ANALYSIS OF CALENDAR EFFECTS AND MARKET ANOMALIES ON THE JOHANNESBURG STOCK EXCHANGE

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ANALYSIS OF CALENDAR EFFECTS AND MARKET ANOMALIES ON THE JOHANNESBURG STOCK EXCHANGE

By

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DECLARATION

I, ACHIAPO JESSICA LISETTE ATSIN (213221837), hereby declare that the dissertation for MAGISTER COMMERCII ECONOMICS is my own work and that it has not previously been submitted to another university or for another qualification.

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ABSTRACT

This study sought to empirically investigate the existence of calendar effects and market anomalies on the JSE using monthly and daily closing prices of the ALSI, Top 40, Mid Cap and Small Cap index; as well as, daily closing prices on the Value, Growth and Dividend Plus index during the sample period 2002 – 2013. The anomalies analysed are the January effect, the weekend effect, the size effect, the value effect, and the dividend yield effect. The empirical analysis uses a number of MSAR with a different number of regimes and lag orders. The results from the investigation of the January effect show the non-existence of the January effect and the value effect on the JSE during the periods 2002 – 2013 and 2004 – 2013, respectively. However, the weekend effect was found significant in the Mid Cap and the Small Cap index, and the size effect was also found significant during the same period 2002 - 2013. Finally the results from a Granger causality test concluded that there is a relationship between the returns on the Dividend Plus index and the ALSI, effectively proving the existence of the dividend yield effect on the JSE between 2006 and 2013. Additionally, the anomalies found imply the opportunity for investors to make returns above buy-and-hold.

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LIST OF ACRONYMS

ACF	Autocorrelation Function Test
AIC	Akaike Information Criterion
ALSI	All Share Index
AltX	Alternative Exchange
AMEX	American Exchange
BDG	Broadcasting Data Group
CAPM	Capital Asset Pricing Model
CRSP	Centre for Research in Security Prices
CSD	Central Securities Depository
DCM	Development Capital Market
DFA	Dimensional Fund Advisors
Div/P	Dividend-Price Ratio
DJIA	Dow Jones Industrial Average
FIRSTB	First Bank
FMCA	Financial Markets Control Act
FSB	Financial Services Board
FTSE	Financial Times Stock Exchange
GARCH	Generalised Autoregressive Conditional Heteroskedasticity
GLS	Generalised Least Squares
HML	High Minus Low
ICB	Industry Classification Benchmark
IMF	International Monetary Fund
IPO	Initial Public Offering
JET	JSE Equities Trading

JSE	Johannesburg Stock Exchange
LM	Lagrange Multiplier
LSE	London Stock Exchange
MRS	Markov Regime-switching model
MSAR	Markov Switching Autoregression
NASDAQ	National Association of Securities Dealers
NSINDEX	Nigeria Stock Index
NYSE	New York Stock Exchange
OLS	Ordinary Least Squares
P/E	Price-Earnings Ratio
SAFEX	South African Futures Exchange
SARB	South African Reserve Bank
SECA	Stock Exchanges Control Act
SENS	Stock Exchange News Service
SET	Stock Exchange of Thailand
SETS	Stock Exchange Trading System
SIC	Schwartz Information Criterion
SMB	Small Minus Big
STRATE	Share Transaction Totally Electronic
UBA	United Bank for Africa
UNIONB	Union Bank
USA	United States of America
VAR	Vector Autoregression
VCM	Venture Capital Market
VWAP	Volume Weighted Average Price

WFE	World Federation of Exchanges
Yield X	Exchange for Interest Rate and Currency Instruments

CHAPTER ONE

INTRODUCTION

1.1 Background and Problem Statement

The efficient market hypothesis is based on the work published by Fama in 1970 that suggests that the price of financial assets already reveals all available information and current knowledge on them (Bodie, Kane & Marcus, 2011). In other words, the price of assets adjusts automatically following new information thus asset price movements are not predictable. However, other theories backed by empirical analysis advocate that certain days, months or times of the year show abnormal price and risk-adjusted returns changes. Because these “seasonal (or calendar) effects” seem to contradict the efficient market hypothesis, they are called efficient market anomalies (Bodie et al., 2011). According to Brooks (2008), in financial time series data, if one of these seasonalities is present but not accounted for by the model-building process, the model produced is likely to be misspecified. The most common of the theories falling under the calendar effects are the day-of-the-week effect, the week-end effect, the January effect, the month-of-the-year effect, the Holiday effect and the end-of-the-tax-year effect. Although there are arguments about how realistic these seasonalities are, there is extensive evidence that makes their existence on a number of international markets indubitable.

The Johannesburg Stock Exchange (JSE) is a securities exchange. With an estimated 397 listed companies, 871 listed securities and a market capitalisation of US$ 895,545 million in February 2013, it constitutes the largest of the 29 stock exchanges found in Africa and was ranked 19th in terms of market capitalisation on the World Federation of Exchanges (WFE) ranking as at 31 January 2013 (JSE, 2014). Because the JSE channels funds into the economy and provides investors with returns on their investments in the form of dividends, it represents the market of choice for domestic and foreign investors looking to gain exposure to leading capital markets in South Africa and the broader African continent.

The JSE, as a platform connecting buyers and sellers in four different markets, is also expected to be affected by the no-free-lunch proposition applied to financial markets. That is, according to the proponents of the efficient market hypothesis, in an environment as competitive as the South African securities market, investors should not expect to find bargains and the market should be efficient. Similarly, there should be no predictability in terms of stock returns. It could be tempting to affirm that the strategies designed to take advantage of mispriced securities in order to make profits are useless. However, the existence of seasonalities in other international markets prevents one from making that assumption and provides a basis for further studies.

The research questions that emerge following the preceding discussions are as follows: are the effects identified in other international markets, namely, the Weekend effect, the January effect, the size effect, the dividend yield, and the value effect also present in the South African security market? Is the January effect related to the size effect? Do the seasonal patterns found in the South African market yield returns above buy and hold?

1.2 Objectives of the study

The objective of this study is to provide an empirical analysis of the calendar effects on the South African financial market.

However, the specific objectives are to:

(1) Investigate the existence of calendar effects, namely, the weekend effect and the turn-of-the-year effect, and other market anomalies such as the value effect, the size effect and the dividend yield effect in the South African stock market.

(2) Examine the relationship between the size effect and the turn-of-the-year effect.

(3) Determine if the seasonal patterns and market anomalies uncovered yield returns over and above buy-and-hold.

1.3 Relevance

The prospect for abnormal profits in the financial market has led practitioners to direct their interest to market anomalies. Therefore, investigating the existence of calendar effects and market anomalies in the South African securities market could help provide valuable information to investment analysts, and investors. It will also help in understanding market efficiency on the JSE. Evidence of the existence of calendar effects as well as market anomalies on the stock market contradicts the efficient market hypothesis. Although there are extensive studies involving international markets, the calendar effects in the South African financial market are yet to be widely analysed. More specifically, the existence of the weekend effect, the value effect, the size effect and the dividend yield effect has not yet been investigated in the available literature. This study therefore aims at contributing to the already available literature by focusing on the South African market. Moreover, although the existing literature commonly makes use of the GARCH and the OLS models, this study makes use of the regime switching model which is an equally appropriate econometric tool, but has not been used in the past.

1.4 Structure

The rest of the dissertation is organized as follows. Chapter two describes the microstructure of the JSE. Chapter three provides a review of the theories as well as the empirical studies previously conducted on the subject. In Chapter three, the choice of the methodology is justified by reviewing the different tools used in the existing literature. Chapter four discusses the methodology that will be used in the analysis as well as the econometric model proposed for the study. The chapter also contains a detailed description of the data. Chapter five is an empirical discussion of the different calendar effects and market anomalies considered and Chapter six provides a conclusion to the study and recommendations for future research.

CHAPTER TWO

OVERVIEW OF THE JOHANNESBURG STOCK EXCHANGE

2.1 Introduction

For its indication of investors' expectations of future economic conditions, the stock (or equity) market is generally considered as a leading indicator of economic activity. In conducting an analysis of a country's equity market, it is necessary to understand the background of the market in terms of the financial system in which it operates. As a middle income emerging country, South Africa has an economy marked by important natural resources, a refined industrial base as well as contemporary telecommunications and transport infrastructure. The country has a very developed legal sector and a sophisticated financial sector which, it is often claimed, compares favourably to the financial systems of more developed economies (Skerrit, 2009). Evidence supporting this claim is an acknowledgment by the IMF (2007) declaring that the South African financial system is generally sound and well regulated. Furthermore, with the strong foundations laid by South Africa's well-developed legal and institutional framework, the range and depth of its financial infrastructure and financial markets, and the soundness of its banking system, the country has been able to build a stock market that is by far the largest of Africa's 22 stock exchanges and is currently ranked among the 20 largest in the world (JSE, 2014). The following sections provide a broad overview of the South African equity market, describing the market's microstructure and highlighting its unique characteristics. The last section of the chapter conducts a superficial investigation of the existence of calendar effects on the JSE.

2.2 History of the Johannesburg Stock Exchange (JSE)

Fourteen months after the proclamation of the Witwatersrand goldfields, on the 8th November 1887, Benjamin Minors Woolman, a London businessman, established the Johannesburg Stock Exchange. The bourse was founded to enable the new mines and their financiers to raise capital for the development of the mining industry and the subsequent formation of investment companies (Samkange, 2010). With the expansion of the South African economy, an increasing number of industrial companies joined the mining companies that were initially listed on the JSE. Although most of the companies currently listed on the JSE are non-mining companies, it is argued that the exchange still reflects the riches of the gold mining industry, as was the case in the late 1800s, since the current top ten companies (in terms of market capitalisation) are predominantly mining companies (Samkange, 2010). In fact, the number of listed companies grew from only 151 mining, financial and industrial companies in 1932 to 397 companies in 2013, eight decades later. The rapid growth of the JSE is also reflected in the need to relocate to bigger buildings six times in 90 years (Moolman & Du Toit, 2005).

In 1963, following the 1947 legislation covering financial markets, the JSE joined the World Federation of Exchanges (WFE) which represents at least 97 percent of the world stock market capitalisation. By being affiliated to such a federation, the JSE embraces an international network of trust and cooperation between nations, and has access to a forum dominated by the sharing of ideas and knowledge (Samkange, 2010). The JSE was also affected by the mushrooming of listed companies worldwide during the 1980s, leading to the creation of two new categories of stocks, namely, the Development Capital Market (DCM) and the Venture Capital Market (VCM). While the DCM caters for small companies and has fewer requirements in terms of profits and company size, the VCM lists companies undertaking greenfield ventures, provided that they meet certain requirements (Moolman & Du Toit, 2005). In line with mature markets such as those of the United States of America (USA) and London, the JSE was deregulated in 1995, through a restructuring program. This initiative effectively eliminated the restriction of membership open only to natural persons of South African citizenship. It, therefore, increased liquidity and trade volume, by opening the market to all, including legal persona. Since then, foreign investors have been net buyers in excess of R9.3 billion, compared to only R0.185 billion in 1994 (Moolman & Du Toit, 2005). This shows that foreign investment plays a more substantial role on the JSE, accounting for more than 20 percent of its market capitalisation, and sometimes for more than half of its daily trading (Moolman & Du Toit, 2005). The bourse followed the international trend and ended floor trading in June 1996, upgrading to electronic trading on the JET (JSE Equities Trading) System. It demutualised and listed on its own exchange in 2005 (JSE, 2014). An alternative exchange called AltX was launched in 2003 for small and medium sized listings that do not necessarily meet the requirements of the JSE main board. The DCM and the VCM are expected to be incorporated into the AltX in the near future. The launch of the AltX was followed by the launch of the YieldX, an exchange for interest rate and currency instruments (JSE, 2014). In 2001, the South African Futures Exchange (SAFEX) was acquired by the JSE, followed by the Bond Exchange of South Africa, acquired in 2009 (JSE, 2014).

The JSE currently offers five financial markets: Equities, Bonds, Financial, Commodities and Interest rate derivatives. As a result of a partnership between the JSE and the FTSE Group, the JSE aligned its equities trading model with that of Europe and reclassified its instruments in line with the FTSE Global Classification system. The exchange index series is now called the FTSE/JSE Africa Index Series and its two benchmark indices are the FTSE/JSE All Share Index and the FTSE/JSE Top 40 Index. The FTSE/JSE All Share Index covers 99 percent of market capitalisation, while the FTSE/JSE Top 40 Index tracks the top listings in a representative spread of sectors (JSE, 2014).

2.3 Characteristics of the JSE

The South African securities exchange is considered large by world standards. It was the fourth largest emerging market at the end of 2000 and it accounts for 80 percent of the total African stock market capitalisation (Jefferis & Smith, 2004). Table 2.1 represents a summary of the JSE's ranking between 2009 and 2014. During that period, the exchange juggled between the 22nd and the 21st place in terms of market turnover, and the 19th and the 20th place in terms of market capitalisation, ending up in the 18th position in May 2014.

Table 2.1 Ranking in the world league at year end, 2009 – 2014

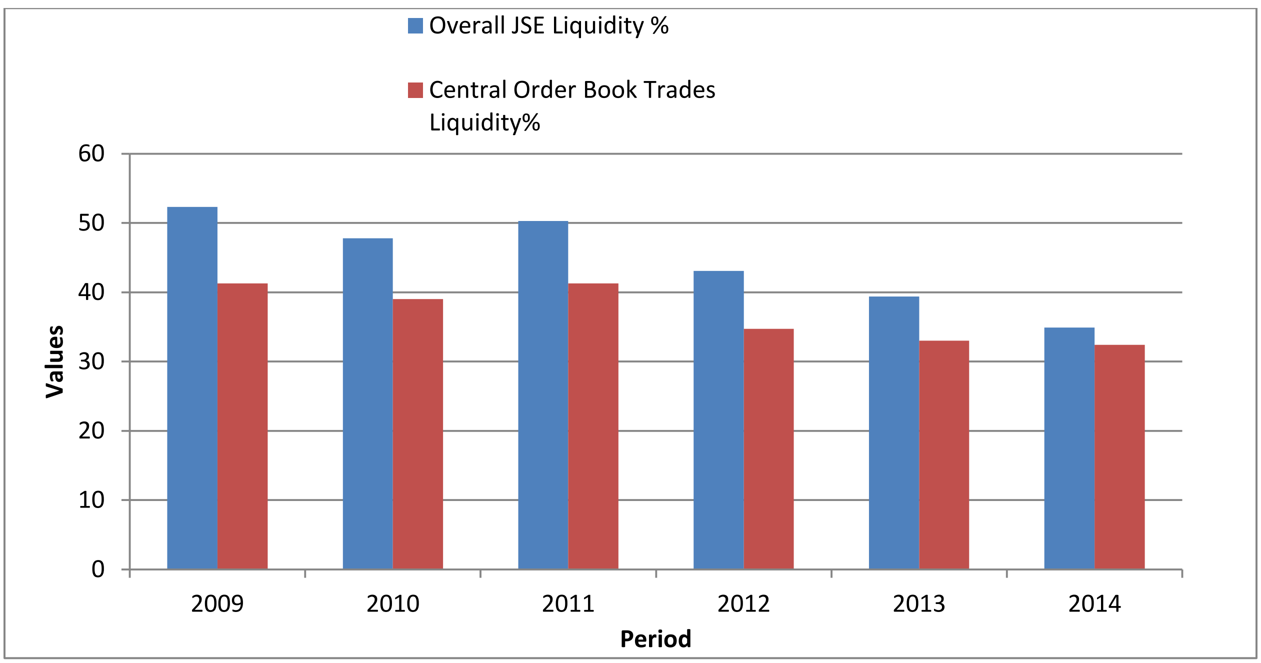
	2009	*2010*	*2011*	*2012*	*2013*	*2014**
Market Capitalisation (US$ million)	19	20	20	19	19	18
Market Turnover (US$ million)	21	21	21	22	22	21
Year to Date Liquidity %	33	25	27	27	26	30
Monthly Liquidity %	---	30	24	30	30	32

Note: The liquidity figure has been adjusted for Off Order Book Principal Trades
*Ranking as at 30 May 2014
Source: JSE (2014)

From the exchange's own description, the JSE is the "engine room" of the South African economy (City of Johannesburg, 2014). It provides an orderly platform for trading securities, as well as an effective price determination facility and price risk management mechanism. To facilitate the raising of primary capital, which is its primary function, the JSE re-channels cash resources into productive economic activity, and builds the economy while enhancing job opportunities and wealth creation. According to the City of Johannesburg (2014), the Securities Exchange is privately owned and funded. Furthermore, it is governed by a Board of Directors and its activities are licensed and regulated by two Acts of Parliament. More specifically, the equities markets are governed by the Stock Exchanges' Control Act, 1 of 1985 (SECA), while the derivatives markets are regulated by the Financial Markets Control Act, 55 of 1989 (FMCA).

Because of its characteristic as an emerging market, the JSE features some barriers to investment such as the legal barriers, indirect barriers as well as some risks specific to an emerging market, namely, liquidity, political, economic policy and currency risk (Samkange, 2010).

Figure 2.1 Annualised JSE liquidity, 2009 – 2014



Source: JSE (2014)

The JSE is relatively illiquid with an overall liquidity percentage of 34.9 percent at the end of June 2014 (See Figure 2.1). Moreover, the share ownership is largely dominated by a small number of large conglomerate companies that originally were mining houses. This situation is due to the existence of exchange controls on capital flows, effectively bottling up capital inside the country by restricting outward flows of funds by both companies and institutional investors. Although the situation has improved considerably, increasing from 5 percent to 50 percent in 15 years, the JSE still remains quite illiquid given that, in 2005, the liquidity of the Australian Securities Exchange and the Tokyo Stock Exchange were 83 percent and 92 percent respectively (Samkange, 2010).

Table 2.2 below summarises the number of JSE listings between 2009 and 2014. The overall JSE listing numbers show a considerable decline in the number of companies listed on the JSE with 81 companies delisting between 2009 and 2013, compared to only 53 new listings for the same period (See Table 2.2).

Table 2.2 Number of companies/securities listed on the JSE, 2009 – 2014

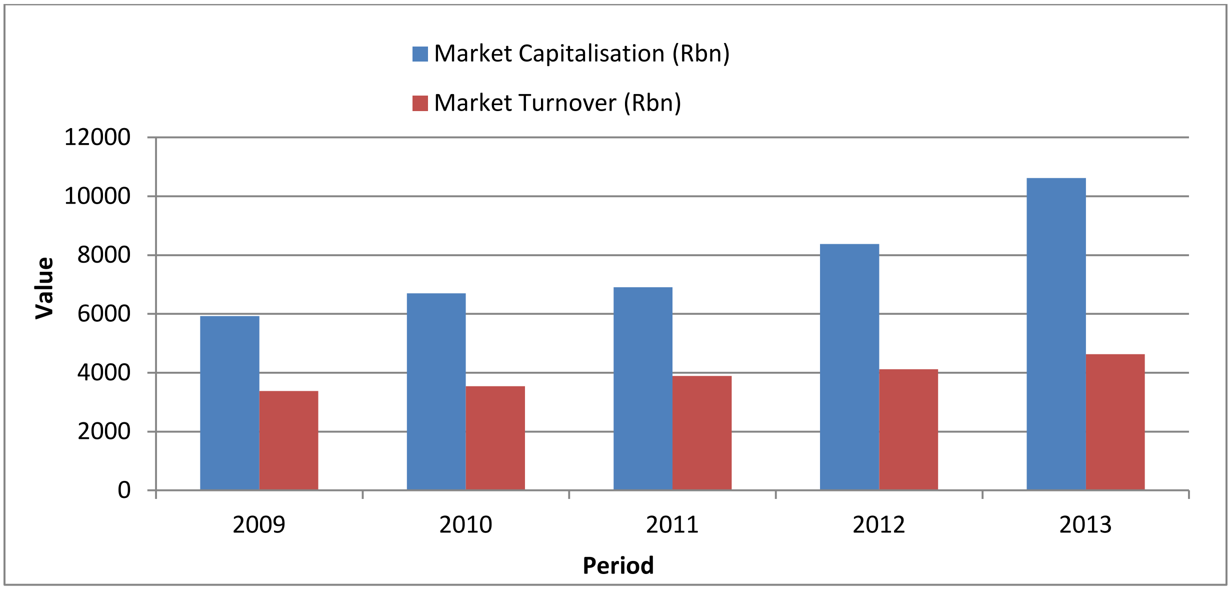
Overall JSE	*2009*	*2010*	*2011*	*2012*	*2013*	*2014**
New Listings	10	14	16	12	13	4
Delistings	25	17	17	18	26	2
Foreign Listings	47	47	51	52	56	58
Domestic Listings	363	360	355	348	333	329
Companies Listed	**410**	**407**	**406**	**400**	**389**	**387**
No of Securities Listed	**966**	**839**	**833**	**872**	**881**	**889**

Source: JSE (2014)

Samkange (2010) argues that the low levels of liquidity may be cited as one of the reasons for the fall in the number of listings on the exchange. In fact, the low levels of liquidity prevent investors from trading their shares and make them less willing to list on the JSE.

Figure 2.2 below depicts the exchange's market capitalisation and market turnover between 2009 and 2013.

Figure 2.2 Overall JSE market capitalisation and market turnover, 2009 – 2013



Source: JSE (2014)

An additional characteristic of the JSE in particular, is the thin trading trend present in most emerging markets. That is, 90 percent of the market capitalisation of the JSE is made up of the Top 40 listed companies, which also represent the most liquid of the listings (Samkange, 2010).

In terms of regulations, the JSE is the primary regulator for the exchange, settling and enforcing listing and membership requirements, as well as trading rules (JSE, 2014). The JSE is supervised in the performance of its regulatory duties by the Financial Services Board (FSB). According to the World Economic Forum's Global Competitiveness survey for 2013-2014, South Africa is ranked first in the world in terms of regulation of securities exchanges. However, a considerable change in the regulatory landscape in South Africa is expected in the future as the country looks to implement a twin peaks model of oversight. Following that change, the South African Reserve

Bank (SARB) will have the charge of exercising prudential supervision; while the then reinforced FSB will lead the market conduct regulations (JSE, 2014).

Some widespread implications are also expected to result from another regulatory change namely the 2011 decision to alter South Africa's inward listing rules. This decision allows foreign domiciled companies to be treated as domestic listings (JSE, 2014). Although foreign companies were previously allowed to list on the JSE, they were subject to foreign exchange rules, limiting the amount of equities that local investors could hold. By lifting these restrictions, the JSE makes an important regulatory shift and makes itself a more attractive listing destination to foreign firms (JSE, 2014).

2.4 Market participants

In addition to institutions such as the FSB, whose function is to regulate the financial markets in general and the JSE specifically, the securities exchange is the "playing field" for a number of other participants. The market participants are involved directly or indirectly with the daily functioning of the JSE. They can be classified into four broad categories, according to the specific function that they exercise.

The first category consists of the deficit unit or borrowers of funds. These are the companies in need of capital and get listed on the JSE. The listed companies then issue different types of shares in the primary share market in order to raise the capital needed.

The second category consists of the surplus unit represented by the lenders of funds also known as public investors. This group includes private individuals, trusts, pension funds and other institutions that are willing and allowed to invest their excess of capital. Investors can buy and sell listed shares at the prevailing market prices in the secondary share market. By purchasing shares, the investor lends capital to the issuing listed company and becomes a co-owner of the company. The shareholder is therefore entitled to share in profits by way of dividends payment and capital gains or losses, in proportion of the number of shares held.

The third market participants are the stockbrokers. They act as agents for investors and receive remuneration in the form of commission fees for the service provided. In other words, brokers are instructed by the interested investors to trade for them but do not trade for their own account.

The fourth and last market participants are the dealers. In contrast with stockbrokers, dealers trade for their own account in order to make profits rather than holding the shares as assets. Dealers, typically get their returns from the spread between the purchasing price and the selling price of a share over a short interval of time.

Those roles of dealers and stockbrokers are not mutually exclusive. In practice, broker-dealers acting as both agents and principals exist. They are individuals or firms executing orders on behalf of clients, as well as trading for their own account. A broker-dealer, typically, provides investment advice to clients, supplies liquidity through the buying and selling of assets, facilitates trading, publishes investment research and raises capital for companies.

2.5 Trading, Clearing and Settlement in the JSE

After the removal of the open outcry trading floor in June 1996, an order-driven, centralised and automated trading system (the JET) was adopted by the JSE. In this continuous order-driven market, actors issue instructions for specific actions, following the arrival of publicly verifiable information, such as a price change. This action shows that the market participants are willing to buy or sell quantities of stocks at specific prices, or to execute against displayed orders. They therefore add orders or execute them against existing orders by sending messages electronically to the automated trading system. An auctioneer is in charge of adjusting the price of the security until the total orders to buy equal the total orders to sell. This system is the central trading platform that supports multiple trading services, representing a single method for entering both orders and quotes as well as facilitating the immediate execution and reporting of trades. The JET system was converted, in May 2002, into the Stock Exchange Trading Systems (SETS) used on the London Stock Exchange (LSE) (Samkange, 2010).

Before 1994, only authorised stockbrokers could trade on the JSE in a single capacity. That is, brokers were permitted to only buy and sell shares on behalf of their clients and could not trade for their own account (Samkange, 2010). In November 1995, the SECA introduced the dual capacity trading system, effectively changing the way in which securities were traded on the JSE. Following that change, brokers were allowed to act as agents and trade on behalf of their clients, while simultaneously holding packages of stocks for their own account. As part of the determined restructuring, the JSE introduced an electronic settlement system called STRATE (Share Transactions Totally Electronic) to replace the previous manual settlement of script. STRATE is South Africa’s Central Securities Depository (CSD) which provides electronic settlement of shares and bonds transactions concluded on the JSE, enhancing the security of settlement in the equities market (STRATE, 2014). Its main objective is to mitigate risk, bring efficiencies to financial markets and improve the country’s profile as an investment destination (Samkange, 2010).

With the electronic records instantly updating via book-entry at the point of settlement, transactions are guaranteed to be settled on the specified settlement date. On the said date, the relevant cash and securities accounts are debited or credited, effectively minimising the risk of delayed settlement as well as the risk of loss of earning. Since the inception of STRATE, the

JSE, to this day has a “zerofailed” trade record in terms of settlement in the cash equity market (Samkange, 2010).

In the YieldX and equity derivatives markets, Safcom, the only licensed clearing house in South Africa, acts as the risk manager by being the central counterparty through which all trades are cleared and settled. In other words, the seller no longer submits his share certificate to the Transfer Secretary through his stockbroker. In the past, South Africa followed the account period methodology for the settlement of transactions in those markets. That methodology entailed that the settlement of trades of any given week took place from the Tuesday of the following week. However, under STRATE, the rolling settlement has been introduced on a T+5 basis (with T being the trade date). This means that the settlement takes place five business days after the trade was made. Since trades happen every day, settlement can also happen every day with the ownership right to securities being transferred to the holder on the settlement date. Dematerialisation (the move from physical share certificates to electronic recording) only happens after the ownership right has been transferred (Samkange, 2010).

2.6 Information distribution in the JSE

According to Section 3.4 of the JSE’s Listings Requirements, issuers are under the obligation to disclose price sensitive information “without delay”, through the Stock Exchange News Service (SENS) (Samkange, 2010). This service was launched in 1997, serving as the primary and prioritised platform available to listed companies to disseminate any corporate news or price-sensitive information on a real time basis. Its main objective is to ensure early, equal and widespread dissemination of information affecting share prices and also to improve communication listed companies and investors (City of Johannesburg, 2014).

In the spirit of uniformity in the bid, and to keep the market informed and protected at all times, the JSE established some guidelines in its Listings Requirements, for companies disseminating information via SENS. The rules prohibit the release of price sensitive information to any third party during JSE's trading hours until the information is made public through SENS; and outside trading hours, unless prior arrangements have been made for such information to be published through SENS before the next opening of the JSE. Every time an announcement is to be released through SENS, a neutral warning is sent through the JSE SETS system five minutes before the release, to give traders the opportunity to remove their orders from the system. The previously authenticated and approved announcements received by SENS are then transmitted electronically to the major channels for public access. Thereafter, the company is required to publish announcements in the press, because of its responsibility in establishing a clear communication policy. Market participants can access SENS via a direct to the JSE or by subscribing to one of the recommended data vendors such as TSA Data and Profile Group (Samkange, 2010).

Additionally, the JSE provides live equities data in the form of Broadcasting Data Groups (BDG) through its world-class live public data delivery system called InfoWiz. This information dissemination system is equivalent to the one operated by the LSE, London's InfoLect system. As a result of the partnership between the JSE and the LSE, the trading engine and information dissemination feed-handler is hosted in London and remotely connected to the JSE over a 9000km transcontinental undersea cable and an innovative, integrated solutions design. Thus, trade information on JSE's listings is disseminated by the LSE to more than 104 000 trading terminals worldwide (City of Johannesburg, 2014). Trade information about listings includes best bid, offer and mid prices, as well as details of the number and volume at best price. In addition to official closing prices and start of day reference data, investors also have access to official closing price full market depth, the volume weighted average price (VWAP) based on automatically executed order book trade, trade report volume and price as well as the cumulative volumes showing the cumulative number and volume of automatic manual trades (Samkange, 2010).

2.7 Calendar effects on the JSE

This section attempts to examine the existence of some calendar effects such as the January effect and the weekend effect; and some market anomalies such as the size effect, the value effect and the dividend yield effect, on the JSE. Seven of the main indices are used in this section: the All Share, Top 40, Mid Cap, Small Cap, Value, Growth and Dividend Plus index.

The All Share index (ALSI) represents 99 percent of the full market capitalisation of all eligible ordinary shares listed on the JSE Main Board and screened for liquidity. It included 160 companies in December 2013 and the index is reviewed quarterly in March, June, September and December. The Top 40 index is composed of the 40 largest companies (in terms of full market capitalisation) which are part of the ALSI. The Mid Cap index includes the next 60 largest companies from the ALSI after the selection of the Top 40. Finally, the remaining companies from the ALSI, after selection of the Top 40 and the Mid Cap, constitute the Small Cap index. Like the ALSI, the Top 40, Mid Cap and Small Cap are also reviewed quarterly (JSE, 2014). The Value index reflects portfolios focusing on the price and value of characteristics of securities weighted towards those companies with identifiable value characteristics. The Growth index, on the other hand, reflects portfolios on earnings and revenue growth weighted towards those companies with identifiable growth characteristics. Both indices are reviewed semi-annually in March and September, and include a variable number of companies which are constituents of the

ALSI (JSE, 2014). Finally, the Dividend Plus is a dividend yield weighted index designed to select and measure the performance of higher yielding stocks within the Top 40 and Mid Cap indices (JSE, 2014). Included in this index are the top 30 stocks by one-year forecast dividend yield, excluding property companies defined as ICB Sectors Real Estate Investment and Services, and Real Estate Investment Trusts. The index is reviewed semi-annually in March and September.

Table 2.3 Summary statistics of daily returns on seven main JSE indices, 2002 – 2013

Statistics	*ALSI*	*Top 40*	*Mid Cap*	*Small Cap*	*Value*	*Growth*	*Dividend Plus*
Mean	0.046	0.048	0.066	0.074	0.057	0.059	0.044
Standard Deviation	1.256	1.393	0.785	0.565	1.208	1.442	1.156
Kurtosis	3.367	3.186	4.494	6.933	3.251	3.817	3.744
Skewness	-0.151	-0.105	-0.610	-1.175	-0.263	-0.118	-0.378
Minimum	-7.581	-7.959	-5.632	-4.586	-7.558	-8.324	-7.502
Maximum	6.834	7.707	4.712	2.941	5.821	8.194	5.381
Observations	3039	2882	2882	2882	2500	2500	1998

Source: Author's estimations

Table 2.3 represents a summary of descriptive statistics of daily returns on the indices considered. The table shows statistics such as the mean, standard deviation, kurtosis, skewness, minimum, maximum and the number of observations for all of the seven data sets under consideration. From the table, it can be noticed that the difference between the means for all seven data sets varies between 0.044 percent (Dividend Plus index) and 0.074 percent (Small Cap index). When focusing on the size indices (categorised in terms of market capitalisation), it is seen that the average daily return increases as the size of the company decreases. That is, the Top 40 index records the lowest mean daily return, followed by the Mid Cap, and then the Small Cap which has the highest mean of the three. Moreover, the ALSI, which includes all of the three indices mentioned before, records the lowest mean daily return compared to the size-specific groups. Additionally the mean daily return on the Growth index is seen to be slightly higher than the mean return on the Value index, while both indices' means are greater when compared to the benchmark index (ALSI). However, the mean daily return on the Dividend Plus index shows a small difference when compared to the benchmark, with the latter being higher than the former.

The standard deviation values show a range between 0.565 (Small Cap) and 1.442 (Growth). Between the size indices, volatility seems to decrease the lower the market capitalisation. That is, the Top 40 index is the most volatile of the three, with a standard deviation of 1.393, while the Small Cap is the least volatile with a standard deviation of 0.565. Still using the ALSI as a benchmark to compare volatility in the style indices, the Value index (standard deviation = 1.208) appears to be slightly less volatile than the ALSI (standard deviation = 1.256), while the Growth index (standard deviation = 1.442) is more volatile than the ALSI. Finally, the dividend plus index is found to be less volatile than the benchmark.

The distribution of daily returns for all indices is seen to be negatively skewed with skewness values varying between -1.175 (Small Cap) and -0.105 (Top 40). This means that for all indices there are more negative than positive returns observations. In all cases, the kurtosis is above 3 (the expected value for a normal distribution), meaning that the daily return distributions are leptokurtic. In other words, the daily returns have higher peaks and fatter tails (i.e a higher probability of extreme values), relative to normal distributions. This shows the non-normality of the daily returns in the seven indices.

In order to detect the presence of any effect in the data sets, it is necessary to conduct a test of significance of the differences in the means. Thus, the student t-test is conducted on the ALSI, Top 40, Mid Cap and Small Cap index.

To examine the January effect, the difference between the mean returns in January and the mean returns in the other months of the year is tested. The results of the Student t-test (i.e the t-statistics) are summarised in the second column of Table 2.4. The t-statistics for all four indices show that the null hypothesis of a difference in mean equal to zero is not rejected at the 1 percent, 5 percent and 10 percent level of significance. In other words, there is no significant difference between the mean return in January and the mean returns in the other months of the year for the ALSI, Top 40, Mid Cap as well as the Small Cap.

Table 2.4 Student t-test of mean difference for the January, Weekend and Size effects

Calendar effects	***January effect***	***Weekend effect***	***Size effect***
ALSI	-0.503	0.039	---
Top 40	-0.398	0.306	0.029
Mid Cap	-0.848	-2.793***	-0.696
Small Cap	-0.167	-3.499***	-1.099

Note:*, **, *** represent significance at the 10%, 5% and 1% level, respectively.
Source: Author's estimations

The examination of the weekend effect is done by testing the difference between the mean daily returns on Mondays and the mean daily returns on the other days of the week for all four indices. The t-statistics are reported in the third column of Table 2.4. The null hypothesis of no difference between the average of Mondays' returns and the average return for the other days of the week is not rejected for the ALSI and the Top 40 index. However, the null hypothesis is rejected at the 1 percent level of significance in the case of the Mid Cap and the Small Cap. That is, while the difference between the Mondays' mean and the means for the other days of the week is not statistically significant in the ALSI and the Top 40, there is a statistically significant difference between the means in the Mid Cap and the Small Cap. These results suggest the existence of the Monday effect in the Mid Cap and the Small Cap during the sample period.

When examining the size effect, the ALSI is used as a benchmark and the mean daily return on the index is compared to the mean daily returns on each of the other size indices (i.e. the Top 40, Mid Cap and Small Cap). The t-statistics reported in the fourth column of Table 2.4 lead to the failure to reject the null hypothesis of no difference in the means between the ALSI and the three size indices, at the 1 percent, 5 percent and 10 percent level of significance. Thus, there is not enough statistical evidence to infer that there is a difference between the mean daily return on the ALSI and the mean daily return on the Top 40, Mid Cap and Small Cap.

Table 2.5 Student t-test of mean difference for the Value and Dividend effects

Market anomalies	***t-statistics***
Value index	0.053
Growth index	0.031
Dividend Plus	0.052

Note:*, **, *** represent significance at the 10%, 5% and 1% level, respectively
Source: Author's estimation

Table 2.5 reports the result from the Student t-test run in order to detect the existence, or otherwise, of the value effect and the dividend yield effect. The t-statistics obtained when testing the null hypothesis of no difference in means between the ALSI (benchmark) and the Value index is lower than the two-tailed critical values at the 1 percent, 5 percent and 10 percent level of significance. Therefore, the null hypothesis cannot be rejected and it is concluded that there is no difference in means between the ALSI and the Value index during the sample period. Similarly, the test of difference in means between the Growth index and the ALSI leads to the conclusion that there is no difference in means between the Growth and the ALSI. These two conclusions deny the presence of the value effect in the market during the sample period.

Finally, the student t-test is used to detect the existence of the dividend yield effect on the JSE. The result of the pair wise t-test reported in Table 2.5 suggests that there is no significant difference between the mean return on the Dividend Plus and the mean return on the ALSI. That is, the absolute value of the t-statistic is smaller than the two-tailed critical values at the 1 percent, 5 percent and 10 percent level of significance, leading to the non rejection of the null hypothesis of a difference in means equal to zero, at all three levels of significance.

2.8 Conclusion

Ever since its formation, the JSE has proven itself as the best stock exchange on the African continent (with the highest market capitalisation and market turnover) and one of the most promising among emerging markets. The exchange underwent a number of major changes and has been bold in restructuring; transforming it into one of the most technologically advanced emerging markets. Although, it still has the characteristics of an emerging market with its low liquidity level, high volatility and contrasting microstructure, it has made notable progress in terms of trading system and shareholders communications technology and can be seen as the only African market similar to a developed market in terms of size and the flow of information. It is clear that the South African exchange is committed to upholding the economic ethos of modern times and promoting itself as a world class securities exchange (Samkange, 2010).

A preliminary investigation of the existence of some calendar effects, namely the January effect, the weekend effect, the size effect, the value effect and the dividend effect on selected JSE indices has been conducted. The descriptive statistics indicated the non-normality of the distributions of returns for all the indices considered, which is consistent with the theory of financial instruments. Besides the weekend effect, detected in the Mid Cap and the Small Cap index through a significant difference in mean returns between Mondays and the other days of the week, none of the other effects investigated have been detected. Because this analysis was only preliminary and superficial, a formal, more in-depth analysis will be conducted in later chapters.

CHAPTER THREE

LITERATURE REVIEW

3.1 Introduction

The main focus of this dissertation is the examination of the calendar effect on the JSE. It is thus necessary to review the varied theoretical framework covering the effects studied. This is done by reviewing the theoretical underpinning of market efficiency, and establishing the background of the market anomalies.

The chapter is structured as follows. Section 3.2 discusses the theoretical literature on the efficient market hypothesis and the market anomalies. Section 3.3 focuses on the empirical studies previously conducted on the efficient market hypothesis and market anomalies, while the final section Section 3.4 provides a conclusion to the chapter.

3.2 Theoretical literature

3.2.1 The efficient market hypothesis

The financial economics field owes the refined work behind the efficient market hypothesis to Professor Eugene Fama who first started the development of the theory as part of his PhD dissertation. In 1970, he published a paper reviewing both the theory and the empirical evidence found to support the theory (Naffa, 2009). In essence, the efficient market hypothesis relates to the fundamental idea of a random walk. The main belief behind it is that securities markets are extremely efficient in reflecting all available information about individual stocks and about the stock market as a whole (Malkiel, 2003). In other words, the surfacing of new information produces prompt adjustment of the prices of securities.

The fundamental definition of the efficient market theory revolves around the term "all available information". Depending on what is meant by that term, it is important to distinguish between the three versions of the efficient market hypothesis: the weak, the semi-strong and the strong version. Firstly, the weak version stipulates that the price of a security already incorporates all information that can be drawn from examining market trading data (i.e. the history of past prices, trading volume or short interest); and if the aforementioned data were able to predict future performance, all investors would have learned to take advantage of that opportunity which would have lost its value in the long run. Therefore the analysis of market trends is ineffective (Bodie et al., 2011). When testing the weak form of the efficient market hypothesis, methods employed include historical data analysis using statistical and econometric tools. Prevalent are the analysis of the stock's market value, P/E ratio, DIV/P ratio and book-to-market value ratio. Technical analysis is also conducted.

Secondly, the semistrong version of the efficient market hypothesis declares that in addition to the history of market trading data, the price of a security also reflects all publicly available information regarding the prospects of the firm (i.e. fundamental data on the firm's product line, management, financial report documents, earning forecasts). This version is the accepted paradigm and is what is generally referred to in the literature (Jensen, 1978). The procedure involved in testing for the semi-strong form of market efficiency is related to event studies. New information usually emerges in the companies' quarterly or annual reports; or as events such as mergers, acquisitions, purchase of treasury shares, new issuances or splits. Such news should quickly be incorporated in the related stock prices. The speed at which the market adapts to the new information can also be measured.

Finally, the strong version is the extreme form of the efficient market hypothesis. It states that, in addition to all information about the firm's prospect easily accessible by the public, a stock price also reflects inside information, that is, information only available to company insiders. This version implies a certain degree of insider trading which is in violation of the law and hence is unexpected (Bodie et al., 2011).

Consequently, testing the strong version boils down to testing for the existence of insider trading. In attempts to reveal the investment activity of interest groups with the monopoly over key decisions in the companies, price adjustments taking place before important announcements are made public, are monitored.

An assumption of the efficient market hypothesis is that market participants, besides being utility maximising agents, also have rational expectations. This entails that although individuals may make mistakes in their predictions, people will generally adapt their expectations taking into consideration new available information. As some investors will overreact and others will underreact, the reactions will be random, yet with a constant volatility and a known distribution function (Naffa, 2009).

One of the implications of the efficient market theory is that active trading is futile since it would not provide returns over and above returns obtained from passive management. Additionally, neither technical analysis (which makes use of historical data like the stock prices and volume of trade in an attempt to forecast the future direction of a stock price) nor fundamental analysis (which measures the intrinsic value of the security by analysing the economic fundamentals, the underlying forces that affect the economic well-being and financial sustainability, of the related business) would be able to help an investor get returns above returns obtained from a randomly selected portfolio of individual stocks with comparable risk (Malkiel, 2003).

Although the advocates of the efficient market hypothesis were able to provide the literature with empirical evidence where markets were proved efficient (with only rare exceptions), by the start of the 21st century, financial economists and statisticians began to challenge the simple models of efficient capital markets with a belief that stock prices are at least partially predictable. From that arose the idea of market anomalies.

3.2.2 Market anomalies

According to Lo (2007), an anomaly is a pattern in asset returns that cannot be explained by the market efficiency theory, is regular and reliable (implying a degree of predictability), and is widely known (implying that investors can take advantage of it).

Similarly, Keim (2008) defines financial market anomalies as the cross-sectional and time series patterns in security returns that are not predicted by a central paradigm or theory. Identifying a number of anomalies, he ascertained that cross-sectional patterns include anomalies such as the value effect, the dividend yield effect and the size effect. However, Keim (2008) argued that the value and size effects, although separately identified, are not independent phenomena because all securities characteristics share a common variable which is the price per share of the firm's common stock. About time series patterns in returns, Keim (2008) identifies the weekend effect which, because of its existence in many different markets, cannot be explained by differences in settlement periods for transactions occurring on different weekdays, measurement error in recorded prices, market maker trading activity, or systematic patterns in investor buying and selling behaviour. Also identified is the turn-of-the-year or January effect. According to Keim (2008), the size premium is evident only in January. One hypothesis explaining the January size premium is the effect of the year-end tax-related selling done by individual taxable investors of stocks that have declined in price. However, despite the evidence of tax-related trading occurring at the end of the tax year, there is no clear link between such trading and stock return behaviour established.

All things considered, calendar anomalies are an indication of market inefficiency. Nevertheless, misspecification of the underlying model used to measure market efficiency may well lead to spurious discoveries of calendar anomalies and hence of market inefficiency.

The Weekend Effect

The theory behind the weekend effect, also called the Monday effect, is built on the observation that stock prices do not take into account the money-value of the two-day weekend and start off on a Monday morning where they left off on Friday at closing time. This anomaly suggests that Fridays have the tendency to exhibit relatively larger returns than Mondays (Naffa, 2009). Vulić (2009) finds this anomaly to be particularly puzzling – Mondays' returns are expected to be higher than any other days' as Mondays' returns cover three days in all.

The January Effect

In the stock market, it is believed that the month of January plays a considerable role in predicting the trend of the stock market for the remainder of the calendar year. The phenomenon of the January effect occurs between the last trading day in December of the previous year and the fifth trading day of the new year in January. Karadžić and Vulić (2011) argue that this effect is a result of tax-loss selling leading investors to sell their losing positions at the end of the month of December. This anomaly is, therefore, mainly characterised by an increase in the buying of securities by market participants before the end of the year at a lower price, in order to sell them in January to generate profit from the price differences. However, after investors discover the January effect, they will expect the stock price to appreciate in January and will, consequently, purchase before January and sell at the end of January. This demand will drive up the prices before January and push down the prices at the end of January, which should result in the diminishing or even the disappearance of the January effect (Karadžić & Vulić, 2011).

The Size Effect

This anomaly is also called the small-firm effect. The size of company is determined by its market capitalization. Banz (1981) and Reinganum (1981) demonstrated that small-size firms on the NYSE earned higher average returns than is predicted by the Sharpe – Lintner capital asset pricing model (CAPM) during the period from 1936 to 1975 (Schwert, 2003). According to Malkiel (2003), this effect is the strongest one found so far. It is depicted by the tendency of smaller-company stocks to yield returns that are larger than those of the larger-company stocks over long period of time. Malkiel (2003) emphasises that, in this case, it is critical to examine the extent to which the higher returns of small companies are reliable enough to produce predictions allowing market participants to generate excess risk-adjusted returns. In the capital asset pricing model, a stock's "beta" is defined as the extent to which the return of the stock is correlated with the return for the market as a whole; and is considered the correct measure of risk for that stock. Hence, if this "beta" is accepted as such, the size effect can be interpreted as indicating an anomaly and market inefficiency, since when using this measure, portfolios consisting of smaller companies stocks have excess risk-adjusted returns (Malkiel, 2003). Another crucial point to look at is the dependability of the size anomaly. It is argued that in most world markets, larger rates of returns were recorded from larger capitalization stocks compared to smaller capitalization stocks. This may be due to the growing institutionalization of these markets which made portfolio managers prefer larger companies that are highly liquid to smaller companies which present challenges when it comes to liquidating significant blocks of stock (Malkiel, 2003). Finally, survivorship bias is also a possible explanation of the size effect in some studies. In effect, the computerised databases of companies currently available only include the firms that have survived and not the ones that went bankrupt after some time. Therefore, when examining the previous performance of small companies currently in business, the performance of ones that failed during the same period of the study is not measured (Malkiel, 2003).

The Value Effect

This anomaly refers to the positive relation between stock returns and the ratio of the value to the market price of the same security. The value could be measured by the earning per share, or the book value of common equity per share. Although it has proven to be robust over time and across markets, there is still a debate about the underlying source of the returns.

The Dividend Yield Effect

The dividend yield is the ratio of the cash dividend of a stock to its price. Keim (2008) highlights that, although the construction of the dividend yield is similar to the value ratios, the explanatory power of the dividend yields is attributed to the differential taxation of capital gains and ordinary income.

3.3 Empirical literature

3.3.1 The efficient market hypothesis

The efficient market hypothesis is a cornerstone of modern financial economics theory. As such, it has been extensively examined in numerous studies. In general, testing for market efficiency is equivalent to examining the presence/absence of calendar anomalies in that market.

According to Clarke, Jandik and Mandelker (2001), much of the existing evidence shows that markets are highly efficient and investors do not stand to gain from active portfolio management strategies. Besides being fruitless, attempts to beat the market can reduce returns due to costs incurred.

Although, it could be expected that small capital markets would be inefficient, Karadžić and Vulić (2011) in their analysis of the Montenegrin capital market showed the opposite. The anomalies investigated were the January effect, the holiday effect and the turn-of-the-month effect. The evidence indicated that at least one of the three anomalies tested had disappeared from the market. This suggested that the Montenegrin capital market was becoming more efficient. The authors explained that this is resulting from the fact that market participants are becoming more knowledgeable and experienced; there are advances in information technology and communications, and lower cosst of information (Karadžić & Vulić, 2011).

Evidence from the Nigerian stock market is presented by Gimba (2012) in a paper testing the weak version of the efficient market hypothesis. The study used daily and weekly price series of the market index (NSINDEX) and the five oldest stocks listed on the Nigerian stock exchange, namely First Bank (FIRSTB), United Bank for Africa (UBA), Union Bank (UNIONB), CADBURY and NESTLE, covering the period from the first trading day in January 2005 to

December 2009. To test the weak form of the hypothesis, three different tools were used, they are: the autocorrelation, runs and variance ration tests. The results of the autocorrelation test conclusively rejected the null hypothesis of random walk for the NSINDEX and for four of the five selected individual stocks. The results obtained from the runs test, when using the data corrected for thin trading , failed to reject the hypothesis of random walk for the daily returns of UNIONB and NESTLE and weekly returns of FIRSTB and NESTLE. Finally, the results of the variance ratio test under assumptions of homoskedasticity and also heteroskedasticity similarly rejected the random walk hypothesis for the NSINDEX and the five individual stocks. This led Gimba (2012) to the conclusion the Nigerian stock market is inefficient in the weak form of the hypothesis.

Stefan (2009) conducted a test of the semi-strong version of the efficient market hypothesis on 30 stocks of the S&P 500 Index. The aim of the study was to discover the types of stocks that are more price-sensitive to new information. The study covered the period of the 2008 economic crisis, from 30 July 2008 to 2009 and used weekly stock returns of the 30 stocks selected. For each of the 30 stocks, the OLS regression was run and the estimated coefficients and corresponding p-values were recorded. The statistics showed that for six out of the 30 stocks, there is a positive relationship between the number of new information and the change in price. Stefan (2009) concluded that these results showed that during the financial crisis (from July 2008 to January 2009), the efficient market hypothesis was unable to explain the price fluctuations of assets in the stock market.

In an attempt to provide empirical evidence of the hypothesis pertaining to emerging financial markets, Islam, Watanapalachaikul and Clark (2007) tested market efficiency in the Thai stock market. The Run test (a non-parametric test whereby the number of sequences of consecutive positive and negative returns is tabulated and compared against its sampling distribution under the random walk hypothesis) was examined using monthly and daily returns of the Stock Exchange of Thailand (SET) index data for the total period from 1975 to 2001, the pre-crisis period from 1992 to 1996 and the post-crisis period from 1997 to 2001. Similarly, the autocorrelation function (ACF) test (a measure of the correlation between the current and lagged observation of the time series of stock returns) was run in order to identify the degree of autocorrelation in the monthly and daily returns of the SET index data for the same periods. From the results obtained from both tests, it was concluded that the emerging Thai stock market was inefficient during the study period. The ACF test particularly showed a strong autocorrelation existing in the data during both the pre-crisis period and the post-crisis period (Islam et al., 2007).

Following the growing number of studies advocating the existence of market anomalies, Sullivan, Timmermann and White (1999) raised the following question: "Do the apparent regularities in the stock markets imply a rejection of the simple notions of market efficiency, or are they just a result of a large, collective data-snooping exercise?" In a study covering the period January 1897 – December 1996, they test the implications of calendar effects for the efficient market hypothesis. A number of tests are run using daily returns of the DJIA index and S&P 500 futures. The different tests that were run were: Reality Check P-values, Mean return criterion, Sharpe Ratio criterion, Out-of-Sample estimation and In-Sample Data Snooping Biases. According to Sullivan et al. (1999), the evidence on calendar anomalies looks much weaker, when assessed in the context of either the full universe, or a restricted version of calendar rules that could be considered. In fact, no calendar appears to be capable of outperforming the benchmark market index. It was concluded that data-snooping had, probably, occurred across several type of assets.

3.3.2 Market anomalies

There is a wide range of studies internationally available providing evidence of the existence of the market anomalies in markets worldwide.

A study of the month-of-the year and pre-holiday seasonality in African stock markets, conducted by Alagidede (2008), shows that there are high and significant stock returns in days preceding a public holiday only in South Africa and not in the other African stock markets under consideration. The study also suggests that there is evidence of the prevalence of the month-of-the-year effect in African stock returns, especially in Nigeria where it is pronounced. However, Alagidede (2008) demonstrated that the turn-of-the-tax-year effect, which is very common in the industrial markets, is not present in the African markets.

In the international sphere, Hansen and Lunde (2003) analysed 27 stock indices from 10 industrialised countries. These countries were Denmark, France, Germany, Hong Kong, Italy, Japan, Norway, Sweden, the United Kingdom, and the USA. It was found that the calendar effects were significant in most return series and the largest anomalies were shown by the end-of-the year effects. The strongest evidence of calendar effects in the study is uncovered in small market capitalization (small-cap) indices in which calendar effects are found to be significant. The subsample analyses also found the results to be robust (Hansen & Lunde, 2003).

A study of the security markets in the United Kingdom, Greece and the USA, conducted by Floros and Salvador (2014) using the Markov regime switching model, showed that there are differences in the seasonal patterns in cash and futures indexes due to the existence of basic risk.

Also, calendar effects are found to be conditioned to the market situation. In fact, during a low volatile situation, the effects tend to be positive but they turn negative if the market is under a high volatile period (Floros & Salvador, 2014).

The following sections, more specifically group the empirical literature according to the anomalies that are focused on in this study.

The Weekend Effect

The weekend effect has been extensively examined in the USA financial market. Jones and Ligon (2009) and Sharma and Narayan (2012) conducted analysis of the effect in the USA for different periods, using different methodologies and data. Jones and Ligon (2009) examined initial returns of IPO daily closing price and volume data using an OLS regression with dummy variables. The study period was from 1980 to 2003. The results of the study showed that the Monday effect was present in the full sample throughout the sub-period from 1980 to 1994. During the sub-period from 1995 to 2003, the effect was only detected for IPOs for which the first reported trade was made on their offer date. Moreover, the volume of IPOs offered on Fridays was very high, then declined significantly on the following Monday and remained relatively low for the rest of the trading week. Also, the proportion of IPOs offered on Fridays that first trade on their offer date was found to be much higher than that of other days of the week, which indicated that Friday IPOs may begin trading earlier in the day (Jones & Ligon, 2009). Additionally, Sharma and Narayan (2012) studied aggregate data, namely, value-weighted returns (with and without dividends) and equal-weighted returns (with and without dividends), as well as disaggregate data, namely, 560 firms listed on the New York Stock Exchange (NYSE). The study covered the period from 5 January 2000 to 31 December 2008 and the methodology used was the GARCH (1,1). It was observed that the weekend would affect a firm's returns differently depending on the sector to which it belonged and it was found to mostly be negative for firms in 13 sectors. Furthermore, the impact of the weekend effect on firms' returns volatility was found to be much stronger than the relationship between calendar anomalies and firm returns. Finally, the statistically significant weekend effect was found to be highly positive on returns of small size firms, while it was statistically significant and negative for large size firms.

In South Africa, Jooste (2006) uncovered the presence of the Monday effect while studying the day-of-the-week effect on seven major JSE indices. The data used was the closing prices of the All Share, Industrial 25, Mid Cap, Small Cap and Top 40 indices over the period from 20 December 1995 to 11 November 2006 and the Resource 20 and Financial 15 indices over the period from 2 March 1998 to 11 November 2006. The results from a Student's t-test showed that all the selected sectors of the South African stock market tend to produce higher returns on Mondays than any other day of the week, hence concluding that there is a very strong Monday effect in the South African market. It is interesting to note that the pattern in the South African market is the inverse of the common pattern witnessed in various international markets where negative Monday returns were recorded (Jooste, 2006). The negative Monday returns were the case in Asian markets such as Hong Kong, Indonesia, Malaysia, Japan, Singapore, Taiwan and Thailand examined by Lean, Smyth and Wong (2005) for the period 1 January 1988 – 31 December 2002.

The January Effect

The literature pertaining to this pattern is extensive as it constitutes one of the first anomalies discovered.

Evidence of the tax calendar-related rational opportunistic trading patterns by fund investors and managers was found in the USA during the period from 1990 to 2009. In their study, Chen, Estes and Ngo (2011) used the generalised method of moments to analyse the daily municipal bond returns and bond fund flows. The authors found that fund shareholders conducted tax-loss selling in December in order to re-invest in January. However, unlike fund shareholders, fund managers acted contrarily as they bought in December and sold in January.

Still in the USA, Moller and Zilca (2008) found a strong mean reverting component beginning in the latter part of January and a shorter duration of the seasonal effect. They studied monthly stock returns of all stock on the NYSE, AMEX and NASDAQ for the period 1927 – 2004, using the bootstrapping procedure. Their results also showed higher abnormal returns in the first part of January and lower abnormal returns in the second part of January in years recent to the study. Finally, they noticed a substantial decline in trading volume intensity in the second part of January in the years recent to the study.

In the Montenegrin capital market, which is considered as an emerging market, Karadžić and Vulić (2011) found that the January effect was present before the financial crisis of 2008 but not during the crisis. However, they argued that the absence of this effect in the crisis period may be the result of the small sample used for the analysis, due to the lack of available data.

Accounting for the South African literature, the study conducted by Jooste (2006) showed that there is a strong tendency for market returns to be positive during the month of January. Using the same data set used to test for the day-of-the-week effect and the same test (Student's t-test), it was found that, of the seven indices analysed, four (The ALSI, Mid Cap, Small Cap and Top 40) showed daily returns that were statistically significant during the month of January. Moreover, the Small Cap was found more statistically significant than the other indices (i.e. the Small Cap was significantly different from zero at the 1 percent level of significance during the month of January, while the Mid Cap was significant at the 5 percent level and the ALSI and Top 40 indices were significant at the 10 percent level of significance during the same month). Indeed, these findings led to the conclusion that the January effect exists in the South African stock market and provides evidence supporting the international claim that the January effect is most prominent for small-size firms (Jooste, 2006). However, Jooste (2006) found that the January effect was a poor predictor of returns during the rest of the year, contrary to the S&P 500's which is able to predict market directions in the USA. Because some patterns are said to disappear after a period of time, Jooste (2006) advocated the use of index futures when exploiting the patterns as it is more cost-effective.

The Size Effect

The earliest studies on the size effect include the study by Friend and Lang (1988) who based their empirical tests on the asset pricing model which allows the expected return of a common stock to be a function of risk (measured by the beta, variance of return and the quality rating) and included an additional size factor which is the market value of equity. The data used for the study included all common stocks quoted on monthly CRSP return files for at least five years for the period 1962 – 1986 and with the quality rating in S&P stock guide. Additionally, the authors make use of the grouping techniques to group individual securities into portfolios on the basis of the market value and security beta, and re-estimating the relevant risk measures of the portfolios in a subsequent period and finally performing either an OLS regression which assumes homoskedastic errors or a GLS regression which allows for heteroskedastic errors on portfolios for each month. The results showed that the higher the risk in terms of beta, variance of returns and quality rating, the higher the return, the larger the firm's size, the lower the return (Friend & Lang, 1988). This confirmed the existence of the small-firm effect in the US stock market.

Similarly, Keim (1983) examined the size-related anomalies and stock return seasonality in the NYSE and AMEX. The sample used for the study was drawn from the CRSP daily stock files for the period 1963 – 1979 and included firms which were listed on the NYSE or the AMEX and had returns recorded on the files during the entire calendar year under consideration. Evidence from the study indicated that the relation between abnormal returns and size was always negative and more pronounced in January when daily abnormal return distributions exhibited larger means compared to the remaining eleven months of the year. This was the case even in years when large firms earned larger risk-adjusted returns than small firms, on average. In addition, approximately 50 percent of the average magnitude of the size effect was due to January abnormal returns, over the period 1963 – 1979 (Keim, 1983).

The size effect was more recently analysed by Schwert (2003) in the USA using monthly returns on the DFA fund, the CRSP value-weighted portfolio of NYSE, AMEX and NASDAQ stocks for the period January 1982 – May 2002. The statistics obtained showed that the estimates of the abnormal monthly returns were between -0.2 percent and 0.4 percent per month, although none were reliably below zero. It was then concluded that the small-firm anomaly may have disappeared since the initial publication of the papers that discovered it. On the other hand, the differential risk premium for small-capitalization stocks has been found to be much smaller since 1982 than it was in the previous years (Schwert, 2003).

The emergence of the size effect was one of the bases for the development of the Fama and French (1993) three-factor model. When they discovered that the size and value effects were significant in the market when using the CAPM, they argued that the results implied an empirical failure of the CAPM rather than market inefficiency. The CAPM predicts that the average relationship between a stock's "beta" and its return is upward sloping. However, Fama and French (1993) found that relationship to be flat during the period 1963 – 1990. After estimating the CAPM with multiple value and size variables included as explanatory variables, it was seen that value and size hold the greatest explanatory power when describing the cross sectional returns and it was concluded that book-to-market ratio and size are proxies for the influence of two additional risk factors omitted in the CAPM. They even suggested that size may be a far better proxy for risk than beta (Fama & French, 1993).

The shortcoming of the CAPM was already highlighted by Ball (1978) as the explanation for the size effect. In effect, Ball (1978) explained that the characteristics that would cause a trader who follows this strategy to add a firm to his/her portfolio would be stable over time and easy to observe. That is, information collection costs, turnover and transactions costs would be low making it available to a large number of potential arbitrageurs at a very low cost, if such a strategy earned reliable abnormal returns (Schwert, 2003).

The Value Effect

Similar to the size effect, the value effect was observed by Ball (1978) and Fama and French (1993) as being evidence likely to indicate that the CAPM was faulty rather than market inefficiency. As a result, Fama and French (1993) explored several of the anomalies that were identified in previous literature using their three-factor model where the test is based on the null hypothesis that abnormal returns are equal to zero. The statistics obtained from the test showed that abnormal returns were not reliably different from zero for portfolios of stocks sorted by equity capitalization (size), book-to-market ratios (value), dividend yield, or earnings-to-price ratios. These results successfully justified their argument about the inefficiency of the CAPM.

More recently, Davis, Fama, and French (2000) collected book-to-market data from 1929 through 1963 in order to analyse a sample that did not overlap with the one studied in Fama and French (1993). They found that the apparent premium associated with value stocks was similar in the pre-1963 data to the post-1963 evidence. Their results also indicated that the size effect was absorbed by the value effect in the earlier sample period. In 1998, they also conducted an analysis of a sample covering 13 countries (including the USA) over the period 1975-1995. They uncovered that the value effect existed in that sample for the period covered. Thus, in samples that pre-date the publication of the original Fama and French (1993) paper, the evidence supports the existence of a value effect (Schwert, 2003).

However, Schwert (2003) conducted a study of the DFA Value portfolio from 1994 to 2002 and found that the abnormal return coefficient was statistically insignificant. The author thus concluded that, as with the size anomaly, the value anomaly seemed to have disappeared from the US market, or at least had attenuated.

Loughran (1997) presents a criticism of the value effect. To analyse the book-to-market ratio across the dimensions of firm's size, exchange listing, and calendar seasonaliy, Loughran (1997) used data consisting of daily returns of all NYSE, AMEX and NASDAQ operating firms listed on both the University of Chicago's CRSP daily tapes and the 1995 Compustat tapes. The sample period covered was 1963 – 1995. All financial institutions were excluded from the sample and all included firms had two years of returns on CRSP before entering the sample. Furthermore, size quintiles were created using only the market capitalization of NYSE securities and book-to-market (BE/ME) quintiles were formed within each size quintile, using all sample firms (NYSE, Amex, and Nasdaq). The results showed that for the largest size quintile, book-to-market ratio had no reliable predictive power for returns during the sample period. Additionally, when value-weighted returns by BE/ME quintiles were recorded, it was found that growth firms (firms with low book-to-market ratios) outperformed value firms (firms with high book-to-market ratios) by 140 basis points per year outside of the 1974 – 1984 sub-period. Thus, Loughran (1997) concluded that the book-to-market effect found by Fama and French (1998) is mostly a manifestation of the low returns on small newly-listed growth stocks outside of January, coupled with a seasonal January effect for value firms. The author further explained the discrepancies between the academic literature and the practitioner experience by mentioning that the value effect for large firms (in which most managers invest) has been statistically insignificant at least since 1963.

The Dividend Yield Effect

Among the oldest available literature examining the dividend yield effect is Fama and French's (1988) study of the power of dividend yields to forecast stock returns. For their analysis, they used continuously compounded returns $r\ (t,\ t + T)$ on both the value-weighted and the equal-weighted portfolios of the NYSE stocks constructed by the CRSP. The returns were compounded for return horizons T of one month, one quarter, and one to four years and the sample period was 1927 – 1986. Fama and French (1988) found a positive relationship between the forecasting power of the dividend yields and the return horizon. In other words, the power of dividend yields (measured by regression R^2) to forecast stock returns increased with the return horizon. For instance, dividend yields explained only 5 percent of the variances of monthly or quarterly returns. However, dividend yield often explained more than 25 percent of the variances of two-to four-year returns. Fama and French (1988) simply gave the explanation that high correlation causes the variance of expected returns to grow faster than the return horizon. Additionally, the growth of the variance of unexpected returns with the return horizon is attenuated by a discount-rate effect.

A similar conclusion was drawn from Campbell and Shiller's (1988) study of the dividend-price ratio, expectations of future dividends and discount factors tested for annual observations on prices and dividends for the S&P 500 extended back to 1871 and monthly returns on the value-weighted NYSE index from 1926 to 1985 (inclusive and exclusive of dividends to enable computation of the levels of dividends and prices up to an arbitrary scale factor). The results from the study also provided a metric to evaluate the relative importance of real dividend growth, measured real discount rates and unexplained factors in determining the dividend-price ratio.

3.4 Conclusion

In the field of financial economics, the efficient market hypothesis represents the basis for the study of financial markets. Stock prices reflect all available information on the market. Over time, the theory evolved from an idea proclaimed by a few scientists to a dominant paradigm, attracting the attention of researchers and practitioners. The empirical evidence obtained from previous tests of the efficient market hypothesis is mixed. While most of the studies show that markets are generally efficient, it was observed that emerging stock markets are mostly inefficient. Proposed explanations for this phenomenon include the inherent characteristics of these markets, such as their low liquidity, thin and infrequent trading and the lack of experienced market participants (Gimba, 2012). Although there are empirical studies proving that markets are efficient, the number of exceptions found gave birth to the notion of market anomalies. These anomalies are defined as the empirical results that are inconsistent with mainstreamed theories. Mainly identified are the calendar effects (associated with time series patterns) such as the day-of-the-week effect, the weekend effect, the turn-of-the-year (January) effect, the month-of-the-year effect; and the market anomalies (associated with cross-sectional patterns) such as the size effect, the value effect and the dividend yield effect. However, scientists agree that the existence of anomalies does not invalidate the idea of market efficiency, even though some of the studies of market anomalies gave robust evidence of their existence. It is also advised to be careful not to overemphasize the anomalies and predictable patterns because, if they do exist, they could become undependable and disappear in the future as a result of being over publicised and overexploited. Moreover, it is well known that given enough time and resources, scientists can "torture" almost any pattern out of most datasets. Caution is therefore crucial when dealing with many of the predictable patterns found so far as they may simply be the result of data mining.

Finally, Thury and Zhou (2005) make a crucial remark by noting that the adjustments for calendar effects are not advocated as a final aim in itself but as an approach to improve the quality and interpretability of data, which then could be analysed more successfully by high powered statistical and econometric techniques.

In the following section, the methodology as well as the data used to conduct the analysis in the paper will be described. Since most of the studies reviewed in this chapter made use of popular tools such as the CAPM and the GARCH models, this analysis makes use of a rather neglected econometric method, the Markov regime switching model (MRS).

CHAPTER FOUR

METHODOLOGY

4.1 Introduction

The analysis of market anomalies and calendar effects in this dissertation focuses on the following anomalies: *(1)* the weekend effect, *(2)* the turn-of-the-year (January) effect, *(3)* the size effect, *(4)* the value effect and *(5)* the dividend yield effect. A number of tools have been developed in order to model non-linearity in time series and cross-sectional data. The model chosen for this study is the Markov regime switching model which is a multiple-regime model.

This section provides insights into the theoretical and analytical frameworks of the Markov regime switching model. The data collection issues are also highlighted.

4.2 Theoretical framework

The switching model represents an attractive alternative for many reasons.

Guidolin and Timmermann (2008), in their analysis of the size and value effect on USA stock market returns for the sample period 1927 – 2005, highlighted the economic importance of regimes as one of those reasons. In effect, the analysis showed that regimes can have a large impact on the optimal asset allocation even in cases when investors have not identified the prevailing state. By investigating the effect of parameter estimation errors on the optimal portfolio weights, they demonstrated that disregarding regimes would lead to a suboptimal portfolio allocation and would lead investors to invest too little in the market portfolio and too much in the SMB (size) portfolio (Guidolin & Timmermann, 2008). Moreover, in order to quantify the economic significance of regimes, Guidolin and Timmermann (2008) undertook utility cost calculation with a computation of the reduction in expected utility resulting from overlooking regimes; and also with an evaluation of the out-of-sample performance of a variety of model specifications including regime-switching, single-state, and VAR models. The loss in expected utility from ignoring regimes proved to be important across a range of regime switching models, and the out-of-sample recursive analysis showed that models accounting for regimes produce a higher average realised utility even after accounting for parameter estimation error (Guidolin & Timmermann, 2008).

Although a number of regime switching models exist in the econometrics and statistics fields, Chu, Liu and Rathinasamy (2004) demonstrated that the MRS model is the most appropriate alternative to model time series subject to regime shifts. For instance, the two-regime models with permanent shift, which are well known in the empirical finance literature, proved to be restrictive as they explicitly assume only two regimes. The multiple regime models with permanent shift, although sounding more promising, face the challenging task of correctly identifying the multiple change points. In the case of the two-regime models with temporary shifts, the most challenging aspect is to estimate the duration of the temporary shift (Chu et al., 2004).

Furthermore, the MRS models can be divided into two different categories according to the nature of the transition probabilities. There are models with fixed transition probabilities between the regimes and those involving the regime transition probabilities dependent on other variables (i.e. time-varying transition probability Markov Switching models). In addressing the issue of whether the transition probabilities between the regimes are further explained by other variables, Çevik, Korkmaz and Atukeren (2012) explain that evidence shows fertile research covering the relationship between economic sentiments, such as business confidence or consumer confidence, and stock market cycles. Since these variables fall outside the scope of the present study, the focus will be kept on the simple MRS model with fixed transition probabilities between the regimes.

4.3 Analytical framework

The Markov regime-switching model is a nonlinear multiple-regime model and stands to be a more flexible model of regime shifts, making it the most attractive alternative for this study. It is a generalisation of the simple dummy variables approach which provides a statistical method of segmenting the sample data into different regimes through probabilistic inference. In other words, the model helps to derive the probability of the return of a given month belonging to a certain regime (Chu et al., 2004). In this model, the number of regimes is not assumed or predetermined, but is rather estimated depending on the data. The data is modelled as an autoregressive process with parameters subject to regime switching as determined by the outcome of a first-order Markov process or chain, which is a stochastic process. The approach assumes a different behaviour from one regime to another. For instance, assuming that the universe of possible occurrence is split into K states or regimes called S_t, with t = 1,..., K, the shift of S_t between regimes is ruled by the Markov process. This can be expressed as:

$$P[a < y_t \leq b \mid y_1, y_2, ..., y_{t-1}] = P[a < y_t \leq b \mid y_{t-1}] \quad (3.1)$$

The above equality states that if a variable follows a first-order Markov chain, only the current period's probability and a transition matrix will be necessary to forecast the probability of that variable being in a given regime during the next period. The transition probabilities form a *M x M* matrix:

$$P = \begin{bmatrix} P_{11} & P_{12} & \dots & P_{1m} \\ P_{21} & P_{22} & \dots & P_{2m} \\ \dots & \dots & \dots & \dots \\ P_{m1} & P_{m2} & \dots & P_{mm} \end{bmatrix} \qquad (3.2)$$

where P_{ij} is the probability of observing regime *j* at time *t*, given that the regime at time t-1 was equal to *i*.

Therefore, it can be said that $\sum_{j=1}^{m} P_{ij} = 1 \; \forall \, i$ and the transition probabilities characterise regime shifts of the time series data.

A vector of current state probabilities is then obtained and is defined as $\pi_t = [\pi_1 \, \pi_2 \; ... \; \pi_m]$; where π_i is the probability that the variable is currently in regime *i*. Thus given the current period's probability π_t and the transition probabilities matrix P, the probability that the variable will be in a given regime next period is: $\pi_{t+1} = \pi_t P$; and the probabilities for S steps into the future will be: $\pi_{t+s} = \pi_t P^s$.

When the number of regime is determined, the frequency distribution of high return regimes is examined to discern the presence of the relevant anomalies. The model's parameters can be estimated using the maximum likelihood approach.

The daily closing prices are used to compute the daily return for each index. The equation is as follows:

$$R_d^I = 100 \times \ln \frac{I_d}{I_{d-1}} \qquad (3.3)$$

where R_d^I is the continuously compounded rate of change in the price of index I on day d and I_d is the closing price of index I on day d.

Similarly the monthly closing prices are used to compute monthly return for each index. The equation is similar to equation (3.3) above:

$$R_m^I = 100 \times \ln \frac{I_m}{I_{m-1}} \tag{3.4}$$

where R_m^I is the continuously compounded rate of change in the price of index I on month m and I_m is the closing price of index I on month m.

In order to ensure that the use of a regime switching model is relevant, the descriptive statistics of the distributional properties of the return series are reported when starting the analysis. These statistics are the mean, standard deviation, skewness, kurtosis, Jarque-Bera test and the Lagrange Multiplier (LM) test. If the statistics indicate that the series is highly leptokurtic relative to normal distribution and parameter instability is detected, there is justification for the use of a regime switching model. The LM test of Andrews is conducted to detect parameter instability. The test will be applied to the equally weighted daily return of stock and the equally weighted monthly return of stock on each index. The test statistics must lead to the rejection of the hypothesis of parameters constancy. If that is the case, then the variables R_d^I and R_m^I follow a Markov switching model.

In that case, the model can be defined as follows:

$$R_t - \mu_t = \phi_1 (R_{t-1} - \mu_{t-1}) + \phi_2 (R_{t-2} - \mu_{t-2}) + ... + \phi_r (R_{t-r} - \mu_{t-r}) + \varepsilon_t \tag{3.5}$$

where R_t is the stock return at time t and ε_t is assumed to be normally distributed with zero mean and a constant variance σ^2. μ_t is the regime-dependent mean and has its own dynamics specified as a K-state first-order Markov chain: $\mu_t = \beta_{S_t}$; where S_t is an unobserved state variable at time t with values in a finite state space S= {1,2...K}. S_t represents the regime at time t and is characterised by the following first-order Markov chain:

$$P(S_t = j \mid S_{t-1} = i, S_{t-2} = k, ..., R_{t-1}, R_{t-2}, ...) = P(S_t = j \mid S_{t-1} = i)^\circ p_{ij}\text{, for } i,j=1,2...K. \quad (3.6)$$

The probability law represented by the above mentioned Markov chain defines the sequence {S_0, S_1, S_2,...}, the historical regimes of the mean return μ_t. The important property of the probability law is that the conditional distribution of the next regime S_{t+1} must only depend on the current regime S_t and not on the distant past information set {S_{t-1}, S_{t-2},...,R_{t-1},R_{t-2},...}. The unknown parameters included in the model, i.e. the lag coefficients {ϕ_1, ϕ_2,...,ϕ_r}, the mean returns of the different regimes {β_1, β_2,...,β_k}, the transition probabilities p_{ij} and the constant variance σ^2 are estimated using the maximum likelihood method.

In order to estimate the optimal lag number and the appropriate number of regimes, a variety of Markov-switching models are fitted with r = 1 to i lags and K = 2 to j regimes in the conditional mean equation (3.5). The best model is picked based on the Schwartz Information Criterion (SIC). As the MRS model is characterised by a typically large number of parameters, the SIC uses a heavier penalty factor for over-parameterization, thus, making it more appropriate in choosing the best model in comparison to the Akaike Information Criterion (AIC). For the selected model, the lag coefficients and the mean returns of the regimes are estimated. The transition probability matrix is also derived. Using that matrix, inference can be made about the following period's state. That is, given the current state, the probability of the stock returns belonging to the same state or a different one can be inferred.

4.4 Data issues

The data used for the study are sourced from the JSE. In order to analyse the weekend effect, the January effect and the size effect, the daily and monthly closing prices of four headline JSE stock indices, namely, the All Share (J203), Top 40 (J200), Mid Cap (J201) and the Small Cap (J202) index over the sample period 24 June 2002 to 31 December 2013 are studied.

The data set for the analysis of the value effect comprise daily closing prices of the Value index (J330) and the Growth index (J331), covering the sample period 23 August 2004 to 31 December 2013.

When examining the dividend yield effect, daily closing prices of the Dividend Plus index (J259) is used. This data set covers the period from 21 August 2006 to 31 December 2013.

The difference in the sample period covered is the cause of the unavailability of data for the Value and Growth indices before the 23 August 2004, and for the Dividend Plus index before the 21 August 2006. Additionally, as Singh (2014) suggests, the missing values from the data sets due to holidays are replaced with the past one month average of the particular day. For instance, if the one of the Monday's values is missing because the day was a holiday, the average of the stock price of the previous three Mondays is considered in its place.

4.5 Conclusion

This chapter described the econometric tool used to conduct the analysis in this study. The choice of the Markov switching model was justified by a number of studies (i.e. Guidolin &

Timmermann, 2008 and Chu et al., 2004) which emphasised the important impact of regimes on the optimal asset allocation and demonstrated the loss in expected utility arising from ignoring the existence of regimes in a dataset. Furthermore, compared to other regime switching models such as the two-regime models with permanent shift, the multiple regime models with permanent shift and the two-regime models with temporary shifts, the MRS model is a less restrictive option and presents less challenges in the determination of the number of regimes, the estimation of the duration of the temporary shifts and the identification of the multiple change points. All of the abovementioned reasons made the MRS a more attractive option for the study.

Therefore, the empirical analysis of the anomalies will be conducted using the methodology described in the chapter. The MRS models will be estimated using daily and monthly returns on seven main JSE indices for the period 2002 - 2013. The procedure and the findings will be reported in the following section.

CHAPTER FIVE

EMPIRICAL ANALYSIS AND FINDINGS

5.1 Introduction

The main objective of this chapter is to present the empirical analysis conducted using the Markov regime switching model. For every effect/anomaly studied, the optimal lag order and the number of regimes will be selected for each data set. After the model selection, the model parameters will be estimated and the transition probability matrices will be presented. Finally, the constant expected duration of regimes and the regime probabilities will be examined. Sections 5.2 and 5.3 discuss the January effect and the weekend effect respectively. The analysis of the size effect, the value effect and the dividend yield effect are discussed in Sections 5.4, 5.5 and 5.6, respectively. Section 5.7 concludes the chapter.

5.2 The January or Turn-of-the-Year effect

This section attempts to detect the existence, or otherwise, of the January effect using monthly returns on different indices: the All Share, Top 40, Mid Cap and Small Cap. The first phase of the empirical analysis involves the selection of the best model in terms of the optimal lag order and the appropriate number of regimes. A variety of Markov switching models are fitted with r =1 to 3 lags and k = 2 to 7 regimes[1] in the conditional mean equation. Among these 18 models, the best model is chosen based on the lowest value of the SIC recorded. Table 5.1 summarises the results of the selection for the four indices. For the ALSI, the best model determined by the

[1] r represents the number of lags and k represents the number of regimes.

SIC should have two regimes and two lags while it should have two regimes and three lags for the Top 40. In the case of the Mid Cap and the Small Cap, the best model should have two regimes and one lag (See Table 5.1).

Table 5.1 Selected Lag order and regimes for monthly stock returns

Indices	*Number of Regimes*	*Number of Lags*
ALSI	2	2
Top 40	2	3
Mid Cap	2	1
Small Cap	2	1

Source: Author's estimations

In other words, a two-regime Markov switching autoregressive (MSAR) model with lag order two is the best fit for the monthly returns on the ALSI. The best fit for the monthly returns on the Top 40 is a two-regime MSAR model with lag order three, the one for both the Mid Cap and the Small Cap is a two-regime MSAR model with one lag. When using each of these selected models, the different transition probability matrices are derived and reported in Table 5.2. The number reported in the *i*th row and the *j*th column represents the probability of observing regime *j* at time t, given that regime *i* is observed at time t-1. Note that the sum of each row is equal to one.

For the ALSI selected two-regime MSAR, the estimated mean returns of each regime are as given in the second column of Table 5.2, in parentheses. Based on these values, the two regimes will be referred as *(1)* the bull regime[2] and *(2)* the bear regime[3]. Table 5.2 shows that if the market is currently in the bull regime, there is a practically zero percent probability that it will still be in the bull regime in the next month, and there is a 100 percent chance that it will be in

[2] The bull regime refers to a period of increase in the stock prices (i.e. positive abnormal returns).
[3] The bear regime refers to a period of decrease in the stock prices (i.e. negative abnormal returns).

the bear regime in the next month. However, if the current regime is "bear" there is a 57 percent chance that the state in the next month will be the same and a 42 percent chance that it will switch to the bull regime.

Table 5.2 Transition probability matrices for monthly stock returns

Indices	*Regime at time t-1*	*Regime at time t*	
		1	*2*
ALSI	*1* *(1.920)*	2.39E-08	1.000
	2 *(-6.768)*	0.429	0.571
Top 40	*1* *(-0.357)*	0.958	0.042
	2 *(0.094)*	0.413	0.587
Mid Cap	*1* *(-0.357)*	0.246	0.754
	2 *(0.091)*	0.044	0.956
Small Cap	*1* *(-0.327)*	0.483	0.517
	2 *(0.112)*	0.046	0.954

Note: the mean returns of each regime are included in parentheses.
Source: Author's estimations

The ALSI transition probabilities already hint at the duration of the regimes. That is, it is evident that the bull regime will never last longer than a month. This is confirmed by the constant expected duration of regimes reported in Table 5.3. As can be seen for the ALSI, the bull regime only lasts a month and the bear regime lasts 2.331 months.

For the Top 40, Mid Cap and Small Cap selected two-regime MSAR models, the estimated mean returns of each regime are also as given in the second column of Table 5.2, in parenthesis. For all three models, the regimes will be referred to as *(1)* the bear regime and *(2)* the bull regime. From Table 5.2, it can be seen that if the Top 40 monthly returns are currently in the bear regime, there is 95.8 percent chance that it will remain in the same regime the following month and a 4.2 percent chance that it will be in the bull regime next month. Alternatively, if the current state is a bull regime, there is a 41.3 percent chance that it will still be a bull regime the following month and a 58 percent chance that it will be a bear regime the following month.

Table 5.3 shows that for the Top 40 monthly returns, the bear regime lasts 23.79 months while the bull regime only lasts 2.42 months. In the case of the Mid Cap monthly returns, there is a 24.6 percent probability that if the current state is a bear regime, the state in the following month will also be a bear regime, while there is a 75.4 percent probability that it will switch to a bull regime. Alternatively, the probability that it will remain in the bull regime the following month, if it is currently in the bull regime, is 95.6 percent while the probability that it will switch to the bear regime is of 4.4 percent. Contrary, to the Top 40 monthly returns, the bull regime in the Mid Cap monthly returns lasts longer (22.67 months) than the bear regime (1.33 months).

Table 5.3 Constant expected duration of regimes in the monthly stock returns

Indices	*Regimes*	
	1	*2*
ALSI	1.000	2.331
Top 40	23.788	2.422
Mid Cap	1.327	22.673
Small Cap	1.932	21.775

Source: Author's estimations

For the Small Cap monthly returns, if they are currently in the bear regime, there is a 48.3 percent chance that they will still be in the bear regime the following month while there is a 51.7 percent chance that they will switch to the bull regime. However, if the current state is a bull regime there is 95.4 percent chance that it will still be a bull regime the following month and a 4.6 percent chance that it will switch to a bear regime. Similarly to the Mid Cap returns, the bull regime in the Small Cap monthly returns lasts longer (21.78 months) than the bear regime (1.93 months).

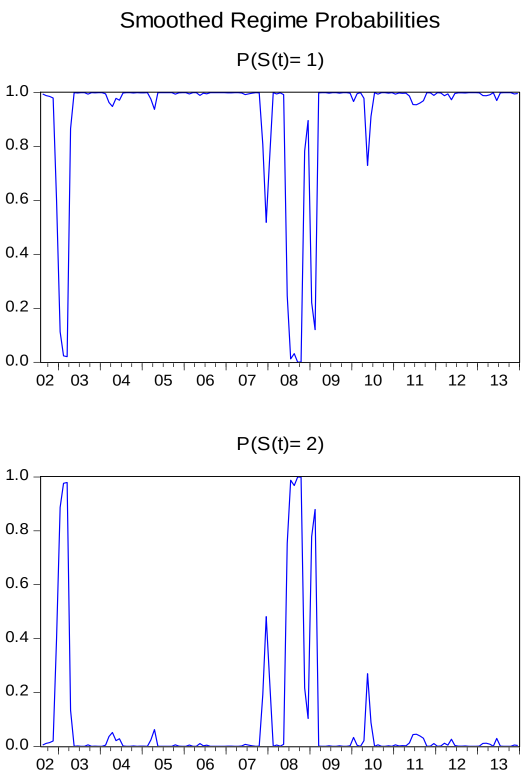
Significance for the January effect

For all the indices analysed, there are two different regimes specified by the Markov switching model: the bear and the bull regime. Figure 5.1 below shows the smoothed probability of regimes for the four indices studied. For the ALSI and the Top 40 monthly returns, most of the abnormal returns are observed between 2002 and 2003 and between 2007 and 2010 while, most of the abnormal returns on the Mid Cap and the Small Cap are observed between 2002 and 2003, in 2006 and between 2007 and 2010. The period between 2002 and 2003 covers the period after the period of global instability which led to the depreciation of the rand by 21% against the US dollar between September and December 2001. The period between 2007 and 2010 covers the period before and after the economic crisis of 2008. This predicament was caused by a subprime crisis and the burst of the housing bubble in the US leading to a great recession. The year 2010 also coincided with the year when the FIFA World Cup was held in South Africa, thus attracting investments.

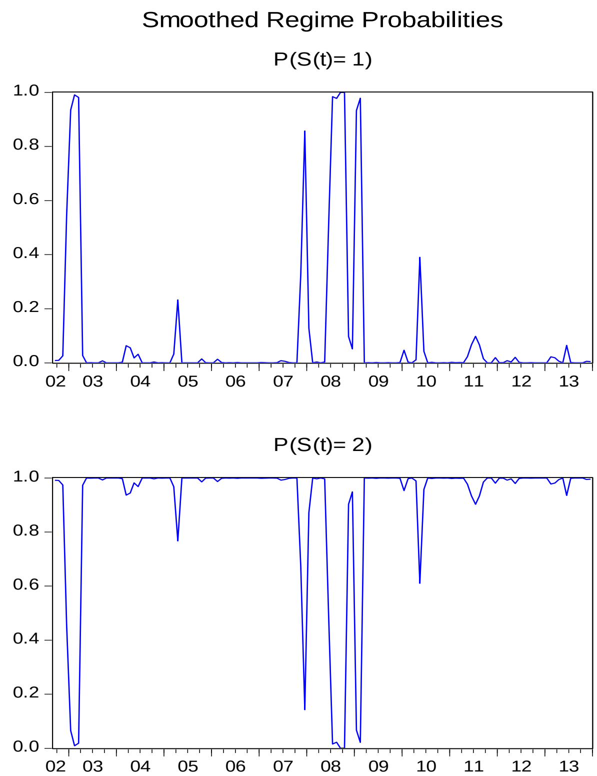
Table 5.4 gives the frequency distribution of the two regimes for all monthly stock returns. The table shows that only six of the eleven January returns on the ALSI belong to the bull regime, compared to seven in February, May, July, September and November, eight in August and November, and nine in December.

Figure 5.1 Smoothed regime probabilities for monthly returns on the four indices, 2002-2013

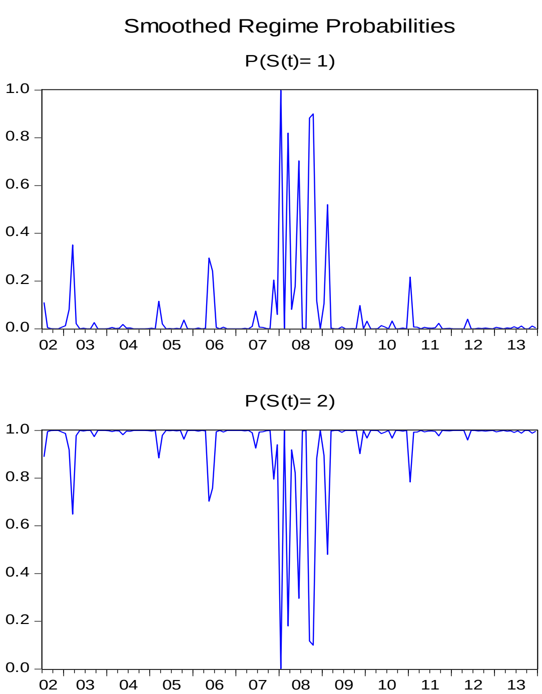
ALSI INDEX



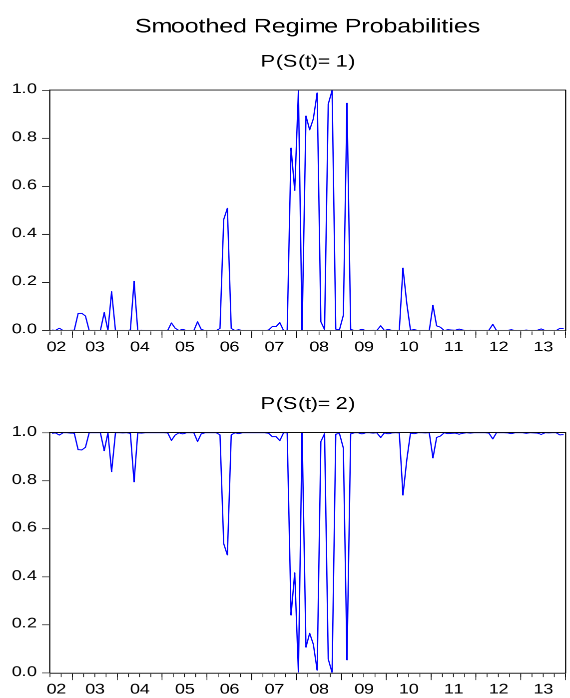
TOP 40 INDEX



MID CAP INDEX



SMALL CAP INDEX



This shows that during the period 2002 – 2013, the positive monthly returns on the ALSI were mostly not recorded in January. Since other months have higher frequencies of positive returns than the month of January there is not enough evidence of the January effect in the ALSI between 2002 and 2013.

Table 5.4 Frequency distribution of the two regimes for the four indices monthly stock returns

Indices	*Regimes*	*Jan*	*Feb*	*Mar*	*Apr*	*May*	*Jun*	*Jul*	*Aug*	*Sep*	*Oct*	*Nov*	*Dec*
ALSI	*Bull*	6	7	5	6	7	3	7	8	7	8	7	9
	Bear	5	4	6	5	4	8	4	3	4	3	4	2
Top 40	*Bull*	6	6	5	5	7	3	8	8	8	8	7	8
	Bear	5	5	6	6	4	8	3	3	3	3	4	3
Mid Cap	*Bull*	5	7	7	8	5	4	9	7	8	9	7	10
	Bear	6	4	4	3	6	7	2	4	3	2	4	1
Small Cap	*Bull*	7	8	7	9	5	5	8	9	8	8	7	9
	Bear	4	3	4	2	6	6	3	2	3	3	4	2

Source: Author's estimations

Similarly to the ALSI monthly returns, the Top 40, Mid Cap and Small Cap monthly returns do not exhibit enough evidence of the January effect since the highest frequency of positive returns are not recorded in the month of January. Alternatively, for all four indices, the month of December records the highest frequency of positive returns and the lowest frequency of negative returns. This suggests the presence of a "December or end-of-the-calendar-year effect", providing a basis for future studies. Furthermore, it can be noticed from Table 5.4 that the month of June records the highest frequency of negative returns and the lowest frequency of positive returns on all four indices, suggesting that the month of June during the period 2002 – 2013 was a bad month for investors.

5.3 The Weekend or Monday effect

In this section, daily returns of the ALSI, Top 40, Mid Cap and Small Cap covering the period 24 June 2002 – 31 December 2013 are used to study the existence, or otherwise, of the weekend effect on the JSE. To start the analysis of the weekend effect, the same procedure as the one used in the examination of the January effect is employed in order to choose the best model for the daily returns on the four indices. Table 5.5 gives the results of the selection and shows that the best model for the daily returns on the ALSI is a four-regime MSAR model with lag order 1. The best models for the daily returns on the Top 40 and the Mid Cap are five-regime MSAR models with lag order 3, and the best model for the daily returns on the Small Cap is a four-regime MSAR model with lag order 3.

Table 5.5 Selected Lag order and regimes for the daily stock returns

Indices	*Number of Regimes*	*Number of Lags*
ALSI	4	1
Top 40	5	3
Mid Cap	5	3
Small Cap	4	3

Source: Author's estimation

The transition probability matrices for the daily stock returns on all four indices, estimated using the selected models, are reported in Table 5.6. The estimated mean returns for the ALSI are as reported in parentheses in the second column of Table 5.6. Based on the values of the estimated mean returns, the four regimes will be referred as *(1)* the bear regime, *(2)* the normal regime, *(3)* the bull regime and *(4)* the negative outlier regime. The same applies to the Small Cap which also has a four-regime MSAR with estimated mean returns also reported in the table.

Table 5.6 Transition probability matrices for the daily stock returns

Indices	*Regime at time t-1*	*Regime at time t*				
		1	*2*	*3*	*4*	*5*
ALSI	*1 (-0.024)*	0.532	4.27E-69	0.226	0.242	
	2 (0.091)	2.56E-61	0.992	1.57E-47	0.0082	
	3 (2.767)	0.546	0.150	0.164	0.140	
	4 (-2.668)	0.632	4.68E-09	0.164	0.204	
Top 40	*1 (-0.023)*	0.571	0.23	0.199	1.51E-21	0
	2 (3.011)	0.485	0.166	0.108	0.146	0.096
	3 (-2.992)	0.703	0.193	0.021	3.45E-08	0.083
	4 (0.092)	1.52E-25	3.30E-16	0.003	0.992	0.005
	5 (-1.858)	3.01E-10	2.36E-94	1	5.82E-28	1.13E-09
Mid Cap	*1 (-3.319)*	0.272	8.44E-09	1.05E-18	2.08E-23	0.728
	2 (-1.381)	0.019	0.251	0.58	0.108	0.042
	3 (0.162)	0.017	0.255	0.581	1.08E-79	0.146
	4 (0.112)	1.82E-51	0.008	1.20E-46	0.992	0
	5 (1.652)	0.039	0.141	0.519	7.78E-36	0.302
Small Cap	*1 (-0.936)*	0.308	0.567	0.056	0.07	
	2 (0.131)	0.032	0.958	0.003	0.007	
	3 (-2.886)	0.222	0.569	0.107	0.102	
	4 (1.316)	7.16E-30	1	6.89E-32	0	

Note: the mean returns of each regime are included in the parentheses.
Source: Author’s estimations

Table 5.6 shows that if the ALSI is currently in the bear regime, there is an almost zero percent chance that it will be in the normal regime the following day while the chances that it will stay in the bear regime (53.2 percent) are greater than the chances that it will switch to the bull regime

(22.6 percent) or to the negative outlier regime (24.2 percent). Furthermore, while the chances of the ALSI switching from the normal regime to a bear regime, a bull regime or a negative outlier regime are very slim (2.56E-59 percent, 1.57E-45 percent and 0.82 percent, respectively), it will most likely remain in the normal regime the following day. Finally, there are greater chances that the ALSI will switch from a bull regime or a negative outlier regime to a bear regime than to any other regimes. For the Small Cap which exhibits the same number of regimes, it can be seen that there are higher probabilities that the returns will be in the normal regimes the following day, no matter which regime it is in currently. Also, the returns will never remain in the bull regime. This is confirmed by the expected duration of regimes reported on in Table 5.7. That is, in the Small Cap, the bull, negative outlier and the bear regime will only last 1, 1.12 and 1.45 days respectively, while the normal regime lasts 24 days. Similarly, the normal regime also lasts the longest for the ALSI (121.9 days).

The Top 40 and the Mid Cap both have a five-regime MSAR with estimated mean returns as given in Table 5.6. The five regimes are referred as *(1)* bear, *(2)* bull, *(3)* second negative outlier, *(4)* normal and *(5)* first negative outlier regimes in the case of the Top 40; and *(1)* negative outlier, *(2)* bear, *(3)* bull, *(4)* normal, *(5)*positive outlier in the case of the Mid Cap.

Table 5.7 Constant expected duration of regimes in the daily stock returns

Indices	*Regimes*				
	1	*2*	*3*	*4*	*5*
ALSI	2.136	121.901	1.196	1.256	
Top 40	2.331	1.198	1.022	126.004	1
Mid Cap	1.374	1.336	2.389	131.047	1.432
Small Cap	1.445	24.041	1.12	1	

Source: Author's estimations

From Table 5.6, it can be seen that in the Top 40, the returns will never switch from a bear regime to a first negative outlier regime (0 percent probability) or a normal regime (1.51E-19 percent probability). Second negative outlier regimes will most probably (a 70 percent chance) switch to bear regimes the following day and there is a 99.2 percent chance that the normal regime today will still be a normal regime tomorrow. Finally, first negative outlier regimes will always (100 percent probability) become second negative outlier regimes. In the case of the Mid Cap, if returns are currently in the negative outlier regime, there is a 72 percent chance that they will switch to the positive outlier regime the following day. Moreover, they will never switch form a normal regime to a positive outlier regime and they will most certainly (a 99.2 percent chance) remain in the normal regime the next day. Returns in the bull regime today have a 58 percent chance of remaining in the bull regime tomorrow and a 25 percent chance of switching to the bear regime.

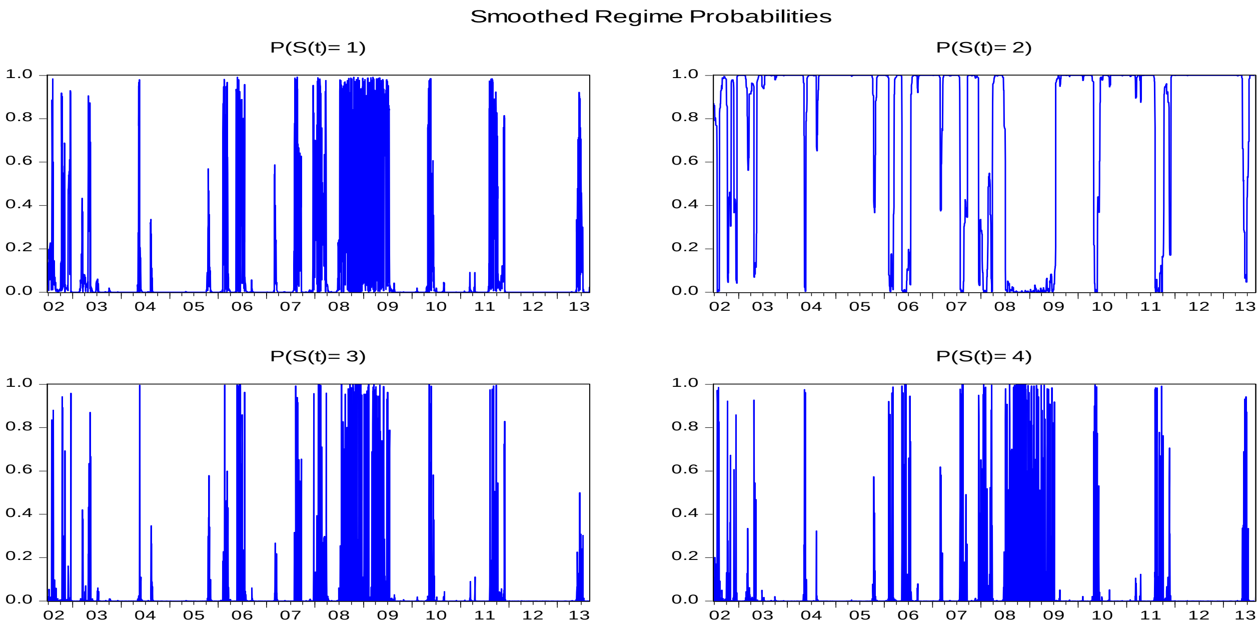
Table 5.7 shows that the longest regime is the normal regime for both the Top 40 and the Mid Cap. The other regimes will only last one or two days.

Significance for the weekend effect

Figure 5.2 below represents the smoothed regime probabilities for the daily returns on the ALSI, Top 40, Mid Cap and Small Cap index between 2002 and 2013. From the figure it can be seen that for all indices, the negative abnormal returns are most heavily concentrated during the periods 2002 - 2003, and 2007 – 2010. As explained previously, this may be due to the period of global instability which affected the rand-dollar exchange rate between September and December 2001 and also the global financial crisis of 2008 which led to a recession.

Figure 5.2 Smoothed regime probabilities for daily returns on the four indices, 2002-2013

ALSI INDEX



Top 40 INDEX

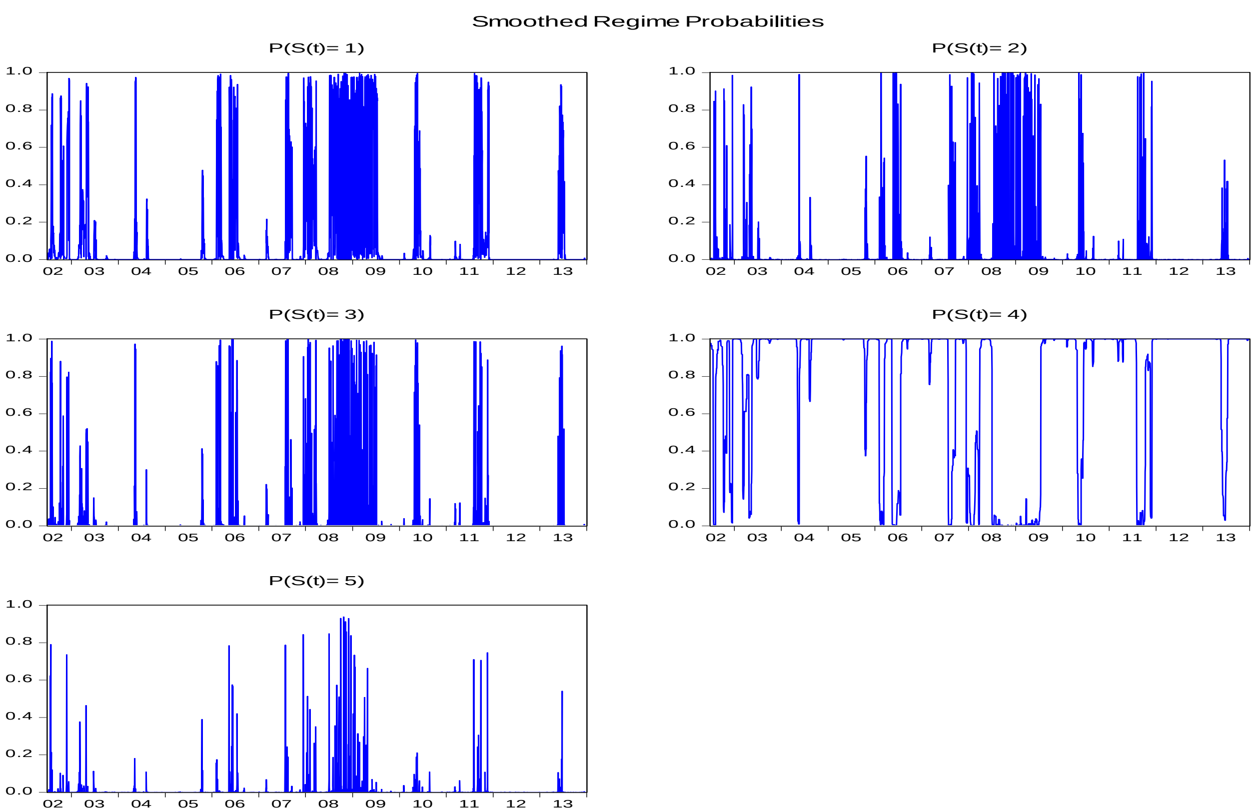
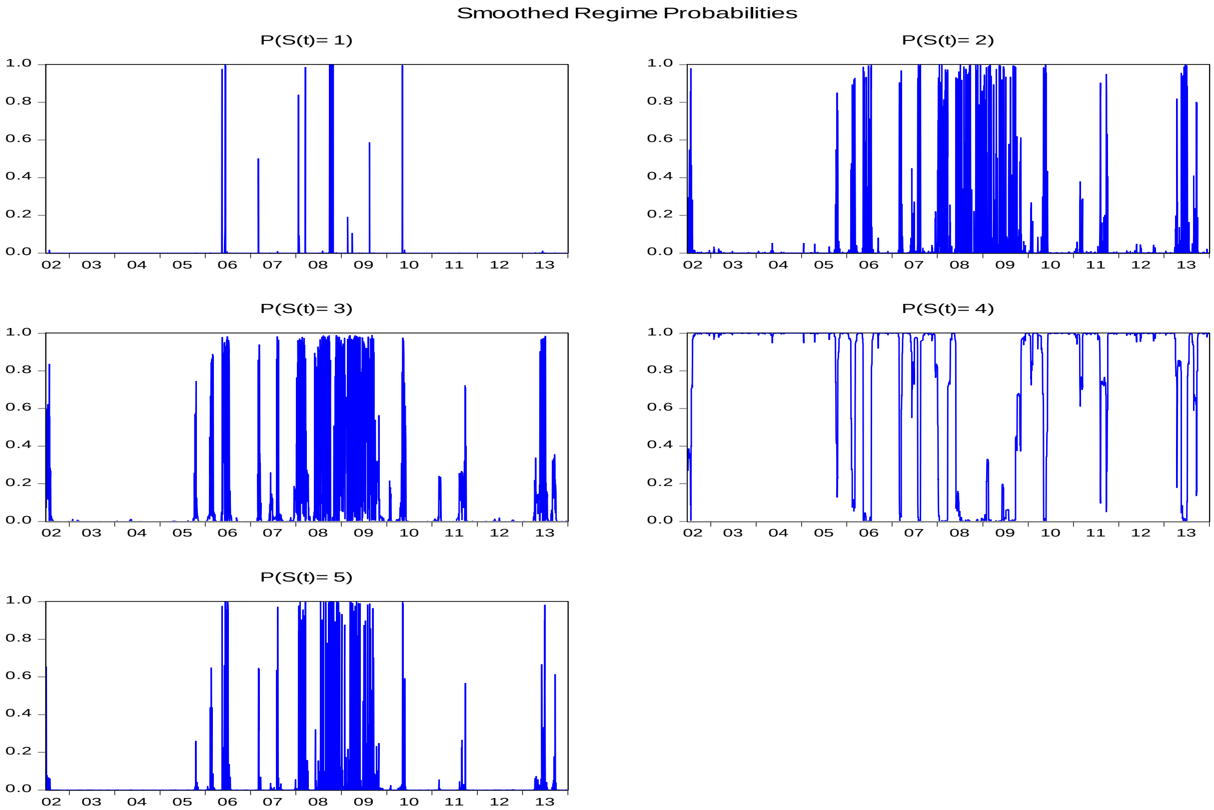


Figure 5.2 (Continued)

MID CAP INDEX



SMALL CAP INDEX

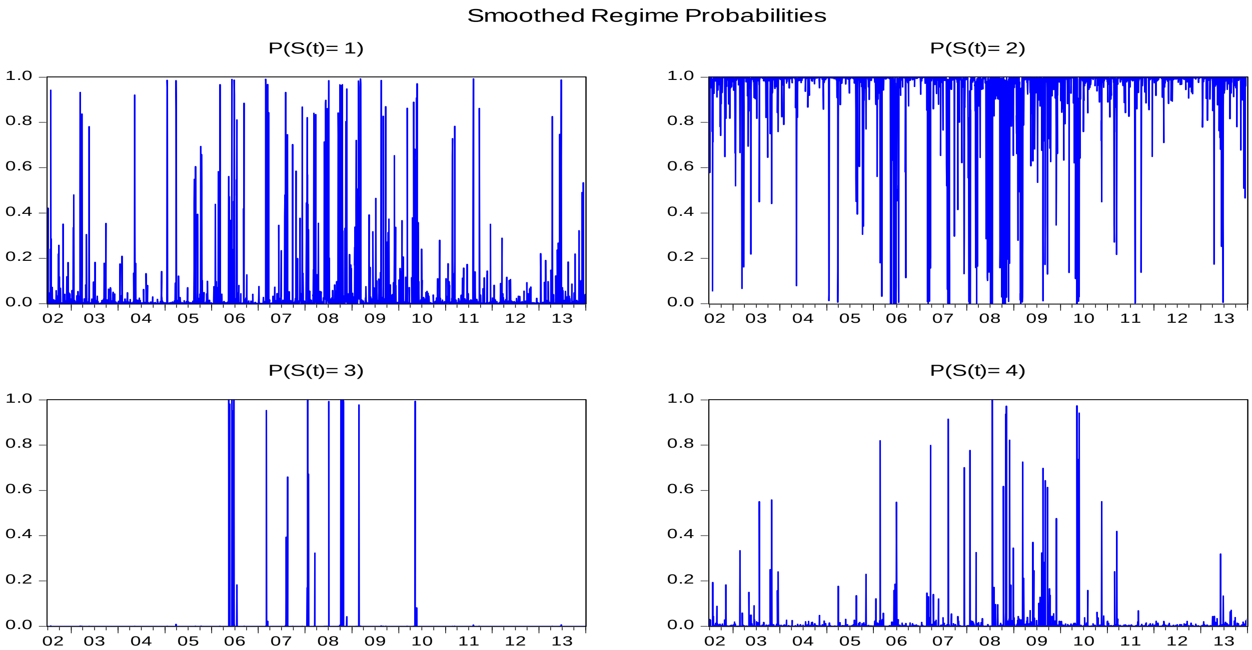


Table 5.8 reports the frequency distribution of each regime for the five business days for all four indices. The frequency distribution shows a higher frequency of negative abnormal returns on the ALSI on Fridays compared to Mondays. The same applies to the Top 40 which records a higher frequency of negative abnormal returns on Fridays than on Mondays. In both indices there is also a higher frequency of positive abnormal returns on Mondays compared to Fridays. It is therefore difficult to agree on the existence of the weekend effect on the ALSI and the Top 40 index.

Table 5.8 Frequency distribution of the regimes for the four indices daily stock returns, 2002 - 2013

Indices	*Regimes*	*Monday*	*Tuesday*	*Wednesday*	*Thursday*	*Friday*
ALSI	*Bear*	171	180	188	162	195
	Normal	213	202	192	221	202
	Bull	105	104	105	113	100
	Negative Outlier	92	98	100	88	85
Top 40	*Bear*	19	22	22	15	25
	Bull	118	121	116	134	109
	2nd Negative Outlier	44	35	32	37	32
	Normal	210	191	189	209	196
	1st Negative Outlier	208	233	244	206	238
Mid Cap	*Negative Outlier*	14	7	9	10	8
	Bear	262	259	236	227	227
	Bull	130	122	131	138	146
	Normal	64	60	66	63	67
	Positive Outlier	129	154	160	163	152
Small Cap	*Bear*	235	241	222	217	205
	Normal	240	229	248	246	278
	Negative Outlier	25	15	13	11	6
	Bull	99	117	119	127	111

Source: Author's estimations

However, the Mid Cap and the Small Cap index record a higher frequency of negative abnormal returns on Mondays compared to Fridays and a higher frequency of positive abnormal returns on

Fridays compared to Mondays. Although, Fridays did not record the highest frequency of positive abnormal returns compared to other days of the week, these results suggest the existence of the weekend effect in the Mid Cap and the Small Cap during the sample period 2002 - 2013. Note that for all indices, Thursdays seemed to be good days for investors during the sample period recording the highest frequency of positive abnormal returns.

5.4 The Size effect

In this section, the size effect is examined. Prior to estimating the model, the SMB (Small Minus Big) portfolio has to be built. The SMB portfolio is one that accounts for the spread in returns between small-sized companies and large-sized companies (in terms of market capitalisation). Thus, according to Fama and French (1993), the portfolio is long in small firms and short in big firms, while controlling for the book-to-market ratio, using the formula:

$$r_t^{SMB} = \frac{1}{3}\text{(Small Value + Small Neutral + Small Growth)} - \frac{1}{3}\text{(Big Value + Big Neutral + Big Growth)} \qquad (5.1)$$

However, the JSE already has indices built according to the size of the companies' market capitalisation. Therefore, this analysis makes use of these indices to examine the size effect. That is, the spread in returns between small-sized and large-sized companies is calculated by subtracting the monthly returns on the Top 40 index from the monthly returns on the Small Cap index for the sample period, namely, January 2003 – December 2013, thus obtaining a SMB portfolio for the same period. The SMB portfolio is compared to the overall market portfolio (i.e the ALSI) to determine the existence of the size effect. The same method used in the analysis of the previous anomalies is used to select the best model for the SMB portfolio. The results from the selection are reported in Table 5.9. The best model for the SMB, as selected by the SIC, is a two-regime MSAR with lag order 3. The model used for the ALSI is the same as the one found in the analysis of the January effect, the two-regime MSAR with lag order 2.

Table 5.9 Selected Lag order and regimes for the monthly stock returns on the ALSI and SMB portfolio

Indices	*Number of Regimes*	*Number of Lags*
ALSI	2	2
SMB	2	3

Source: Author's estimation

After estimation of the models, the transition probability matrices obtained are summarised in Table 5.10 below. The estimated mean returns are as reported in the second column of the table. The regimes will be referred as *(1)* the bear regime and *(2)* the bull regime, and vice versa for the ALSI.

Table 5.10 Transition probability matrices for the monthly stock returns on the ALSI and SMB portfolio

Indices	*Regime at time t-1*	*Regime at time t*	
		1	*2*
ALSI	*1* *(1.920)*	2.39E-08	1
	2 *(-6.768)*	0.429	0.571
SMB	*1* *(-0.303)*	0.665	0.335
	2 *(0.048)*	0.023	0.977

Note: the mean returns of each regime are included in the parentheses.
Source: Author's estimations

From Table 5.10, it can be seen for the SMB portfolio returns that there is a 66.5 percent chance that if the current regime is a bear regime, it will still be a bear regime the following month and a 33.5 percent chance that it will switch to a bull regime. Similarly, the returns will most probably (a 97.7 percent chance) still remain in a bull regime the following month than shift to a bear regime (a 2.3 percent chance). To confirm the suggestions made by the transition probabilities, the expected duration of the regimes are reported in Table 5.11.

Table 5.11 Constant expected duration of regimes in the monthly stock returns on the ALSI and SMB portfolio

Indices	*Regimes*	
	1	*2*
ALSI	1	2.332
SMB	2.987	43.498

Source: Author's estimations

It can be noticed that the bull regime lasts longer (43.498 months) for the returns on the SMB portfolio than for the returns on the ALSI (one month), while the bear regime only lasts 2.99 days.

Significance for the size effect

Although it is tempting to deduce the existence of the size effect from the expected duration of the different regimes, it is relevant to examine the frequency distribution for both the SMB portfolio and the ALSI, in Table 5.12.

Table 5.12 Frequency distribution of the regimes for the ALSI and the SMB portfolio monthly stock, 2003 – 2013

Indices	*Regimes*	*Jan*	*Feb*	*Mar*	*Apr*	*May*	*Jun*	*Jul*	*Aug*	*Sep*	*Oct*	*Nov*	*Dec*	***Total***
ALSI	*Bull*	6	7	5	6	7	3	7	8	7	8	7	9	**80**
	Bear	5	4	6	5	4	8	4	3	4	3	4	2	**52**
SMB	*Bull*	6	8	5	6	4	6	5	6	8	7	5	7	**73**
	Bear	5	3	6	5	7	5	6	5	3	4	6	4	**59**

Source: Author's estimation

From the above table, it can be seen that although the total frequency of positive returns on the SMB portfolio is lower than that of the ALSI, it is still greater than the total frequency of negative returns. In other words, small-sized companies yielded higher returns than large-sized companies. This confirms the existence of the size effect between 2003 and 2013. The month of May was a bad month for investors during the sample period with the SMB portfolio recording the highest frequency of negative returns while the months of February and September were good months, with the portfolio recording the highest frequency positive returns.

5.5 The Value effect

When examining the value effect, Fama and French (1993) introduced the use of the HML portfolio. HML stands for High Minus Low and represents the spread in returns between value and growth stocks. In this instance, the portfolio is long in firms with a high book-to-market ratio and short in firms with a low book-to-market ratio, while controlling for size. To the compute the HML portfolio, Fama and French (1993) propose the formula:

$$r_t^{HML} = \frac{1}{2}\text{(Small Value + Big Value) - }\frac{1}{2}\text{(Small Growth + Big Growth)} \qquad (5.2)$$

Since the JSE already has indices built according to the companies' book-to-market ratio, those indices will be used to build the HML portfolio for this study. Thus, the daily returns on the Growth index are subtracted from the daily returns on the Value index covering the sample period 5 January 2004 – 31 December 2013.

Again the same method as before is used to select the appropriate model for the daily returns on the HML portfolio. The selected models, as per the SIC, are five-regime MSAR models with lag order 1 for both the HML portfolio and the ALSI (See Table 5.13)

Table 5.13 Selected lag order and regimes for the daily stock returns on the ALSI and HML portfolio

Indices	*Number of Regimes*	*Number of Lags*
ALSI	5	1
HML	5	1

Source: Author's estimation

The selected models produced the transition probabilities shown in Table 5.14. The estimated mean returns are as reported in the second column of the table.

Table 5.14 Transition probability matrices for the daily stock returns on the ALSI and HML portfolio

Indices	*Regime at time t-1*	*Regime at time t*				
		1	*2*	*3*	*4*	*5*
ALSI	*1* *(4.96)*	0.135	0.391	0	0.08	0.394
	2 *(1.7)*	0.022	0.274	0.075	0.086	0.543
	3 *(0.107)*	0	0	0.992	0.008	0
	4 *(-2.971)*	0.038	0.284	0	0.112	0.566
	5 *(-0.552)*	0.024	0.382	0	0.219	0.375
HML	*1* *(-38.186)*	0	0	0	1	0
	2 *(0.057)*	0	0	1	0	0
	3 *(-0.198)*	0	0.237	0.165	0.565	0.0322
	4 *(0.115)*	0	1	0	0	0
	5 *(2.95)*	1.80E-130	3.51E-10	0.675	0	0.325

Note: the mean returns of each regime are included in parentheses.
Source: Author's estimation

In the case of the ALSI, the five regimes are referred as: *(1)* the positive outlier regime, *(2)* the bull regime, *(3)* the normal regime, *(4)* the negative Outlier regime and *(5)* the bear regime. In the case of the HML portfolio, they are *(1)* the negative outlier regime, *(2)* the normal regime, *(3)* the bear regime, *(4)* the bull regime and *(5)* the positive outlier regime.

Table 5.14 shows that for the ALSI there are almost equal probabilities that the returns will switch from a positive outlier regime to a bull regime (a 39.1 percent chance) or a bear regime (a 39.4 percent chance). However, the positive outlier regime will never become a normal regime (a zero percent chance) the following day. The normal regime will most probably (a 99.2 percent chance) still be a normal regime the following day and has no chance of switching to any other regime. Similarly, if the returns are currently in the bear or the negative outlier regime, there is no chance that they will switch to the normal regime the following day. In the case of the HML portfolio, if the returns are currently in the negative outlier regime, they will always switch to a bull regime the following day, while if they are in the normal regime they will always switch to the bear regime the following day. Furthermore, returns in the bull regime will always switch to the normal regime the following day. A current bear regime has more chances of becoming a bull regime (56.5 percent probability) than a normal regime (23.7 percent probability) the following day and a current positive outlier regime has more chance of becoming a bear regime (67.5 percent probability) than remaining the same (32.5 percent probability).

Table 5.15 Constant expected duration of regimes in the daily stock returns on the ALSI and HML portfolio

Indices	*Regimes*				
	1	*2*	*3*	*4*	*5*
ALSI	1.156	1.378	122.51	1.125	1.6
HML	1	1	1.198	1	1.482

Source: Author’s estimations

From Table 5.15, it can be seen that, for the HML portfolio, all regimes last about a day, while for the ALSI, the normal regime is the longest (122.51 days).

Significance for the value effect

Again, the frequency distribution of the regimes is examined for the daily stock returns on the ALSI and the HML portfolio between 2004 and 2013. The values are summarised in Table 5.16.

Table 5.16 Frequency distribution of the regimes for the ALSI and the HML portfolio daily stock returns, 2004 – 2013

Indices	*Regimes*	*Monday*	*Tuesday*	*Wednesday*	*Thursday*	*Friday*	***Total***
ALSI	*Negative Outlier*	35	23	23	28	23	**132**
	Bear	196	213	214	177	223	**1023**
	Normal	102	102	99	106	98	**507**
	Bull	147	144	137	171	144	**743**
	Positive Outlier	24	22	31	22	15	**114**
HML	*Negative Outlier*	195	185	192	186	180	**938**
	Bear	73	73	68	62	79	**355**
	Normal	50	45	36	42	43	**216**
	Bull	123	134	136	152	141	**686**
	Positive Outlier	81	85	89	79	78	**412**

Source: Author's estimations

As can be seen from the above table, the total frequency of negative abnormal returns on the HML portfolio is greater than the total frequency of positive abnormal returns. This implies that during the sample period 2004 – 2013 there were more negative than positive returns on the portfolio. In other words, "value" firms (firms with higher book-to-market ratio) yielded lower returns than "growth" firms (firms with lower book-to-market ratio). This contradicts the theory of the value effect and leads to the conclusion that the effect did not exist on the JSE during the period 2004 – 2013.

5.6 The Dividend Yield effect

The theory of the dividend yield effect stipulates that the dividend yield of a company affects its stock price. Therefore, in order to analyse the dividend yield effect, two MSAR models will be estimated; the first one specifying the dividend plus as a dependent variable and the ALSI as a regressor and the second one specifying the ALSI as a dependent variable and the dividend plus as a regressor. The best models are selected still using the SIC and are specified in Table 5.17 below. The first model is a four-regime MSAR model with lag order 1 and the second one is a five-regime MSAR model with lag order 1.

Table 5.17 Selected Lag order and regimes for the daily stock returns on the ALSI and Dividend plus index

Dependent variable	*Number of regimes*	*Number of lags*
Dividend yield	4	1
ALSI	5	1

Source: Author's estimations

After estimating the models, the transition probabilities and the specified equations for the first model are as follows:

1: DIVIDEND_PLUS = 0.60*ALSI + 0.334 + [AR(1)=0.078] (5.3)

2: DIVIDEND_PLUS = 0.631*ALSI + 2.300 + [AR(1)=0.078] (5.4)

3: DIVIDEND_PLUS = 0.672*ALSI + 0.004 + [AR(1)=0.078] (5.5)

4: DIVIDEND_PLUS = 0.750*ALSI – 1.410 + [AR(1)=0.078] (5.6)

The estimated mean returns are as reported in parentheses in Table 5.18. The four regimes will then be: *(1)* the bull regime, *(2)* the positive outlier regime, *(3)* the normal regime and *(4)* the bear regime. From Table 5.18, it can be seen that if the returns on the dividend plus are currently in the bull regime, there are more chances that they will remain in the bull regime (66.3 percent probability) than change to a bear regime or a positive outlier regime (20.5 percent probability and 12.5 percent probability, respectively); and almost no chance that they will switch to a normal regime. If currently in a normal regime, the returns will most probably remain in a normal regime the following day. Also, there are more chances of a positive outlier regime or a bear regime changing to a bull regime the following day (54.2 percent and 59.6 percent, respectively) than of them changing to a bear regime (25.5 percent and 37.8 percent, respectively).

Table 5.18 Transition probability matrices for the daily stock returns on the ALSI and dividend plus index

Indices	*Regime at time t-1*	*Regime at time t*				
		1	*2*	*3*	*4*	*5*
Dividend Plus	*1 (0.334)*	0.663	0.125	0.007	0.205	
	2 (2.300)	0.542	0.111	0.094	0.253	
	3 (0.004)	9.89E-82	4.20E-106	0.998	0.002	
	4 (-1.410)	0.596	0.026	2.79E-10	0.378	
ALSI	*1 (0.026)*	0.977	0.003	0.01	0.01	0
	2 (-2.009)	0.1	0.3	0	0.212	0.388
	3 (-0.022)	0.017	0	0.983	0	2.63E-05
	4 (1.089)	0.167	0.255	0	0.316	0.262
	5 (0.141)	0	0.343	0	0.513	0.144

Note: the mean returns of each regime are included in parentheses.
Source: Author’s estimations

Considering the second model, the specified equations are the following:

1: ALSI = 0.874*DIVIDEND_PLUS + 0.026 + [AR(1)=-0.068] (5.7)

2: ALSI = 0.753*DIVIDEND_PLUS - 2.009 + [AR(1)=-0.068] (5.8)

3: ALSI = 1.219*DIVIDEND_PLUS - 0.022 + [AR(1)=-0.068] (5.9)

4: ALSI = 0.587*DIVIDEND_PLUS + 1.089 + [AR(1)=-0.068] (5.10)

5: ALSI = 1.906*DIVIDEND_PLUS + 0.141 + [AR(1)=-0.068] (5.11)

Thus, the five regimes are referred as: *(1)* the normal regime, *(2)* the negative outlier regime, *(3)* the bear regime, *(4)* the positive outlier regime and *(5)* the bull regime. As can be seen in Table 5.18, for the returns on the ALSI, a normal regime will most probably (a 97.7 percent chance) remain "normal" the next day and a bear regime will probably (a 98.3 percent chance) still be a bear regime the next day. There is no chance of a normal regime becoming a bull regime, of normal, positive outlier or bull regimes becoming bear regimes and of a bear regime becoming any of the other regimes, the following day.

Table 5.19 Constant expected duration of regimes in the daily stock returns on the ALSI and dividend plus index

Indices	*Regimes*				
	1	*2*	*3*	*4*	*5*
Dividend Plus	2.97	1.125	413.03	1.607	
ALSI	43.99	1.43	57.613	1.462	1.168

Source: Author's estimations

From the expected duration of regimes summarised in Table 5.19, it can be seen that the normal regime lasts the longest for the returns on the dividend plus index (413.03 days) while the bull regime lasts almost three days and the other regimes each last about a day. For the returns on the ALSI the bear regime lasts the longest (57.613 days), followed by the normal regime (43.99 days). The other regimes each only last about a day.

Significance for the dividend yield effect

In order to examine the relationship between the dividend plus and the ALSI, the granger causality/block exogeneity test is conducted. The results are summarised in Table 5.20. The null hypotheses tested are: *(1)* changes in the returns on the dividend plus do not Granger cause changes in the returns on the ALSI and, *(2)* changes in the returns on the ALSI do not Granger cause changes in the returns on the dividend plus.

Table 5.20 Granger Causality/Block exogeneity test

Null Hypothesis:	*F-Statistic*	*p-value*
DIVIDEND_PLUS does not Granger Cause ALSI	1.62639	0.2024
ALSI does not Granger Cause DIVIDEND_PLUS	1.66323	0.1973

Source: Author's estimations

For both hypotheses, the p-values are greater than 0.01, 0.05, and 0.1. Therefore, the null hypotheses cannot be rejected at the 10 percent level of significance. It can then be concluded that the change in the returns on the dividend plus Granger causes the change in the returns on the ALSI and the change in the returns on the ALSI Granger causes the change in the returns on the dividend plus. This conclusion effectively confirms the existence of the dividend yield effect on the JSE during the period 2006 – 2013.

5.7 Conclusion

This chapter presented the empirical analysis conducted to study the existence of the January effect, the weekend effect, the size effect, the value effect and the dividend yield effect on the JSE.

The examination of the January effect was conducted using monthly returns on the ALSI, Top 40, Mid Cap and Small cap index between 2002 and 2013. In all instances, two regimes were detected, the bull and the bear regimes. It was found that, although the total frequency distribution of positive returns in January was greater than the total frequency distribution of negative returns, the month of January did not exhibit the highest frequency of positive returns compared to other months of the year. The month of December, however, represented the most favourable month with the highest frequency of positive returns. These findings contradict the idea behind the January effect, leading to the conclusion that there was no January effect on the JSE between 2002 and 2013.

When examining the weekend effect, the analysis was done using daily returns on the ALSI, Top 40, Mid Cap and Small Cap index between June 2002 and December 2013. For the ALSI and the Small Cap index, four-regime MSAR models were selected and for the Top 40 and the Mid Cap index, five-regime MSAR models were selected. It was found that the weekend effect did not exist on the ALSI and the Top 40 index during the sample period since the frequency of positive returns on both indices were higher on Mondays compared to Fridays and the frequency of negative returns on both indices were higher on Fridays compared to Mondays; this contradicts the idea of the weekend effect. However, the opposite situation was found on the Mid Cap and Small Cap index returns suggesting the existence of the effect on both indices during the sample period.

Concerning the size effect, a SMB portfolio was built using the monthly returns on the Small Cap index and the Top 40 index. The returns on that portfolio were found to exhibit two regimes, of which the one grouping the positive abnormal returns recorded a higher frequency than the regime representing the negative abnormal returns. This led to the conclusion that the size effect existed on the JSE during the period 2003 – 2013.

Additionally, the value effect analysis was led by the computation of a HML portfolio, using the daily returns on the Value index and the Growth index for the period 2004 - 2013. The returns on the HML portfolio exhibited five regimes of which two were constituted of positive abnormal returns and two included negative abnormal returns. It was found that the total frequency of negative abnormal returns was higher than the frequency of positive abnormal returns. Therefore, the value effect was not present on the JSE during the sample period.

Finally, the Granger causality test help determine that there is a relationship of causality between the dividend plus and the ALSI. That is, the change in the returns on the dividend plus Granger causes the change in the returns on the ALSI and vice versa. This result confirmed the existence of the dividend yield effect on the JSE between 2006 and 2013.

CHAPTER SIX

CONCLUSION

6.1 Summary of findings

A rising trend towards investment in financial instruments constitutes one of the many reasons fuelling the current growing interest in studying financial markets. With the ever-increasing level of globalisation, emerging markets are more targeted now than they were decades ago. This is more so for the South African market as it is one of the most developed markets in the world. The main objective of this dissertation was to determine the level of efficiency of the South Africa Securities exchange by exploring the existence of some calendar effect and market anomalies on the Johannesburg Stock Exchange.

The anomalies chosen to be examined in this dissertation were the January, weekend, size, value and dividend yield effect, in order to contribute to the existing literature on the South African securities exchange. In a preliminary investigation of the existence of the varying calendar effects on the JSE, descriptive statistics of the data were examined. The results indicated the non-normality of the distributions of returns for all the indices considered, which is consistent with the theory of financial instruments. Besides the weekend effect, detected in the Mid Cap and the Small Cap index through a significant difference in mean returns between Mondays and the other days of the week, none of the other effects investigated were detected.

A more formal empirical analysis made use of the Markov regime switching model with fixed transition probabilities between the regimes. Firstly, in analysing the January effect, using monthly returns on the ALSI, Top 40, Mid Cap and Small cap index between 2002 and 2013, two-regime MSAR regimes were detected with lag order two, three one and one for the ALSI, Top 40, Mid Cap and Small Cap index respectively. Since, the month of January did not exhibit the highest frequency of positive returns compared to other months of the year and the month of December had the highest frequency of positive returns, it was concluded that there was no January effect on the JSE between 2002 and 2013. This result is inconsistent with the results found by Jooste (2006) who, using dummy variables in a linear modelling framework, presented evidence of the existence of the January effect on the JSE's ALSI, Top 40, Mid Cap and Small Cap between 1995 and 2006. However, it is similar to the conclusions made by Gultekin and Gultekin (1983) as well as Auret and Cline (2011) in their study of the South African stock market in the sample period 1996-2006, therefore providing some continuity.

Secondly, the weekend effect was examined using daily returns on the ALSI, Top 40, Mid Cap and Small Cap index between June 2002 and December 2013 and four-regime MSAR models were selected for the ALSI and the Small Cap, while five-regime MSAR models were selected for the Top 40 and the Mid Cap. It was found that the weekend effect did not exist on the ALSI and the Top 40 index during the sample period, since the frequency of positive returns on both indices were higher on Mondays compared to Fridays and the frequency of negative returns on both indices were higher on Fridays compared to Mondays. However, the weekend effect was found on the Mid Cap and Small Cap index returns during the sample period, with the frequency of positive returns on both indices being higher on Mondays compared to Fridays and the frequency of negative returns on both indices being higher on Fridays compared to Mondays.

These results concord with Jooste's (2006) findings, although the author found evidence of the weekend effect in all seven indices studied between 1995 and 2006. The conclusion also conforms the fact, highlighted by Jooste (2006), that the weekend effect pattern in South Africa is the inverse of the common pattern witnessed in various international markets such as the Asian markets between 1998 and 2002.

Thirdly, a SMB portfolio was built using the monthly returns on the Small Cap index and the Top 40 index in order to examine the size effect. The returns on that portfolio were found to exhibit two regimes, of which the one grouping the positive abnormal returns recorded a higher frequency than the regime representing the negative abnormal returns. This led to the conclusion that the size effect existed on the JSE during the period 2003 – 2013. However, when looking at the frequency distribution, for individual months, the month of January does not exhibit the highest frequency of positive returns compared to the other months. This shows that the January-size effect is not present on the JSE. The existence of the size effect on the JSE confirms the idea behind Fama and French's (1993) three-factor model pertaining to the importance of size and book-to-market ratio as proxies for the influence of two additional risk factors omitted in the CAPM, although more recent studies in the USA (Schwert, 2003) suggest that the size effect may have disappeared from the market since its initial discovery. Similar to the conclusion drawn by Schwert (2003), Auret and Cline's (2011) conclusion was opposing to the results found in this study, which may be due to the difference in the sample period covered and the database as only the ALSI was used in that study.

Fourthly, a HML portfolio was built, using the daily returns on the Value index and the Growth index for the period 2004 – 2013 in order to analyse the value effect. The returns on the HML portfolio exhibited five regimes of which two were constituted of positive abnormal returns and two included negative abnormal returns. The total frequency of negative abnormal returns was higher than the frequency of positive abnormal returns on the HML portfolio, leading to the conclusion that value effect was not present on the JSE during the sample period. These results, however, contradict the idea behind the Fama and French's (1993) three-factor model and are inconsistent with the evidence presented by Fama and French (1993) that justifies the existence of the value effect in 13 countries between 1975 and 1995. These results are also contradictory to the findings of Guidolin and Timmerman (2008) who found statistically significant differences in the joint distribution of returns on a stock market portfolio and portfolios tracking size and value effects in the USA using regime shifts between 1927 and 2005.

Finally, to examine the dividend yield effect, two MSAR models were run using the daily returns on the dividend plus index and the ALSI during the sample period 2006 – 2013. The first model was a four-regime MSAR model with lag order one, where the dividend plus was specified as the dependent variable and the ALSI as a regressor. The second model was a five-regime MSAR model with lag order one, where the ALSI was the dependent variable and the dividend plus was a regressor. The Granger causality test concluded that the change in the returns on the dividend plus Granger causes the change in the returns on the ALSI and vice versa. This result confirmed the existence of the dividend yield effect on the JSE between 2006 and 2013. The causality found between the returns on the dividend plus and the returns on the ALSI effectively complements the conclusions drawn by Fama and French (1988) and Campbell and Shiller (1988) which highlighted the importance of the relationship between the forecasting power of the dividend yield and the return horizon.

6.2 Implications and Recommendations

The results of the empirical analysis conducted suggest important implications for investors and fund managers. Firstly, the existence of the weekend effect, the size effect and the dividend yield effect on the JSE contribute to confirm the idea that market anomalies are mostly present in emerging markets. Therefore this provides an opportunity for investors and fund managers to make returns above buy-and-hold, if they are able to devise appropriate trading rules to take advantage of this opportunity.

6.3 Limitations of the study and areas of further research

The unavailability of values for business days which were holidays imposed the use of interpolation to replace the missing values. This increases the risk of data mining.

Since the Markov switching model is not a common tool employed in the study of stock market seasonalities, it could be interesting to compare the robustness of its results to those of more popular econometric tools such as the OLS model and the use of dummy variables in a linear modelling framework.

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APPENDIX

Table 1 Summary of empirical literature on the calendar effects

Author(s), Year	Countries	Study Period	Model and Method of estimation	Variable Included	Key findings
Aggarwal, R. and Schatzberg, J.D. 1997	United States	1980 - 1993	ANOVA and nonparametric Kruskal-Wallis procedures	Daily return data, dividend announcement dates and yearly equity valuations.	Significant day of the week variation in deviations from normality, and the inverse relationship of such deviations with firm size are documented. The market model residuals around dividend and earnings announcements to be significantly non-normal with higher kurtosis, indicating that impact of information and, there is limited support for the impact of such announcements on the day of the week pattern of higher moments.

Alagidede, P. 2012	Nigeria, Kenya, Tunisia, Morocco, South Africa, Egypt and Zimbabwe	Egypt: July 1997 - September 2006 Kenya: January 1990 - September 2009 Morocco: January 2002 - October 2006 Nigeria: January 1990 - September 2009 S. Africa: July 1997 - October 2006 Tunisia: December 1997 - September 2009 Zimbabwe: June 1995 - September 2006	OLS with dummy variables, GARCH	Monthly stock prices: NSE All Share Index (Nigeria), NSE20 index (Kenya), Tunnindex (Tunisia), MASI index (Morocco), FTSE/JSE All Share index (South Africa), CASE30 Share Index (Egypt), ZSE Industrial index (Zimbabwe)	The pre-holiday effect is present in South Africa only, and is not applicable to the other stock markets in the sample. January returns are positive and significant for Egypt, Nigeria and Zimbabwe. February returns are higher for Kenya, Morocco and South Africa. Tunisia has no monthly seaonalities.
Ariss, R.T., Rezvanian, R. and Mehdian, S.M. 2011	Gulf Cooperation Council: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, United Arab Emirates	From inception until June 2008	OLS	Daily closing values of all GCC market indices, daily percentage return of stock index	Returns are positive and significant on the last trading day of the week, in line with the literature for Western markets. However, this calendar anomaly does not occur on Fridays, but rather on Wednesdays, and it is more pronounced during non-Ramadan days. While there is no significant difference in

					returns across the Hijiri lunar calendar months, the volatility of returns is significantly reduced during the month of Ramadan.
Balint, C. and Gica, O. 2012	Romania	January 2003 - December 2010	ARCH and GARCH	Monthly closing prices for 30 companies listed on the Bucharest Stock Exchange	On the Romanian market, the January effect occurs before the financial crisis, but during the crisis, due o lower share price, negative values were obtained. Regarding the January effect, it has been observed that during the crisis only for the third portfolio (small-cap), the effect was present, for the other portfolios only negative values were obtained.

Bartholdy, J. and Peare, P. 2004	United States	1970 - 1996	One-factor model (CAPM) and Fama and French three-factor model.	Daily adjusted prices extracted from the CRSP tapes. Daily and Weekly returns. Daily, weekly and monthly yields on 3 months T-bills were used for the risk-free rate for the time series regression, and the yield on 12 month T-bills for the dependent variable in the cross-section regressions	Results from the CAPM model show that 5 years of monthly data and an equal-weighted index provide the best estimate, as opposed to the commonly recommended value-weighted index. However, the model performs very poorly and only explains on average 3% of differences in returns. Estimates obtained based on the Fama and French model show that the model does not do much better because it only explains on average 5% of differences in returns, independent of the index used.
Berument, H., Coskun, M.N. and Sahin, A. 2006	Turkey	12 March 2001 - 22 November 2005	EGARCH	The Turkish lira value of the US dollar, dummy variables for Monday, Tuesday, Thursday, Friday.	Thursdays are associated with higher and Mondays with lower depreciation rates compared to those of Wednesdays. Mondays and Tuesdays are associated with higher volatility than

					Wednesdays.
Borges, M.R. 2009	Austria, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Netherlands, Norway, Poland, Portugal, Spain, Switzerland and United Kingdom.	January 1994 - December 2007	Bootstrap and GARCH (1,1) models	Daily return of the stock market index for each country under consideration: ATX (Austria), OMXC20 (Denmark), OMXHPI(Finland), CAC40(France), DAX(Germany), ASE (Greece), Hungary (BUX), OMXIPI(Iceland), ISEQ (Ireland), MIBTEL (Italy), AEX (Netherlands), OSEAX (Norway), WIG (Poland), PSI20 (Portugal), IBEX (Spain), SMI (Switzerland) and FTSE (UK).	Although returns tend to be lower in the months of August and September, there is no strong evidence of across-the-board calendar effects. The stronger country-specific calendar effects are not stable over the whole sample period, casting doubt on the economic significance of calendar effects.

Charles, A. 2009	France, Germany, US, UK, Japan	7 July 1987 - 27 July 2007	GARCH family models from a forecast framework	CAC40 (France, DAX 30 Germany, DIJA (US), FTSE 100 (UK), NIKKEI 225 (Japan)	The choice of the volatility model seems to play an important role in detecting the day-of-the-week effects on volatility because the results differ depending on the model used. The asymmetry does not seem to influence the seasonal effects. The existence of calendar effects might be interesting only if their incorporation in a model results in better volatility forecasts.

Chen, H., Estes, J. and Ngo, T. 2011	United States	1990 - 2009	Generalized method of moments.	Municipal bond returns, bond fund flows	There is evidence of tax calendar-related rational opportunistic trading patterns by fund investors and fund managers. Fund shareholders conduct tax-loss selling in December and re-invest in January. In April, June and September, fund investors rationally cherry pick to sell their shares of short-term bond funds instead of their shares of long-term bond funds to raise cash to pay estimated taxes. Unlike fund shareholders, fund managers adopt a contrarian strategy of buying in December and selling in January.

Chong, R., Hudson, R., Keasey, K. and Littler, K. 2005	United States, United Kingdom, Hong Kong	January 1973 - July 2003	Time series regressions including dummy variables	Daily index return: S&P500 (US), FT30 (UK), Hang Seng Index (Hong Kong). A dummy variable equal to 1 if date t is a pre-holiday day , and 0 otherwise.	The results indicate a decline of the pre-holiday effect in all three markets, although it is only statistically significant for the U.S. until the late 1990s. There is a reversal of the effect in the period 1991 - 1997, with the mean return on pre-holiday days actually becoming negative, and the subsequent elimination of this negative effect in the final period of 1997 - 2003.
Diaconasu, D.E., Mehdian, S. and Stoica, O. 2012	Romania	2000 - 2011	Dummy variable regression and first-order autoregressive process	Daily closing values of Bucharest Exchange Trading (BET) and Bucharest Exchange trading - Composite (BET-C) indexes	While there is the presence of Thursday effect, there is no Monday of January effect for the entire sample period. Also, the January effect is observed during the pre-crisis period. However, the subsample analysis provides very different results, perhaps due to increasing degree of capital market

					maturity, EU accession and other events such as the financial crisis.
Floros, C. and Salvador, E. 2013	United Kingdom, Greece, United States	2004 - 2011	Regime-Switching model	Daily data from FTSE100 (UK), FTSE?ASE-20 (Greece), S&P500 (US), Nasdaq100 (US) spot and future indexes.	There are differences in the seasonal patterns in cash and futures indexes due to the existence of basic risk. Calendar effects are also conditioned to the market situation. During a low volatile situation these calendar effects tend to be positive, but these effects turn negative if the market is under a high volatile period.

Gultekin, M.N. and Gultekin, N.B. 1982	Australia, Austria, Belgium, Canada, Denmark, France, Germany, Italy, Japan, Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, UK, USA	CIP Indices: January 1959- December 1979 IFS Indices: January 1947 - December 1979	Friedman's test to investigate the seasonality in the stock market for the whole sample. Kruskal-Wallis test to analyse the seasonality of stock market returns for individual countries.	monthly stock market returns (first log differences of price indices)	Strong seasonality in the stock market returns in most of the countries. In countries where there are no capital gains, there is either no seasonality in stock returns or, if there is seasonality, large mean returns are not related to the beginning of the tax year.
Hansen, P.R. and Lunde, A. 2003	Denmark, France, Germany, Hong Kong, Italy, Japan, Norway, Sweden, UK and USA	As far back as the data were available - 06 May 2002	χ^2 test	Denmark: KFX index; France: CAC40, SBF120 index, MIDCAC index Germany: DAX 30, MIDAX, DAX 100 Hong Kong: Hang Seng Composite Index, Hang Seng Main, Midcap index Italy: MIBTEL index, MIB30 index, MIDEX index Japan: Nikkei All Stock Index, Nikkei 225 Stock Average, Tokyo Stock Exchange Small Cap Index Norway: All Share Index,	Calendar effects are significant in most return series. The end-of-the-year effects particularly produce the largest anomalies. Calendar effects are found to be significant in small-cap indices.

				the OBX index, small cap index Sweden: SX-General, OMX UK: FTSE100 index, FTSE350, FTSE250 mid cap index USA: DJIA, S&P 500 Index, S&P MidCap 400 Index	
Higgs, H. and Worthington, A.C. 2005	Australia	1 January 2002 - 1 June 2003	GARCH, RiskMetrics, normal Asymmetric Power ARCH, Student APARCH and skewed Student APARCH	Half-hourly electricity prices and demand volumes.	The skewed Student APARCH model, which takes account of right skewed and fat tailed characteristics, produces the best results in all four markets. The results indicate significant innovation (ARCH effects) and volatility (GARCH effects)

					spillovers in the conditional standard deviation equation, even with marker and calendar effects included. Intraday prices also exhibit significant asymmetric responses of volatility to the flow of information.
Jones, T.L. and Ligon, J.A. 2007	United States	1980-2003	OLS regression including a dummy variable.	Initial returns of IPO daily closing price and volume data, dummy variable which equals to 1 if the offer date of the IPO is a Monday and zero otherwise.	The Monday effect is found to be present in the full sample throughout the sub-period from 1980 to 1994. The Monday effect is also present from 1995 to 2003, but only for IPOs with their first reported trade on their offer date. Volume of IPOs offered on Fridays is very high, then declines significantly on the following Monday and remains relatively low for the rest of the trading week, and the proportion of

					IPOs offered on Fridays that first trade on their offer date is much higher than that of other days of the week, indicating that Friday IPOs may begin trading earlier in the day.
Jooste, D. 2006	South Africa	20 December 1995 - 11 November 2006	Student's t-test	All Share, Financial 15, Industrial 25, Resource 20, Mid Cap, Small Cap, Top 40 indices	There is a strong tendency for market returns to be positive during Mondays, the turn-of-the-month, January months and after index inclusions. The market return during January is a poor predictor of returns during the rest of the year, in contrast to the S&P 500's ability to successfully predict market direction in the

					US.
Ke, M.C., Chiang , Y.C. and Liao, T.L. 2007	Taiwan	January 1992 - April 2006	Kolmogorov-Smirnov test, stochastic dominance theory	New Taiwan dollar per unit of the following foreign currencies: Australia dollar, Canada dollar, Euro, Hong Kong dollar, Japan yen, Swiss franc, United Kingdom pound, US dollar.	The pattern of the day-of-the-week effect is not influenced by the change of trading days during the week. The day-of-the-week effect persists in the Taiwan foreign exchange market even in recent years. Allocating part of investors' assets in risk-free assets can help distinguish the relative performance among weekdays for the various currencies.

Kyrtsou, C., Leontitsis, A. and Siriopoulos, C. 2005	Greece	15 October 1984 - 29 December 2000 (Nasdaq composite) and 25 September 1984 - 29 December 2000 (TSE composite)	Local average, Local PCR and local OLS	Daily index series of the New York (Nasdaq Composite) and Toronto Stock Exchanges (TSE 300 Composite)	Calendar effects can have an important impact on the dynamic structure of financial series and the robustness of forecasting methods. Ignoring such effects could cause misleading results. There is a necessity of filtering financial series.
Lean, H.H., Smyth, R. and Wong, W.K. 2005	Hong Kong, Indonesia, Malaysia, Japan, Singapore, Taiwan, Thailand	1 January 1988 - 31 December 2002	the MV model, the CAPM, the Davidson and Duclos test	daily stock indices of the Hang Seng Index (Hong Kong), Jkarta composite index (Indonesia), Kuala Lumpur composite index (Malaysia), Nikkei Index (Japan), Straits Times Index (Singapore), Taiwan Stock Exhange (Taiwan), the SET Index (Thailand).	Monday returns are dominated by other weekdays and Friday dominates other weekdays. The diminishing of a weekday effect claimed by other recent studies is questionable. There I FSD of other weekdays over Monday returns in the Asian countries studied. The existence of SSD and TSD in some of the markets suggests that risk-averse individuals would prefer (or not prefer) certain

					weekdays in some of the Asian markets to maximize their expected utility. The January effect has largely disappeared from Asian markets and only Singapore is January dominated by some other months at SSD and TSD.
Leontitsis, A. and Siriopoulos, C. 2006	Greece	1984 - 2003	out-of-sample forecasting by neural networks	Daily returns of Nasdaq Composite and TSE 300 Composite indices	Calendar effects may be hidden in indices which represent low-risk stocks. By taking into account the calendar effects, the forecasts are improved and at the same time a doubt is cast on the efficient market hypothesis for the period studied.

Levy, T. and Yagil, J. 2012	US, Canada, Mexico, Brazil, Argentina, Great Britain, France, Germany, Switzerland, Spain, Italy, Austria, Netherlands, Japan, Taiwan, Hong Kong, Malaysia, Israel, Egypt, Australia.	1950 - 2010	GARCH (1,1) model, t-test	Weekly rates of return of the stock indexes of the 20 countries.	Week 44 is positive in 19 of 20 countries in the sample. The positive returns for week 44 appear to be consistent with the May-to-October and Seasonal Affective Disorder anomalies. Week 43's negative performance is quite unique compared to all of the other remaining weeks of the year, which is typical of most of the countries in the sample. Also, as the distance of the country from the equator increases, the significance level of both Week 43's negative performance and Week 44's positive performance increases, which is consistent with both the MTO and SAD anomalies.

Liano, K. 1995	United Kingdom, Germany, Japan, Switzerland	June 1977 - December 1992	OLS regression with a dummy variable	Daily settlement prices of four major currencies futures: British pound, Deutsche mark, Japanese yen, Swiss franc. And a dummy variable that takes on a value of one for the pre-holiday trading days and zero for the non-pre-holiday trading days.	The pre-holiday rates are not significantly different from the non-pre-holiday rates. The chi square statistic shows that the frequency of advances in the pre-holiday trading days is not significantly different from the frequency of advances in the non-pre-holiday trading days. The pre-holiday effect is unique to the stock market.
Liu, L.M. 1980	Taiwan	1963 - 1976	ARIMA model	The monthly highway traffic volume	Calendar intervention may be significant enough to completely disturb the SACF patterns. When calendar intervention is present, a preliminary adjustment of the series is necessary before the identification of a model.

Liu, W.H. 2013	Taiwan, Hong Kong, Shanghai, Shenzhen, Singapore, Philippines, South Korea, Japan, Indonesia and Malaysia.	1995 - 2004	CATREG and CART	Taipei Weighted Price Index, code: TW ; Hang Seng Index, code: HK; Shanghia A-shares, code: SHA; Shenzhen A-shares, code: SZ; Singapore Straits Times Industrial Index, code: SG; Manila Composite Index, code: PH; Seoul Composite Index, code: SK; Nikkei Average, code: JP; Jakarta Stock Exchange Composite Index, code: INDO; Kuala Lumpur Composite Index, code: MA.	The Chinese Farmer's Calendar plays a supplementary role to market information in predicting the market rate of return. In addition to confirmation of lunar calendar effect by the CFC, CATREG outperforms in three markets: Taiwan, South Korea and Singapore. According to CART analysis, all the three markets value the funeral category of the CFC advice and this pattern coincides with the traditional wisdom astrological knowledge. The lunar calendar effect in the three equity markets is confirmed.

Mazunder, M.I., Chu, T.H., Miller, E.M. and Prather, L.J. 2007	Australia, Austria, Belgium, Canada, France, Germany, Hong Kong, Italy, Japan, Malaysia, Mexico, Netherlands, Singapore, Spain, Sweden, Switzerland, UK, USA	19 March 1996 - 31 December 2003	day-of-the-week regression model	The iShares return, a day-of-the-week dummy variable equal to 1 for a specific day of the week, 0 otherwise.	A dynamic trading strategy based on the day-of-the-week effect outperforms a buy-and-hold strategy for most iShares.
McGuiness, P.B. and Harris, R.D.F 2011	Hong Kong, Shangai and Shenzhen	1995 - 2010	Close-to-close daily returns on index	OLS regression	Both the turn-of-the-month and Chinese Lunar New Year return effects appear as features of all three markets. However, the "turn-of-the-month" effect is much more pronounced in Hong Kong and the mainland B-markets than it is in the more segmented and less international (mainland Chinese) A-market. The CLNY effect is concentrated in returns over four trading days: three days prior to and one day after the CLNY holiday.

Meneu, V. and Pardo, A 2003	Spain	January 1990 - December 2000		daily prices, trading volumes and spreads for the five most traded stocks in the Spanish Stock Exchange	There is a pre-holiday effect in the most traded Spanish stocks with respect to Spanish holidays. The strong evidence for equities to experience abnormal large returns just prior to holidays is not a manifestation of other calendar anomalies and is not related to abnormal trading volumes or bid-ask spreads on non-holidays. The pre-holiday return compensates market frictions in some stocks.
Moller, N. and Zilca, S. 2007	United States	1927 - 2004	bootstrapping procedure	Monthly stock returns of all stocks on the NYSE, AMEX and NASDAQ.	A strong mean reverting component beginning in the latter part of January and a shorter duration of the seasonal effect. There are also higher abnormal returns in the first part of January and lower abnormal returns in the

					second part of January in recent years. There exists a substantial decline in trading volume intensity in the second part of January in recent years.
Pauly, R. and Schell, A. 1989	Austria and Germany	January 1973 - June 1987	structural models in the generalised regression form	Index of German retail sales (original data), Index of German retail sales (logarithmic data), Index of Austrian retail sales (logarithmic data)	There are significant overall effects and trading day effects for both retail sales series. Therefore, the calendar influence should be eliminated. The length of month is significant for the German series. Analysing the stability of the calendar coefficients, the tests showed no significant change.

Sharma, S.S. and Narayan P.K. 2011	United States	05 January 2000 - 31 December 2008	GARCH (1,1) model excluding the Wednesday dummy variable. GARCH (1,1) model for four measures of return volatility based on value-weighted returns with and without dividends and equal-weighted returns with and without dividends.	Aggregate data: value-weighted returns (with and without dividends) and equal-weighted returns (with and without dividends). Disaggregate data: 560 firms listed on the New York Stock Exchange.	The day-of-the-week and the weekend affect firm returns differently depending on the sector to which firms belong. Firms belonging to the energy, transportation and financial sectors the day-of-the-week effect. The weekend effect is mostly negative for firms in 13 sectors. The impact of the day-of-the-week and weekend effect on firm returns volatility is much stronger than the relationship between calendar anomalies and firm returns. There is presence of the weekend effect in all 14 sectors; however, the effects are different on different sectors. The negative day-of-the-week effect on firm returns decreases as the firm size

					increases and the positive day-of-the-week effect on firm returns increases as the firm size increases.
Sullivan, R., Timmermann, A. and White, H. 1998	USA	January 1897 - December 1996	Reality Check P-values, Mean Return Criterion, Sharpe Ratio criterion, Out-of-Sample estimation, In-Sample Data-Snooping Biases	DJIA returns, S&P 500 Futures	When assessed in the context of either the full universe, or a restricted version, of calendar rules that could be considered, the strength of the evidence on calendar anomalies looks much weaker. No calendar rule appears to be capable of

					outperforming the benchmark market index.
Sutheebanjard, P. and Premchaiswadi, W. 2010	Thailand	4 January 2005 - 31 March 2009	(1+1) Evolution strategies	SET index (Thailand), Dow Jones index (New York), Nikkei index (Japan), Hang Seng index (Hong Kong), Minimum Loan Rate	The day-of-the-week effect is present in the Stock Exchange of Thailand returns data during the investigated period. The percent of error is highest on Monday and lowest on Friday.
Thury, G. and Zhou, M. 2005	Austria	January 1962 - July 1993	Spectral analysis, ARIMA model	Seven variables X_{it} containing the number of Mondays, Tuesdays,…, Sundays in a month for a given time period. The trading day variables T_{it}	The adjustments for calendar effects are not advocated as a final aim in itself but as an approach to improve the quality and interpretability of data, which then could be analysed more successfully by highpowered statistical and econometric techniques.

Yatiwella, W.B. and De Silva, J.L.N. 2011	Sri Lanka	1985 - 2005	Standard regression model with adjustments for autocorrelation.	Daily closing values of the ASPI and the SI of the Colombo Stock Exchange.	Besides the presence of the day-of-the-week effect over the period, 1995-2005, all other anomalies are not spotted in the Colombo Stock Exchange.