period 1 and 2. For sub period 1, either assuming homoscedasticity Z(q) or heteroscedasticity-consistent Z*(q) , the results show that none of the test statistics at any *q* is significant, therefore the study fails to reject the null hypothesis that the variance ratio is equal to one. Thus, the study concludes that the LuSE is weak form efficient during sub period.

Whilst for sub period 2, the study rejects the null that the variance ratio is equal to one, since for Z(q) only the 16th lags is statistically insignificant. Whilst for Z*(q) the 2nd and 16th lags are significant, therefore the study rejects the null that the variance ratio is equal to one for sub period 2 index series, and therefore not random walk.

5.5. MULTIPLE VARIANCE RATIO RESULTS OF CHOW AND DENNING

The use of the multiple variance ratio tests which jointly test the null hypothesis of random walk helps detect whether you may have wrongly rejected the null hypothesis when it is in fact correct (Smith *et al*, 2002).

5.5.1. DAILY VARIANCE RATIO TESTS RESULTS: CHOW AND DENNING

Table 5.5.A Multiple Variance Ratio by Chow and Denning (1993) daily returns

time period		Z(q)	Z*(q)
LuSE-ASI daily: Entire period	Max|Z|	3.155603[a]	2.377303[b]
		(0.0064)	(0.0174)
Sub-period 1:04/01/2006-11/03/2008	Max|Z|	3.271336[a]	2.378574[c]
		(0.0043)	(0.0677)
Sub-period 2: 13/03/2008-17/02/2014	Max|Z|	3.016695[b]	2.317553[c]
		(0.0102)	(0.0794)

p-value in the parenthesis

The test statistics based on the multiple variance ratios for the different periods are depicted above. The Z(q) test statistics values for each period are significant given 5 percent level of significance. As such the study rejects the null hypothesis that the variance ratio is equal. Whilst the Z^*(q) test statistic values are insignificant at the 5 percent level of significance for all sub periods, as such the study fails to reject the null that the variance ratio is equal to one under the heteroscedasticity assumption, thus the stock price series returns are martingale. (however, if the level of significance was 10% it would have failed the test). Therefore the rejection of the null for Z(q) values may be as a results of heteroscedasticity in the residuals.

5.5.2. MONTHLY VARIANCE RATIO TEST RESULTS: CHOW AND DENNING (1993)

Table 5.5.B Multiple Variance Ratio by Chow and Denning (1993) monthly returns

time period		Z(q)	Z*(q)
LuSE-ASI monthly: Entire period	Max|Z|	5.367037[a]	4.549956[a]
		(0.0000)	(0.0000)
Sub-period 1:01/2006-04/2008	Max|Z|	1.064135	1.28512
		(0.7419)	(0.5878)
Sub-period 2: 05/2008-02/2014	Max|Z|	3.135655[a]	2.469704[c]
		(0.0068)	(0.0530)

p-value in the parenthesis

The results of the multiple variance ratio test statistics for monthly data are depicted above. The results for the entire period show the absolute $Max[Z]$ under the homoscedasticity Z(q) and heteroscedasticity-consistent Z*(q) assumptions are not statistically significant at any level of significance. Therefore, the null that the variance ratio is equal to one is rejected. As such the study rejects the null hypothesis that LuSE stock market returns are weak form efficient.

Whilst for sub period 1 returns, the study fails to reject the null that the variance ratio is equal to one assuming homoscedasticity Z(q) as well as heteroscedasticity-consistent Z*(q), as the $Max[Z]$ are all statistically insignificant. As such, the study can conclude that LuSE is weak form efficient during sub period one. These results are in support of the Lo and Mackinlay variance ratio test.

For sub period 2, under the homoscedasticity Z(q) assumption, the absolute $Max[Z]$ is statistically significant at all levels of significance, therefore the null that the variance ratio is equal to one is rejected. Whilst when considering the heteroscedasticity-consistent Z*(q) assumption, the absolute $Max[Z]$ is just statistically insignificant at 5% level of significance. Therefore, the study fails to reject the null that the variance ratio is equal to one.

5.6. NON PARAMETRIC VARIANCE RATIO TEST BY WRIGHT (2000)

The non-parametric Wright (2000) test which is an individual variance ratio is applied which has greater power against a wider range of alternative models, including autoregressive moving average and its fractionally integrated alternatives (Franch, McGreal, Opong and Webb, 2007). The tables below show the results of the test statistic of the ranks ($R_1$and R_2) and sign S_1 tests.

The results based on non-parametric tests are shown below, and tend to have better power properties than Z(q) and Z^*(q). In addition, the ranks and sign tests are robust for many forms of conditional heteroscedasticity. In addition, $R_1$and R_2 tend to be much stronger than S_1, and as such if $R_1$and R_2 reject the hypothesis, then S_1must reject the hypothesis as well (Frank *et al*, 2007). The non-parametric test is computed using permutation bootstrap, with 5000 replications, and a seed of 1000.

5.6.1. DAILY VARIANCE RATIO NON PARAMETRIC TEST RESULTS

Table 5.6.A. Non parametric test using ranks and signs for entire period: 03/01/2006~17/02/2014

	Number of lags (k)			
	k=2	k=4	k=8	k=16
$\boldsymbol{R_1}$	-1.26212	0.435971	3.729632[a]	6.707158[a]
	(0.2196)	(0.6722)	(0.0000)	(0.0000)
$\boldsymbol{R_2}$	-1.9467[c]	-0.24545	2.914091[a]	5.748419[a]
	(0.0504)	(0.8022)	(0.0022)	(0.0000)
$\boldsymbol{S_1}$	0.156019	1.393895	3.790025[a]	5.945903[a]
	(0.8564)	(0.1540)	(0.0002)	(0.0000)

Test statistic reported for each test. P-value in the parenthesis

Table 5.6.A, shows the results of the ranks and signs variance ratio test results for the entire period are depicted as shown above. The ranks based results show that $R_1$and R_2 are statistically insignificant for the first two lags, whilst the other lags are significant. In addition, the sign based test S_1 is only insignificant for the first two lags (k=2 and 4). Since all lags are supposed to be insignificant, the study therefore rejects the null of the random walk hypothesis. As such, the study can conclude that the LuSE is not weak form efficient, in addition the test indicates that the stock price series are positively serial correlated for longer lags.

5.6.2. RESULTS FOR THE DAILY NON PARAMETRIC RANKS AND SIGNS FOR SUB PERIOD 1 AND 2

Table 5.6.B. Non parametric ranks and signs for sub period 1 and 2

		Number of lag (k)			
Time period		**k=2**	**k=4**	**k=8**	**k=16**
Sub-period 1:	R_1	-0.9862	-1.16942	0.000563	1.039858
		(0.3202)	(0.2362)	(0.9996)	(0.3120)
04/01/2006-11/03/2008	R_2	-1.5099	-2.14082[b]	-1.03346	-0.00915
		(0.1332)	(0.0328)	(0.3106)	(0.9938)
	S_1	0.896258	1.596900	3.102046	4.721956
		(0.4544)	(0.3040)	(0.0692)	(0.0132)
Sub-period 2:	R_1	-1.64908	0.032358	2.669863[a]	4.738406[a]
		(0.1092)	(0.9724)	(0.0064)	(0.0000)
13/03/2008-17/02/2014	R_2	-2.18189[b]	-0.14776	2.413371[b]	4.389657[a]
		(0.0302)	(0.8834)	(0.0170)	(0.0000)
	S_1	-0.39217	0.656813	2.554299[b]	4.073079[a]
		(0.6868)	(0.5134)	(0.0130)	(0.0004)

Test statistic reported for each test. P-value in the parenthesis

The results of the non-parametric ranks and sign test for the different sub periods are depicted above in table 5.6.B. For sub periods 1, all ranks (R_1 and R_2) are statistically insignificant except for k=4, whilst for the signs test (S_1) is insignificant at all lags expect k=16 statistically significant for all lags, therefore the study rejects the null hypothesis of RWH based on the ranks and sign variance ratio test for sub period1.

Whilst for sub period 2 all ranks (R_1 and R_2) as well as the signs test (S_1) are statistically insignificant for the first two numbers of lags (k=2 and 4), whilst the other two lags are statically significant (k=8 and 16) Therefore, the null hypothesis of RWH is rejected based on the ranks and sign variance ratio test for sub period 2.

5.6.3. MONTHLY VARIANCE RATIO TEST RESULTS OF NON PARAMETRIC TESTS

Table 5.6.C. Monthly results for the Non parametric tests for the entire period

	Number of lags (k)			
	k=2	k=4	k=8	k=16
R_1	1.172279[c] (0.0870)	1.563628[a] (0.0014)	2.187781[a] (0.000)	2.287715[a] (0.0018)
R_2	2.182813[b] (0.0286)	3.252293[a] (0.0012)	4.195176[a] (0.0000)	3.190341[a] (0.0012)
S_1	2.132227[b] (0.0276)	3.581987[a] (0.0014)	4.273458[a] (0.0010)	2.272111[b] (0.0518)

Test statistic reported for each test. P-value in the parenthesis

Table 5.6.C, shows the results of the ranks and signs tests for the entire period for monthly data. The results are in agreement to those of Z(q) and $Z^{*}(q)$, although the rejection values are much stronger in this case. As such, the study rejects the null hypothesis that the series is random walk for all tests

5.6.4. MONTHLY NON PARAMETRIC RANKS AND SIGNS FOR SUB PERIOD 1 AND 2

Table.5.6.D. Non parametric test using ranks and signs for sub period 1 and sub period 2

		Number of lag (k)			
Time period		**k=2**	**k=4**	**k=8**	**k=16**
Sub-period 1:	R_1	-0.00159 (0.9994)	-1.12972 (0.3304)	-1.07939 (0.4084)	-0.88906 (0.7508)
04/01/2006-11/03/2008	R_2	-0.20146 (0.8586)	-1.20144 (0.2884)	-1.09599 (0.3974)	-0.88789 (0.7420)
	S_1	2.116951 (0.1570)	2.468854 (0.4170)	3.25300 (0.3322)	2.360973 (0.4394)
Sub-period 2:	R_1	0.817916 (0.4240)	2.157014[b] (0.0256)	1.904044[b] (0.0338)	-0.2028 (0.9098)
13/03/2008-17/02/2014	R_2	1.359465 (0.1714)	2.273173[b] (0.0134)	1.674730[c] (0.0736)	-0.37412 (0.8350)
	S_1	1.083473 (0.2982)	2.638307[a] (0.0046)	2.686058[a] (0.0030)	0.184611 (0.9194)

Test statistic reported for each test. P-value in the parenthesis

The results of the ranks and signs tests for the two sub periods are in table 5.6.D above. For sub period 1, all the ranks and sign are insignificant for all values of k, therefore, the study fails to reject the null hypothesis of RWH. Whilst for sub period 2, R_1 is only significant at K=2 and 4 at 1%, and for R_2 K=4 is statistically significant, whilst S_1 has two lags at k=4 and 8 that are statistically significant. As such, the null hypothesis of RWH for sub period 2 is rejected.

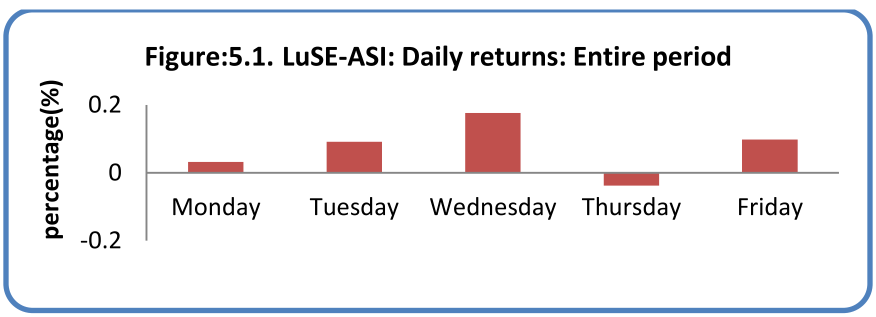
5.7. DAY OF THE WEEK EFFECT ANALYSIS

The tests for the day of the week effect are calculated using data from the LuSE-ASI from 3rd January 2006, to 17th February 2014.

5.7.1. RESULTS FOR ENTIRE PERIOD OF ANALYSIS

Table 5.7.A: Average daily returns: Entire period (03/01/2006~17/02/2014)

Weekday	Monday	Tuesday	Wednesday	Thursday	Friday
Average return	0.032081	0.091268	0.176053	-0.03808	0.097775
standard deviation	0.053776	0.052484	0.051589	0.051403	0.052418



The figure 5.1 above depicts the daily average compounded return and standard deviation of each day of the week. The average returns for each day are positive except on Thursday which has the lowest return of -0.038% per day. In addition, the highest average return is on Wednesday with a return of 0.176% per day. In addition, Monday is found to have the highest standard deviation of all the days. For Solnik and Bousquet (1990) argue with the hypothesis that Monday should have the highest volatility since shocks of market information from the non-trading days during the weekend tend to have a profound effect on Monday. This also seems to the case with the LuSE as Monday has the highest vitality at 0.054 per cent.

Table 5.7.B: Regression analysis: $Y_t = \alpha + \beta_1 Tue + \beta_2 Wed + \beta_3 Thur + \beta_4 Fri + \varepsilon_t$

α	β_1	β_2	β_3	β_5
0.032081	0.059187	0.143972	-0.07016	0.065694
(0.5509)	(0.431)	(0.0535)	(0.3457)	(0.3818)

p-value in the parenthesis

The table above shows the regression results of the returns of Monday relative to the other day of the week. Since the values are all statistically insignificant as indicated by the p-values of the t ratios, the study fails to reject the null hypothesis that the arithmetic daily returns on Monday are no different from the daily returns on the other weekdays. As such, the study can conclude that no day offers significantly higher or lower returns than the other.

5.7.2. SUB PERIOD 1 RESULTS

Table 5.7.C: Average Daily return for each weekday: Sub period 1: 04/01/2006~11/03/2008

Weekday	Monday	Tuesday	Wednesday	Thursday	Friday
Avg. return	0.02835	0.300629	0.523658	0.100462	0.199676
Standard Deviation	0.102829	0.100906	0.098649	0.098649	0.099533

Table 5.7.C above depicts the daily compounded average returns and standard deviation for each day of the week for sub period 1. It is shown that Wednesday has the highest return of 0.523658%, whilst Monday has the lowest return of 0.02835%. In addition, Monday has the highest standard deviation or volatility.

Table 5.7.D: Regression analysis: sub period1:$Y_t = \alpha + \beta_1 Tue + \beta_2 Wed + \beta_3 Thur + \beta_4 Fri + \varepsilon_t$

α	β_1	β_2	β_3	β_5
0.02835	0.272279	0.495308	0.072112	0.171326
(0.7829)	(0.0593)	(0.0005)	(0.613)	(0.2318)

p-value in the parenthesis

The table above shows the regression results of the returns of Monday relative to the other day of the week. Since β_2 is statistically significant relative to the other values. This is an indication of the day of the week effect. As such, the study rejects the null hypothesis that all days of the week have the same arithmetic return during sub period 1. Therefore, it may be argued that during sub period 1 it was most optimal to sell your stock on Wednesday as this particular day resulted in investors' acquiring the highest return. Or on the other hand it is advised not to buy stock on Wednesdays as equities tend to be most expensive on this day. This is similar to study by Basher and Sadorsky (2006) for which a Wednesday effect was identified for the Argentine stock market, although of all 21 emerging markets analysed it is the only one with a significantly positive return on a Wednesday.

5.7.3. SUB PERIOD 2 RESULTS

Table 5.7.E: Average Daily return for each weekday: Sub period 2: 13/03/2008~17/02/2014

	Monday	Tuesday	Wednesday	Thursday	Friday
mean return	0.033482	0.013834	0.045557	-0.08573	0.058771
std.dev	0.062607	0.060978	0.060059	0.059861	0.061188

The table above depicts the daily compounded average returns and standard deviation for sub period 2. All weekdays have positive returns expect Thursday with the lowest at -0.08573%, while Friday has the highest return per day at 0.059%.

Table 5.7.F: Regression analysis sub period 2: $Y_t = \alpha + \beta_1 Tue + \beta_2 Wed + \beta_3 Thur + \beta_4 Fri + \varepsilon_t$

$\boldsymbol{\alpha}$	$\boldsymbol{\beta_1}$	$\boldsymbol{\beta_2}$	$\boldsymbol{\beta_3}$	$\boldsymbol{\beta_5}$
0.033482	-0.01965	0.012075	-0.11921	0.02529
(0.5929)	(0.8221)	(0.8893)	(0.169)	(0.7727)

p-value in the parenthesis

The table above shows the regression results of the returns of Monday relative to the other days of the week. Since all the values are statistically insignificant as indicated by the p-values of the t ratios, the study fails to reject the null hypothesis that the arithmetic daily returns on Monday are no different from the daily returns on the other weekdays. As such, it may be concluded that no day offers significantly higher or lower returns than the other.

5.8. MONTH RELATED SEASONALITY RESULTS

The tests for the any monthly effects are calculated using the LuSE-ASI January 2006, to February 2014 with the use of monthly data. The study analyses 92 monthly returns. Caution should be considered for the monthly returns given the low number of counts given for each month.

5.8.1.MONTHLY RESULTS ANALYSIS: ENTIRE PERIOD

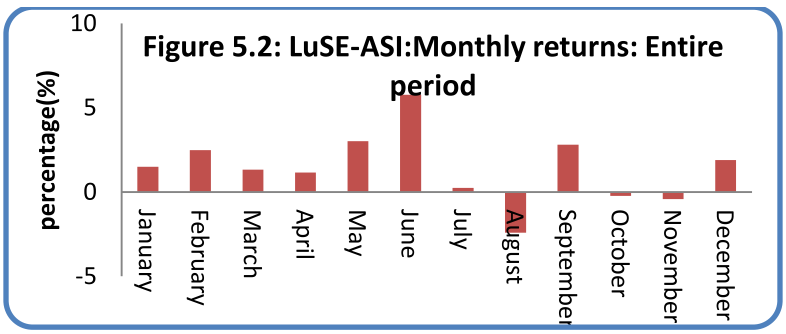


Table 5.8.A: Monthly average return: Entire period (01/2006~02/2014)

January	February	March	April	May	June	July	August	September	October	November	December
1.501133	2.473603	1.326502	1.16045	3.010081	5.759071	0.24394	-2.40545	2.809891	-0.23569	-0.4176	1.89623

Table 5.8.A, shows the average return for each month for the entire period of analysis. June has the highest return at 5.759071% and August has the lowest return at 2.40545%.

Table 5.8.B, below shows the regression analysis which indicates thatβ_1 i=1,2,,3,4,5,6,7,8,9,10,11) are not significant, therefore there is no monthly related effect in the analysis of data. This therefore entails that the monthly returns in January are not different from the monthly returns in other months.

Table 5.8.B: Regression analysis: $Y_i = \alpha + \beta_1 Feb + \beta_2 Mar + \beta_3 Apr +, \dots, + \beta_{11} Dec + \varepsilon_t$

α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	β_{10}	β_{11}
1.50113	0.972471	-0.175	-0.341	1.508948	4.257939	-1.2572	-3.9066	1.30876	-1.7368	-1.9187	0.395097
(0.4529)	(0.7231)	(0.9507)	(0.904)	(0.5934)	(0.1341)	(0.6563)	(0.1689)	(0.6432)	(0.5389)	(0.4974)	(0.8887)

p-value in the parenthesis

5.8.2. SUB-PERIOD 1 RESULTS: MONTHLY

Table.5.8.C: Monthly average return: Sub period 1

January	February	March	April	May	June	July	August	September	October	November	December
12.7841	3.20796	1.223331	0.377709	3.563741	12.70554	1.188172	2.175027	4.521627	4.934449	4.286593	1.925825

Table 5.8.C above depicts the average monthly returns for sub period 1. The results show that January has the highest return at 12.7841% per month, whilst April has the lowest monthly average return at 0.37709%. As such this is consistent with seasonality studies and the January effect, which argues that returns tend to be the highest in January relative to other months of the year.

Table 5.8.D below shows the regression analysis results. Given a level of significance of 5% , the results show that α, β_2, β_3 representing, January, March and April respectively are statistically significant, as such the arithmetic average returns are not statistically identical. In addition, January has the highest return relative to the other months.

Table.5.8.D: Regression analysis sub period 1: $Y_i = \alpha + \beta_1 Feb + \beta_2 Mar + \beta_3 Apr +, \dots, + \beta_{11} Dec + \varepsilon_t$

α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	β_{10}	β_{11}
12.7841	-9.57615	-11.5608	-12.4064	-9.22036	-0.07857	-11.5959	-10.6091	-8.26248	-7.84966	-8.49751	-10.8583
(0.0033)	(0.061)	(0.0273)	(0.0192)	(0.0953)	(0.9881)	(0.0408)	(0.0585)	(0.1316)	(0.1505)	(0.1217)	(0.0534)

p-value in the parenthesis

5.8.3. SUB PERIOD 2 RESULTS: MONTHLY

Table.5.8.E: Monthly average return: Sub period 2

January	February	March	April	May	June	July	August	September	October	November	December
-2.25986	2.106425	1.388404	1.630095	3.083811	3.443583	-0.0708	-3.93228	2.239312	-1.95907	-1.98567	1.886365

Table 5.8.E above depicts the average monthly returns for sub period 2 returns. The results show that June has the highest return at 3.44358% per month, whilst August has the lowest monthly average return at -3.93228%. The results show quite a turnaround in the fortunes of the LuSE relative to the sub period 1 returns were significantly higher than those of sub period 2 which may be as a result of the slowdown in general economic activity worldwide.

Table 5.8.F, below shows the regression analysis for sub period 2 returns which indicates that β_1(i=1,2,,3,4,5,6,7,8,9,10,11) are not significant, therefore there is no monthly effect appears in the analysis of data. Therefore this entail that statically all returns are equally likely to occur.

Table.5.8.F: Regression analysis sub period 2: $Y_i = \alpha + \beta_1 Feb + \beta_2 Mar + \beta_3 Apr +, \ldots, +\beta_{11} Dec + \varepsilon_t$

α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	β_{10}	β_{11}
-2.25986	4.366283	3.648262	3.889953	5.343669	5.703441	2.189054	-1.67242	4.49917	0.300793	0.274189	4.146222
(0.3034)	(0.1614)	(0.2631)	(0.2331)	(0.1033)	(0.069)	(0.4798)	(0.5889)	(0.1492)	(0.9225)	(0.9293)	(0.1832)

p-value in the parenthesis

5.9. DISCUSSION OF RESULTS

5.9.1. RUNS TEST

The results of the runs test indicate that the LuSE stock price series formations are random for all periods of analysis, either for daily as well as monthly data. As such the study does not reject the null that LuSE returns are random walk. However, as noted by Handoker, Siddik and Azam (2011) the runs test is amongst the least restrictive methods for testing the random walk hypothesis and market efficiency. As such the study further seeks the use of more stringent tests such as the variance ratio tests.

5.9.2 LO AND MACKINLAY

The results of the Lo and MacKinlay variance ratio tests for the daily stock price series reject the null hypothesis that the LuSE is weak form efficient either under the Z(q) or $Z^*(q)$ assumption for all periods of analysis. In addition, the variance is found to be greater than one for longer periods of q for sub period 2 as well as the entire period of analysis which is an indication of positive serial correlation, whilst for sub period 1 the variance is found to be less than one for longer periods of q, which is an indication of negative serial correlation.

Whilst for the monthly stock prices series, sub period 1 series do not reject the null that the LuSE is weak form efficient, whilst the entire period of analysis, and sub period 2 stock price series are found not be weak form efficient with variance ratios greater than one.

5.9.3. CHOW AND DENNING

The results of the daily Chow and Denning test under Z(q) for all periods analysed reject the null hypothesis that the variance ratio is equal to one, and therefore not random walk. For $Z^*(q)$ the null hypothesis is not rejected for sub period 1 and 2, however, it is rejected for the entire period of analysis, thus the rejection of the null under the Z(q) assumption maybe as a result of heteroscedasticty for sub period 1 and 2.

Analysis of the monthly stock price series, shows that sub period 1 is the only period that does not reject the null hypothesis under the Z(q) assumption. Whilst for the $Z^*(q)$ assumption, sub period 1 is found to be weak form efficient, whilst sub period 2 just about passes the 5 percent significance level. Although the entire period of analysis is found not to be weak form efficient.

5.9.4. NON PARAMETRIC WRIGHTS TEST

The results of non-parametric ranks and sign variance ratio test find the only period that does not reject the null hypothesis of weak form efficiency is the monthly stock price series for sub period 1, whilst all other periods of analysis reject the null hypothesis that the LuSE is weak form efficient.

5.9.5. SUMMARY OF VARIANCE TESTS

The results of the variance ratio tests show that the LuSE is largely inefficient, the only test period that consistently does not reject the null hypothesis of random walk, is that of the monthly stock price series of sub period1. In addition, the test for weak form efficiency has a tendency of not being rejected under the martingale tests, for instance, under the Chow and Denning test, $Z^*(q)$ is not rejected for any period of analysis for the daily stock series, whilst for the monthly series, the two sub periods (1 and 2) do not reject the null, whilst the entire period of analysis rejects the null that the variance ratio is equal to one. Otherwise, the results find the LuSE not to be random walk and thus weak form efficient. Since the study deals with daily as well as monthly data, although in both cases the study rejects the null hypothesis of random walk, the daily data more strongly rejects the null than the monthly data. Overall the market has variance ratio higher than one for longer q lags, which is an indication of positive serial correlation. As such the LuSE exhibits mean reversion, but with some unpredictable in the stock price series.

These findings are similar to other emerging markets for a study by Hoque, Kim and Pyun (2006) who analysed eight emerging markets in Asia, and found in particular the two markets of Taiwan and Korea to exhibit mean- reverting, but largely unpredictable patterns in the stock price series, and argue that the markets may be exploited by astute investors.

5.10. REASONS FOR WEAK FORM EFFICIENCY

Liquidity has been given as a plausible reason for weak form efficiency. Markets with high levels of turnover relative to market capitalisation have a more active price formation process than markets with lower turnovers. This is due to the reason that markets with lower turnovers, tend to have only a few number of stock trading from one period to the next. This is shown in a study by Smith (2009) for Eastern European stock indexes, for which those with lower turnover such as, Greece, Hungry, Poland and Portugal where not weak form efficient, whilst Turkey which had the highest turnover relative to the others was the only weak form efficient market. As such times of reduced liquidity seem to be associated with a rejection of the RWH, whilst times when liquidity is high seem to be associated with returns that are in conjunction with the RWH, as such times of reduced liquidity may provide opportunities to traders to use technical analysis tools in order to earn greater returns than those of the market given that transaction costs are minimal.

As such, not only is the LuSE, thinly traded, but also a number of firms listed on the bourse have a minute number of shares offered to the public, which escalates the situation.

In addition, a study by Smith *et al* (2002) who analyses seven African stock markets, finds the Johannesburg Stock Exchange (JSE) of South Africa to be the only which is weak form efficient. However, despite the JSE not having the highest turnover of the group at 18.7% which is relatively low for international standards. It is argued that the 'institutional maturity' of the exchange is a factor that singles it out from the rest. As such the more mature the financial sector the more closely the market resembles a random walk. As such when financial markets are sophisticated, it facilitates an efficient flow of information to market participant's resulting in a more efficient market.

In addition, evidence by other studies has found no correlation between the size of the market, and whether the market may be deemed efficient or not (Smith and Ryoo, 2003). As such the relative small size of the LuSE may not be deemed as a necessary cause for it not being weak form efficient.

5.10.1. SUMMARY OF THE DAY OF THE WEEK EFFECT

In terms of the day of the week analysis the study finds that there is no day of the week effect present on the LuSE, this is to say that no day tends to have significantly higher or lower returns relative to other days. Although there is a presence of the day effect is only present in sub period 1, with Wednesday having significant greater returns than other weekdays, which is similar to study by Basher and Sadorsky (2006) for which a Wednesday effect was identified for the Argentine stock market, although of 21 emerging markets analysed it is the only one with a significantly positive return on a Wednesday. However, the day of the week effect disappears in sub period 2, and is absent for the entire period of analysis. As such the study concludes that the arithmetic daily returns on Monday are no different from the daily returns on the other weekdays.

5.10.2. SUMMARY OF THE MONTHLY RELATED SEASONALITY

The results of the study find the presence of the January effect during sub period 1, that is, returns in January are significantly higher than other months although this effect disappears in sub period 2, and is not present for the entire period of analysis. As such, these results are indication of the continuing efficiency of the LuSE as these market anomalies are disappearing with time. As such, the study concludes that the monthly returns in January are not different from the arithmetic monthly returns in other months. Although the results of the monthly related effects should be treated with a little more caution since the data sample was relatively small.

CHAPTER 6: CONCLUSION AND RECOMMENDATIONS

6.1. CONCLUSION

The study analyses the random walk hypothesis as well as seasonality effects of the Zambian market for the period 3rd January, 2006 to 17th February, 2014, for which daily as well as monthly stock price series of the LuSE All Share Index are used for analysis. The results tend to be generally mixed. The Runs Test as well as the Variance Ratio Tests is used to determine whether the Lusaka Stock Exchange is weak form efficient. The variance ratio tests when incorporated into the study conflict the results of the Runs test and thus, making it difficult to reach an outright conclusive decision. However, the comprehensiveness of the variance ratio which are the norm today for testing the RWH by both researchers and practitioners leads to the decision that the LuSE is not weak form efficient according to the random walk hypothesis, although with some caution. The study finds through the use of the Runs Test that stock price movements follow a random pattern, both for daily returns as well as monthly returns. However, the study finds that the LuSE-ASI is not weak form efficient through the use of parametric and non-parametric variance tests, for which the variance ratios tend to be mean averting, that this, they are significantly higher than unity for longer horizons of q. It may therefore be argued that investors may be able to take advantage of this by predicting stock price movements, but since the study passes the Runs test the investors may not be able to always systematically predict stock price movements as the movements have component of randomness in them. Furthermore, in terms of the day of the week effect as well as monthly related effects the study comes to the conclusion that there is no daily or monthly related effects worth exploiting as daily and monthly returns are not significantly different from each other. In terms of trading strategies the studies recommends the use of Random walk strategies, and taking a more long term look at stocks rather than constantly trying to outsmart the market through the use of past price information, more so for investors with minimal knowhow of the LuSE or those who are not astute traders. However, more astute investors may attempt to predict market returns, more so for those with operational experience of the LuSE.

6.2. RECOMMENDATIONS

LuSE

In order to enhance the efficiency of the Zambian market, the LuSE and the SEC should set up and have more dissemination activities through workshops and help desks in order to better sensitize the general public about the benefit of stock markets and holding stocks in firms, in order for the general public to have greater confidence in the operations of the LuSE as well as greater awareness of the operations of the exchange. This will lead to increased activity in the operations of the exchange and will lead to greater local participation resulting in more firms being listed on the exchange and increased trading activity of the exchange.

INVESTORS

In terms of strategies for the investors, the study finds that the LuSE is not weak form efficient through the use of variance ratio tests, as such this provides an opportunity to more astute investors to earn returns greater than those of the market through the use of trading strategies that incorporate past price information such as technical analysis given that transaction cost are minimal. However, due to the mixed nature of the results of the study those who may not be so familiar with the internal dealings of the LuSE and not that competent with the use of technical trading strategies may be better of adopting random walk strategies in order to maximise their stock returns.

6.3. FURTHER RESEARCH SUGGESTIONS

An analysis of the random walk hypothesis may be done in U.S Dollar equivalent returns of the LuSE, in order to determine whether the market is efficient from the perspective of an international investor, as studies have shown that the market tend to be more efficient from the perspective of the international investor while they tend not to be weak form efficient from the perspective of the local investor, probably due to the fact that the local investor has more technical know-how of the internal dealings of the market, and may thus be able to take advantage of this, for which the international investor does not have this advantage.

In addition, an analysis of the LuSE may be undertaken of all stock listed on the exchange rather than the index, as this will result in a more fruitful analysis.

Furthermore, a study may be undertaken to see whether technical trading strategies may be able to accurately predict stock prices movements, and therefore earn investors excess returns in the market.

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