Calendar effects and market anomalies on the Johannesburg Stock Exchange

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CALENDAR EFFECTS AND MARKET ANOMALIES ON THE JOHANNESBURG STOCK EXCHANGE

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Abstract

This study sought to 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 indices 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 Markov Switching Autoregressive models with a different number of regimes and lag orders. The results from the investigation 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, evidence of the weekend effect was found in the Mid Cap and the Small Cap indices, and the size effect was also found to be statistically 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. The evidence of anomalies suggests an opportunity for investors to make returns above buy-and-hold.

Keywords: Calendar effects, market anomalies, JSE, Markov Switching model.

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1 Introduction

With an estimated 397 listed companies, 871 listed securities and a market capitalisation of US$ 895,545 million in February 2013, the Johannesburg Stock Exchange (JSE) 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 exchange 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[1], 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. Consequently, strategies designed to take advantage of mispriced securities in order to make profits will be unhelpful, according to proponents of the efficient market hypothesis. However, the existence of seasonalities[2] 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

[1] A theory 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

[2] Based on theories backed by empirical analysis advocating that certain days, months or times of the year show abnormal price and risk-adjusted returns changes

seasonal patterns found in the South African market yield returns above buy and hold?

Thus, the objectives of this article are to 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; to examine the relationship between the size effect and the turn-of-the-year effect; and to determine if the seasonal patterns and market anomalies uncovered yield returns over and above buy-and-hold.

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. Although there are extensive studies involving international markets, the calendar effects in the South African financial market are yet to be widely analysed. 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 paper uses the regime switching model which is an equally appropriate econometric tool, but has not been used in the past.

The remainder of the paper is organized as follows. Section two provides a review of the theories as well as the empirical studies previously conducted on the subject. Section three describes the methodology and the data used in the study, while section four discusses the empirical analysis and findings. The final section provides the conclusion to the paper.

2 Literature review

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. 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 time series patterns in returns include anomalies such as the weekend effect and the January effect. The weekend effect, 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 (Keim, 2008). Also called the Monday effect, it 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). Similarly to Jones and Ligon (2009) and Sharma and Narayan (2012) who showed the existence of the Monday effect on the USA financial market, in South Africa, Jooste (2006) suggest the existence of the Monday effect on seven major JSE indices namely the All Share, Industrial 25, Mid Cap, Small Cap and Top 40 indices over the period 20 December 1995 - 11 November 2006 and the Resource 20 and Financial 15 indices over the period 2 March 1998 - 11 November 2006. 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; Lean, Smyth and Wong, 2005).

Regarding the turn-of-the-year or January effect, it presumably occurs between the last trading day in December of the previous year and the fifth trading day of the new year in January. It is 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). Jooste (2006) provided evidence of the existence of the January effect in the South African stock market during the period 20 December 1995 - 11 November 2006 as well as evidence supporting the international claim that the January effect is most prominent for small-size firms. However, he 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.

Keim (2008) indentifies 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. According to Malkiel (2003), the size 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. Banz (1981) and Reinganum (1981) demonstrated that small-size firms (as per market capitalisation) 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). The size effect may be due to the growing institutionalization of these markets which makes 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).

The value effect 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. Loughran (1997) presents a criticism of the value effect. When analysing the book-to-market ratio across the dimensions of firm's size, exchange listing, and calendar seasonality, 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.

Finally, 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. Among the oldest available literature examining the dividend yield effect are Fama and French's (1988) study of the power of dividend yields to forecast stock returns and 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. The power of dividend yields (measured by regression R2) to forecast stock returns increased with the return horizon. 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.

Although some of the studies of market anomalies gave robust evidence of their existence, researchers agree that the existence of anomalies does not invalidate the idea of market efficiency. It is 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.

3 Methodology and Data

In the literature, 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.

3.1 Analytical framework

The Markov regime-switching model 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 time period 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 St between regimes is ruled by the Markov process (Chu et al., 2004). This can be expressed as:

$$P[a < y_t \leq b | y_1, ..., y_{t-1}] = P[a < y_t \leq b | y_{t-1}] \tag{1}$$

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 MxM matrix:

$$P = \begin{bmatrix} P_{11} & P_{12} & \dots & P_{1m} \\ P_{21} & P_{22} & \dots & P_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ P_{m1} & P_{m2} & \dots & P_{mm} \end{bmatrix} \tag{2}$$

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 $\Sigma_{j=1}^{m} P_{ij} = 1 \forall i$ and the transition probabilities characterize regime shifts of the time series data.

A vector of current state probabilities is then obtained and is defined as $\pi_t = [\pi_1, \pi_2, \dots, \pi_m]$; 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: $\pi_{t+s} = \pi_t P^s$ (Chu et al., 2004).

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:

$$R_d^I = 100 \times ln \frac{I_d}{I_{d-1}} \tag{3}$$

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) above:

$$R_m^I = 100 \times ln \frac{I_m}{I_{m-1}} \tag{4}$$

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 that case, the model can be defined as follows:

$$R_t - \mu_t = \phi_1(R_{t-1} - \mu_{t-1}) + \phi_2(R_{t-2} - \mu_{t-2}) + ... + \phi_r(R_{t-r} - \mu_{t-r}) + \varepsilon_t \tag{5}$$

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 characterized by the following first-order Markov chain:

$$P(S = j|S_{t-1} = i, S_{t-2} = k, ..., R_{t-1}, R_{t-2}, ...) = P(S_t = j|S_{t-1} = i) \circ p_{ij},\ for\ i, j = 1, 2, ..., K. \tag{6}$$

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 $\{\phi_1, \phi_2, ..., \phi_r\}$, the mean returns of the different regimes $\{\beta_1, \beta_2, ..., \beta_k\}$, 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 (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.

3.2 Data

The data used for the study were obtained from the Johannesburg Stock Exchange. In order to examine 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 were considered.

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 differences in the sample period covered were due to 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 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 Empirical Analysis and Findings

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. Table 1 summarises the results of the selection test based on the SIC for the indices for all the anomalies studied. When using each of these selected models, the different transition probability matrices are derived and reported in Tables 2 to 6 and the estimated mean returns of each regime are as given in the third column of the tables, in parentheses. The number reported in the *ith* row and the *jth* 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. The constant expected duration of regimes is reported in Table 7, while Table 8 and 9 give the frequency distribution of the regimes for all monthly stock returns and for all daily stock returns, respectively.

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

For the two-regime MSAR, the regimes will be referred as (1) the bull regime[3] and (2) the bear regime[4]. Table 2 shows that, for the ALSI, 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 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. It is evident that the bull regime will never last longer than a month (See Table 7). 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 if the current state is a bull regime, there is a 58 percent chance that it will be a bear regime the following month. Then, 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 75.4 percent probability that it will switch from a bear to a bull regime in a month. Alternatively, the probability that it will remain in the bull regime for 2 consecutive months is 95.6 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). For the Small Cap monthly returns, there is a 51.7 percent chance that they will switch from the bear to the bull regime in a month. However, there is a 95.4 percent chance that it will remain in a bull regime for 2 consecutive months. Thus, the bull regime lasts longer (21.78 months) than the bear regime (1.93 months).

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

[4]The bear regime refers to a period of decrease in the stock prices (i.e. negative abnormal returns).

Significance for the January effect

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.

The frequency distribution of returns in Table 8 shows that during the period 2002 – 2013, the positive monthly returns on the four indices 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. 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 8 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.

4.2 The Weekend or Monday effect

The best model for the daily returns on the ALSI is a four-regime MSAR model with lag order 1, five-regime MSAR models with lag order 3 for the Top 40 and Mid Cap, and a four-regime MSAR model with lag order 3 for the Small Cap.

Table 3 shows that if the ALSI is currently in the bear regime, the probability that it will stay in the bear regime (53.2 percent) is greater than the probability that it will switch to any of the other regimes. Furthermore, it will most likely remain in the normal regime for 2 consecutive days. 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. 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). For 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. The longest regime is the normal regime and the other regimes will only last one or two days.

Significance for the weekend effect

For all the 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 rates between

September and December 2001 and also the global financial crisis of 2008 which led to a recession.

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.

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.

4.3 The Size effect

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:

$$r_t^{SMB} = \frac{1}{3}(\text{Small Value} + \text{ Small Neutral} + \text{Small Growth}) - \frac{1}{3}(\text{Big Value} + \text{Big Neutral} + \text{Big Growth}) \tag{7}$$

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 best model for the SMB is a two-regime MSAR with lag order 3 while the best one for the ALSI is the two-regime MSAR with lag order 2 (See Table 1).

From Table 4, it can be seen for the SMB portfolio returns that there is a 66.5 percent chance that the market will still be in a bear regime for 2 consecutive months. Similarly, the returns will most probably (a 97.7 percent chance) remain in a bull regime for 2 consecutive months. Thus, 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 8. 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.

4.4 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 compute the HML portfolio, Fama and French (1993) propose the formula:

$$r_t^{HML} = \frac{1}{2}(\text{Small Value} + \text{Big Value}) - \frac{1}{2}(\text{Small Growth} + \text{Big Growth}) \tag{8}$$

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. The selected models are five-regime MSAR models with lag order 1 for both the HML portfolio and the ALSI (See Table 1).

The transition probabilities in Table 4 and the constant expected duration of regimes in Table 7 both lead to the observation that all regimes in the HML portfolio last about a day; while for the ALSI, the normal regime is the longest (122.51 days).

Significance for the value effect

The total frequency of negative abnormal returns on the HML portfolio is greater than the total frequency of positive abnormal returns (See Table 9). 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.

4.5 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 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 (See Table 1).

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

$$1: \; DIVIDEND_PLUS = 0.60 * ALSI + 0.334 + [AR(1) = 0.078] \tag{9}$$

$$2: \; DIVIDEND_PLUS = 0.631 * ALSI + 2.300 + [AR(1) = 0.078] \tag{10}$$

$$3: \; DIVIDEND_PLUS = 0.672 * ALSI + 0.004 + [AR(1) = 0.078] \tag{11}$$

$$4: \; DIVIDEND_PLUS = 0.750 * ALSI – 1.410 + [AR(1) = 0.078] \tag{12}$$

From Table 6, 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 any of the other regimes. If currently in a normal regime, the returns will most probably remain in a normal regime the following day.

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

$$1: ALSI = 0.874 * DIVIDEND_PLUS + 0.026 + [AR(1) = -0.068] \tag{13}$$

$$2: ALSI = 0.753 * DIVIDEND_PLUS - 2.009 + [AR(1) = -0.068] \tag{14}$$

$$3: ALSI = 1.219 * DIVIDEND_PLUS - 0.022 + [AR(1) = -0.068] \tag{15}$$

$$4: ALSI = 0.587 * DIVIDEND_PLUS + 1.089 + [AR(1) = -0.068] \tag{16}$$

$$5: ALSI = 1.906 * DIVIDEND_PLUS + 0.141 + [AR(1) = -0.068] \tag{17}$$

As can be seen in Table 6, 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. Thus, 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 (See Table 7).

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 10. 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. 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 Conclusion and Recommendations

The main objective of this study was to determine the level of efficiency of the South African Securities exchange by exploring the existence of some calendar effect and market anomalies on the Johannesburg Stock Exchange. The anomalies considered were the January, weekend, size, value and dividend yield effect using the Markov regime switching model with fixed transition probabilities between the regimes. 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; which is inconsistent with the conclusion drawn by Jooste (2006).

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. The findings on the weekend effect confirm 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.

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. 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.

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. 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. This contradicts 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.

Finally, with the aid of the Granger causality test, it was found 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, and 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.

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.

A limitation to the study though is the unavailability of values for business days which were holidays. This led to the use of interpolation to replace the missing values. This increases the risk of data mining. Hence the results of the study have to be interpreted cautiously.

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Table 1: Selected lag order and regimes

Anomalies	Indices	Number of Regimes	Number of Lags
January effect	ALSI	2	2
	Top 40	2	3
	Mid Cap	2	1
	Small Cap	2	1
Weekend effect	ALSI	4	1
	Top 40	5	3
	Mid Cap	5	3
	Small Cap	4	3
Size effect	ALSI	2	2
	SMB	2	3
Value effect	ALSI	5	1
	HML	5	1
Dividend yield effect	Dividend yield	4	1
	ALSI	5	1

Source: Author's estimation using Eviews8

Table 2: Transition probability matrices – January effect

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 using Eviews8

Table 3: Transition probability matrices – Weekend effect

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 parentheses.

Source: Author's estimations using Eviews8

Table 4: Transition probability matrices – Size effect

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 parentheses.

Source: Author's estimations using Eviews8

Table 5: Transition probability matrices – Value effect

Indices	Regime at time t-1	Regime at time t				
		1	2	3	4	5
ALSI	1 (4.96)	0.135	0.39	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 estimations using Eviews8

Table 6: Transition probability matrices – Dividend yield effect

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 using Eviews8

Table 7: Constant expected duration of regimes

Anomalies	Indices	Regimes				
		1	2	3	4	5
January effect	ALSI	1	2.331			
	Top 40	23.788	2.422			
	Mid Cap	1.327	22.673			
	Small Cap	1.932	21.775			
Weekend effect	ALSI	2.136	121.901	1.196	1.256	
	Top 40	2.331	1.198	1.022	126	1
	Mid Cap	1.374	1.336	2.389	131.05	1.432
	Small Cap	1.445	24.041	1.12	1	
Size effect	ALSI	1	2.332			
	SMB	2.987	43.498			
Value effect	ALSI	1.156	1.378	122.51	1.125	1.6
	HML	1	1	1.198	1	1.482
Dividend yield effect	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 using Eviews8

Table 8: Frequency distribution of the regimes for the monthly stock returns

Anomalies	Indices	Regimes	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
January effect	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
	Top 40	Bull	6	6	5	5	7	3	8	8	8	8	7	8	79
		Bear	5	5	6	6	4	8	3	3	3	3	4	3	53
	Mid Cap	Bull	5	7	7	8	5	4	9	7	8	9	7	10	86
		Bear	6	4	4	3	6	7	2	4	3	2	4	1	46
	Small Cap	Bull	7	8	7	9	5	5	8	9	8	8	7	9	90
		Bear	4	3	4	2	6	6	3	2	3	3	4	2	42
Size effect	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 estimations using Eviews8

Table 9: Frequency distribution of the regimes for the daily stock returns

Anomalies	Indices	Regimes	Monday	Tuesday	Wednesday	Thursday	Friday	Total
Weekend effect	ALSI	Bear	171	180	188	162	195	896
		Normal	213	202	192	221	202	1030
		Bull	105	104	105	113	100	527
		Negative Outlier	92	98	100	88	85	463
	Top 40	Bear	19	22	22	15	25	103
		Bull	118	121	116	134	109	598
		2nd Negative Outlier	44	35	32	37	32	180
		Normal	210	191	189	209	196	995
		1st Negative Outlier	208	233	244	206	238	1129
	Mid Cap	Negative Outlier	14	7	9	10	8	48
		Bear	262	259	236	227	227	1211
		Bull	130	122	131	138	146	667
		Normal	64	60	66	63	67	320
		Positive Outlier	129	154	160	163	152	758
	Small Cap	Bear	235	241	222	217	205	1120
		Normal	240	229	248	246	278	1241
		Negative Outlier	25	15	13	11	6	70
		Bull	99	117	119	127	111	573
Value effect	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 using Eviews8

Table 10: 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 using Eviews8