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Calendar Effects on the Johannesburg Stock Exchange: A Markov Switching Approach

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Abstract

Calendar effects, as a stylized facet inherent in financial markets, are important as financial markets globally exhibit seasonal effects with regards to abnormal market returns during certain periods. The existence of these seasonal anomalies is perceived to be in contravention of the notion that markets are inherently efficient, a metric by which an individual market is gauged against the global financial landscape in terms of its transparency and competitiveness. Research coverage on seasonal anomalies locally, is sparse dated, often employing methodologies which do not adequately cater to the time varying levels of volatility inherent in our markets. In this research, daily, monthly and size-effect anomalies are investigated whereby the prevalence of certain monthly calendar effects is shown to exist, by employing a Markov-switching regime switching methodology and allowing transitional probabilities to vary between regimes over time.

Keywords

Johannesburg Stock Exchange, Calendar Effects, Markov Switching, Efficient Market Hypothesis

Declaration

I declare that this research is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any University. I further declare that I have obtained the necessary authorisation and consent to carry out the research.

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1.1 Title

1.2 Introduction to Calendar Effects

Calendar effects, as a stylized facet inherent in financial markets, are important as many financial instruments exhibit seasonal effects with regards to market returns owing to investor behaviour during certain calendar periods (Floros & Salvador, 2014). There are numerous global studies pertaining to the seasonal phenomena of calendar effects in shares, an anomaly in equity returns resulting in systematically higher or lower returns depending on the day of the week or month of the year (Urquhart & McGroarty, 2014). An anomaly may be defined as an incident which cannot be described by a prevailing theory and, in the case of stock markets, disputes the long standing notion that markets are efficient (Mbululu & Chipeta, 2012). The prevalence of these anomalies provides insight into the level of efficiency inherent in a market as well as varying patterns in anomalous returns over certain time periods.

Most notable in the literature pertaining to calendar effects are the January- effect, whereby the month of January exhibits higher returns when compared to other months of the year, as well as the Monday- effect in which Mondays have been shown to underperform other days of the week in developed markets. There is also notable literature describing a size-effect which posits that existence of calendar effects may exacerbated by the market capitalisation of firm i.e. the prevalence of the January- effect may by more prominent in stocks with smaller market capitalisation than their larger capitalised peers.

1.3 Research Relevance

The study of seasonal calendar effects is relevant as they are inconsistent with the Efficient Market Hypothesis (EMH), which asserts that all available information is already priced into the assets, and as a result, excess returns cannot be achieved in a consistent manner (Rossi, 2015). There are a number of empirical studies which suggest calendar anomalies are prevalent in developed markets globally (Floros & Salvador, 2014) which would contradict the assumptions of the EMH, and hence the competitiveness of those markets.

Furthermore, Cho, Choi, Kim and Kim (2016) show that emerging markets experience positive equity inflows and market returns when developed equity markets experience periods of growth, with the South African equity market exhibiting significant levels of correlation with nine out of ten of those developed markets considered in the study at a 5% level of significance. As such, it may be inferred given the suggested prevalence of seasonal anomalies in these developed markets that the South African market too could exhibit anomalous returns owing to high levels of correlation with these markets

This research adds to the existing body of literature pertaining to the perceived level of the efficiency inherent in our markets as well as the existence of calendar effects.

As share prices inherently fluctuate, the determination of seasonality in returns i.e. ascertaining that share prices exhibit regular variations in return over specified calendar periods, the fluctuation of which is distinguishable from other sources of variation driving the prices, will be have powerful predictive qualities (Chu, Liu, & Rathinasamy, 2004). Although progress has been made in our understanding of this topic, views are still varied and there are many opportunities to improve our understanding of calendar effects (Rossi, 2015). Numerous studies have been conducted abroad in developed markets, and to a lesser extent in South Africa, so as these new datasets and methodologies emerge there is evidence that these effects have begun to reverse or even migrate to alternate seasonal periods (Boubaker, Essaddam, Nguyen, & Saadi, 2017), which highlight the importance to provide recency to the topic. Ngene, Tah, and Darrat (2017) affirm, for three significant reasons, the inherent need to study African financial markets, inclusive of South Africa, in the context of the global financial landscape:

1. In order for the global financial market, as a collective of individual markets, to be truly efficient, emerging and frontier markets ought to be considered in the endeavour to truly cater to diversification of portfolio risk.

2. Emerging markets differ significantly with regulatory environments exhibiting vastly different fiscal and monetary policy requirements and, as such, their adherence to or deviation from mean- reversion tendencies, long- term memory relating to volatility and structural breaks should be better understood.

3. Advances in efficiency in markets too advances capital allocation efficiency and so, any inefficiencies in contradiction of the EMH should be understood to effectively allocate capital.

Since initial research appeared on calendar anomalies, potentially due to behavioural biases, they have proven to be of considerable importance in impeding traditional asset pricing models as return predictors, such as the capital asset pricing model (CAPM) (Mahakud & Dash, 2016). The presence of calendar anomalies would suggest that researchers be cognisant of their presence and potential impact on traditional asset pricing models, and configure their models accordingly. Furthermore, researchers may employ different pricing methodologies, or augment existing ones, when pricing firms of differing market capitalisations should the existence of a size- effect be noticeable.

Rossi (2015), in his literature review contrasting the contradicting research pertaining to calendar effects with that of the EMH in markets globally concludes that there is no unified viewpoint as the literature is excessively fragmented. The presence of calendar effects in one market does not necessarily lead to their existence in all markets, and although researchers have made progress in the understanding of these calendar effects, these disparate findings provide warranted opportunities to progress in this field (Rossi, 2015).

Evidence of calendar effects on the Johannesburg Stock Exchange (JSE) would not only add to the empirical literature on calendar effects, but would also be relevant in trading strategies employed by market participants such as financial managers, investment experts and traders in the local market. It would not only be of significance to those wishing to profit off abnormal returns or implementing hedging strategies against adverse movements, but would be of great importance to those implementing pricing methodologies for which calendar anomalies may skew the valuations. The extent to which calendar affects are present, a consequence of inverse proportion to the level of efficiency within the local market, will elucidate the comparative competitiveness and transparency of the local financial market, a metric governing validity by which foreign investors and foreign firms looking to raise additional funds in the local market will scrutinise. Any additional gaining in clarity unveiling the extent to which our markets are efficient and the extent to which they are prone to international shocks or abnormal movements is clarity gained into diversification opportunities and a more efficient allocation of capital. The notion that South African equities are not a separate asset class from developed market equities allows, not only for inclusive participation for growth and diversification purposes for foreign investors, but also to be included in an investible international basket of equities, against which inclusion is a necessity as opposed to an alternative investment source.

1.1 Research purpose

The fundamental question this research aims to answer is: Do certain days of the week or months of the year yield abnormal returns on the Johannesburg Stock Exchange?

The main objectives of the research will be:

- Objective 1: to determine whether certain days of the week exhibit abnormal returns (either positive or negative).
- Objective 2: to determine whether certain months of the year exhibit abnormal returns (either positive of negative).
- Objective 3: to determine the extent to which these abnormal returns are more prevalent in certain firm groupings, based on market capitalisation size, should they be identified.
- Objective 4: to gauge the extent to which calendar effects are in contravention of the EMH, should conclusive evidence support their prevalence.

2 Literature review

2.1 The Efficient Market Hypothesis

The behaviour of share prices has long been an enigma for financial scholars. Fama (1970) is credited in his seminal work on the Efficient Market Hypothesis (EMH) whereby it is proposed that investors act rationally and current share prices fully reflect all available information regarding the value of the firm as individual share prices promptly respond in accordance with new information (Rossi, 2015). The level of market efficiency hinges on the phrase “all available information,” and under the EMH, may be classified into three broad levels, namely the weak, semi- strong and strong form (Urquhart & McGroarty, 2014).

The weak form of the EMH asserts that share prices reflect fully all historical prices i.e. the history of past prices and trading volumes, and as such, investment strategies based on historical data, such as technical analysis, are futile (Beladi, Chao, & Hu, 2016). The semi-strong form of efficiency encompasses historical data as well as all publicly available information pertaining to the prospects of the firm. Under this form of efficiency, long- term sustainable excess returns through fundamental analysis of the firm are not possible with the strong- form efficiency asserting that the share price fully represents all publicly known information regarding the prospects of the firm as well as the information that is not publicly known (Beladi et al., 2016). Although this form of efficiency implies that insider trading is possible, Fama (1970) suggests that it be primarily used as benchmark representing an absolutely efficient state, against which levels of deviations in efficiency may be assessed. Naseer and Tariq (2015) highlight the three pillars upon which the EMH rests:

1. Market participants are rational in their valuation of financial assets and are utility-maximising.
2. In the event that irrational investment strategies do occur, these trades are assumed to be random and offset one another, and as such, are of no consequence to deviations in prices from fair value.
3. Irrational market behaviour is priced out of the market by rational arbitrage seeking investors.

The rationale underpinning the EMH, although intuitive, is loosely narrow in its assumptions of constant levels in efficiency over time (Kumar, 2016). AitSahlia and Yoon (2016) describe the existence of temporal structural breaks within equity price dynamics as result of convergence in both implicit and explicit consensus of market participants. In direct contrast to the weak- form EMH, share returns are known to have predictive power when considering historical prices, challenging their validity (Urquhart & McGroarty, 2016). Contradictions to the EMH include calendar effects, predictable patterns in equity valuation techniques as well as style- based investment strategies which, in recent years, have gained considerable traction in the behavioural finance literature (Naseer & Tariq, 2015). In light of this, empirical evidence supporting the existence of calendar anomalies on the JSE for a period of time would contravene the inherent laws governing the EMH and so would in turn, for those in support of the EMH, yield the levels of efficiency and competitiveness of the local market as questionable.

2.2 Market Anomalies

Since the EMH was introduced, extensive research has been devoted to investigating the efficiency of financial markets with numerous types calendar anomalies prevalent in equity markets having been highlighted globally by scholars. Common period related anomalies relate to days of the week or months of the year exhibiting anomalous returns, most notably the January effect and the Monday effect (Floros & Salvador, 2014). Evidence of seasonal anomalies violates the assumption of weak market efficiency, whereby market participants may be able to generate consistent excess returns. One could expect these exploitative effects to dissipate over time allowing only a short period in which to benefit from abnormal returns until the calendar effect disappears under the assumption of existence of rational arbitrageurs participating within the market. Notwithstanding, the mounting literature pertaining to market anomalies, including calendar effects, has received considerable attention in recent years, arguably owing to firmer support against the broader notion of consistent levels of efficiency of financial markets.

If we were to assume that under the assumptions of the EMH that market participants, besides being utility maximizing agents, also have rational expectations, and those participants which do not trade rationally in accordance with publicly available information do so in a random fashion offsetting any deviating effect on prices (Naseer & Tariq, 2015), then the notion of consistently exploiting predictable seasonal patterns in markets should not be possible. Notwithstanding, the EMH has received an abundance of attention since its inception, though through numerous studies with mounting evidence contrary to the theory, there may still exist a level of predictability (Rossi, 2015). The existence of anomalous returns which are said to be inconsistent with predictions of efficient markets and rational expectations, are also inconsistent with asset pricing theory (Mahakud & Dash, 2016), which would imply a degree of predictability and be widely known and exploitable by market participants. One parallel to the notion that levels of efficiency may vary over time is that they are based on market situation i.e. they are a function of the volatility over a period with calendar effects tending to be more positive in low volatility regimes and negative in higher volatility regimes (Floros & Salvador, 2014). In this vain it seems prudent to be cognisant of, and cater for the different market situations based on periods with fluctuations in volatility regime.

2.3 The Day of the Week Effect

The main assumption behind the day of the week effect is that markets participants exhibit behaviours which effect financial market returns on certain days of the week (Berument & Dogan, 2012). Most prevalent in the literature pertaining to the day of the week effect is the commonly known Monday effect or weekend effect, which posits that Mondays exhibit relatively lower returns when compared to other days of the week, with Friday's exhibiting abnormally higher returns (J. Zhang, Lai, & Lin, 2017). The prevalence of this effect is of particular interest to scholars as, due to the two days of non- trading over the weekend, rational investors would price in the extra two days in the carry of money- value, into the Friday share price i.e. the delayed time between share purchase and settlement thereof means that shares purchased on a Friday would only settle on the Monday, and the share price on Friday would be inclusive of the extra two days of interest prior to the settlement date (Kumar, 2016). Alternate research shows that, on a given Friday, market participants may be preoccupied with the upcoming weekend and therefore market reactions to firm specific announcements, such as earnings announcements, other corporate news events and merger announcements made on Fridays, are subdued, with a more reactive correction taking place on Monday (Michaely, Rubin, & Vedrashko, 2016). This corroborates with the findings of Yuan (2015) who shows that higher attention paid by investors, especially when market indices are high, leads to abnormal selling behaviours, which would be the case on a Monday following a relatively negative Friday announcement.

2.4 The Month of the Year Effect

The most notable month of the year effect is the January effect, also known as the turn of the year effect, which is known to be the most important calendar anomaly in stock markets due to its perceived ability to be able to predict the trend of the market for the remainder of the calendar year (Rossi, 2015). The ensuing result, in terms of predictability, following a recognised positive January effect is the “sell in May, go away” anomaly, or Halloween effect, whereby the period from November to April exhibits overall higher returns than May to August. Andrade, Chhaochharia, and Fuerst (2013) showcase the pervasiveness of this anomaly in 35 out 37 markets globally (including South Africa) between 1998 and 2012, possibly owing to the minimal, twice annually, incurrence of fees in exploiting this trading strategy.

The January effect is characterised by higher average share returns being recorded in the month of January following depressed share price levels exhibited in December. There is no general consensus as to the cause of the January effect, though Wachtel, in his original 1942 study unveiling the presence of the January effect initially described five possible causes for this anomaly in U.S. markets (C. Y. Zhang & Jacobsen, 2013):

1. Higher cash demand during the Christmas period owing to partial liquidation of shareholdings yielding excess supply and suppressed prices.
2. A pre- Christmas behavioural calendar effect.
3. Higher levels in optimism regarding business cycles in the Spring (Northern Hemisphere).
4. General levels of positivity regarding the new year, and
5. That tax- loss selling hypothesis

The tax- loss selling hypothesis, based on the literature, serves as the most formidable basis as origin for the January effect in the U.S. Under this hypothesis, it is assumed that investors sell out of lower performing equities in December, so as to avoid incurring the liability in retaining losing shares in their portfolios, the losses of which are tax deductible, over the course of the calendar year, with demand for those equities increasing again in January (Vasileiou & Samitas, 2015). Although an intuitively sound hypothesis, the January effect is also present in countries who's tax year does not conform to a standard calendar year which questions it's validity, with other avenues of research favouring the concept of window-dressing by fund managers as an alternative reason for the anomaly's existence (Easterday & Sen, 2016). This may be described as the propensity for active fund managers to exhibit characteristics associated with "tournament- like" incentives whereby equity holdings favouring positively performing firms are increased, in relative weighted terms, closer towards quarter- end reporting periods (Brown, Sotes-Paladino, Wang, & Yao, 2017).

2.5 The Size Effect

The size effect, also commonly termed the small- firm effect, is characterised by smaller capitalisation firms exhibiting larger average returns over a long period of time. The relationship between capitalisation and seasonality is well documented with smaller firms exhibiting higher average returns in January than their larger counterparts (Chu et al., 2004). Malkiel (2003) posits that this may be attributed to institutional preference of larger shares which are more liquid in nature. Furthermore, some of the studies may disregard survivorship bias in their data sets, omitting smaller companies that may have fallen out of the dataset over the study period and

2.6 Calendar effect studies

Calendar anomalies are well known globally after abnormal returns in the month of January were first reported by Wachtel in 1942 in the U.S. equity market (Urquhart & McGroarty, 2014). The first empirical evidence of this was published in a seminal paper by Rozeff and Kinney (1976), whereby it was found that the January effect was prevalent on the New York Stock Exchange (Moller & Zilca, 2008). Many more empirical studies have been conducted in the United States, with findings supporting the notion that share returns are generally higher in January, relative to other months of the year, and are generally lower on Mondays when compared to other trading days (Urquhart & McGroarty, 2014).

An early study by Lakonishok and Smidt (1988) in examining the existence of calendar anomalies on the Dow Jones Industrial average Index (DJIA) highlighted significance and persistence of a negative Monday effect over a period of ninety years, from 1897 to 1986. Efforts to isolate the source of the anomaly were partially uncovered by Lakonishok and Maberly (1990), by comparing the trading behaviours of individuals and institutional investors on certain days of the week between 1962 and 1986. They revealed that Mondays experienced the lowest trading volumes on average when compared to other days of the week, with institutional investors exhibiting a far lower propensity to trade on Mondays. Individual, or retail investors, in contrast exhibited a far higher propensity to transact on Mondays with the majority of trade order being sell orders. More recently and contrary to common belief, it has been shown that retail investors do have significant influence in financial index price returns (Chelley-Steeley, Lambertides, & Steeley, 2016). Doyle and Chen (2009) consider a 25 year period from 1993 to 2007 in testing the prevalence of the day of the week effect across thirteen developed financial markets. In conclusion they find the Monday effect to be prevalent and significant in the AMEX, with the DAX also exhibiting significantly lower Monday returns following higher Friday returns. Other weekday effects were also found to be prevalent and significant on the Nasdaq.

Most recently, J. Zhang, Lai, and Lin (2017) apply a rolling window period GARCH model on 28 separate indices from 25 countries (13 emerging market and 12 developed countries), in order to detect the presence of day of the week anomalies. Their research uncovered significant presence of day of the week anomalies in all 25 countries between 1990 and 2016, highlighting the continued persistence of the Monday effect in the U.S market in recent years, as well as a Monday effect in the emerging Chinese markets.

In regards to the January effect, the most hypothesised cause in U.S. share returns being higher in January is due to tax- loss selling of shares in December, whereby investors sell off poorly performing shares in December in order to obtain tax savings by deducting those losses from capital gains (Agnani & Aray, 2011). The reallocation of capital in January stimulates equity demand which translates into higher share prices and naturally higher observed returns in January. Beladi et al. (2016) posit that firm announcements during the month of January can lead to higher risk- adjusted returns during that month, although the ability of firms to consistently benefit from this timing in announcements remains questionable. Further to the timing of announcements, same sector firms tend to make corporate announcements around the same time creating anticipative environments resulting in higher sectoral returns (AitSahlia & Yoon, 2016). Beladi et al. (2016) find that the prevalence of the January effect results in more corporate announcements taking place during January, and should the demand in January be high, then firms announcing share-splits should do so during that period in order to achieve higher returns. Furthermore, with regards to the tax- loss selling hypothesis, they find that this is more prominent in smaller capitalisation firms meaning that smaller firms selling off underperforming assets in December manifests in a resultant small- firm January effect the following month. Easterday and Sen (2016) convey agreement in support of the tax- loss selling hypothesis at the firm level, however, they contend that the resultant January effect is as result of fundamental accounting principles i.e. higher returns in January for certain firms are resultant of higher expected earnings for the quarter, ruling out the notion of abnormal or irrational behaviour by investors and as such are not in contravention of the laws pertaining to efficient markets, nor do they present arbitrage opportunities. This positive view of earnings in January may be exacerbated by supressed market levels in the December. Zolotoy, Frederickson, and Lyon (2017) contend that market participants, from a fundamental standpoint, do not merely value firms based on perceived future earnings in isolation, but rather in the context of current state dependant macroeconomic and financial market conditions. This would suggest that perceived sustainable positive earnings expectations emerging from suppressed market levels warrants greater demand and higher risk- adjusted returns

In an endeavour to better understand the behavioural tendencies of certain market participants, Chelley-Steeley, Lambertides, and Steeley, (2016) contrasted the order flow imbalances, by means of buyer or seller initiated trades, between retail and institutional investors during December and January months. Trades on the AMEX and NYSE exchanges were considered for an extended period of time, from January 1983 to December 2008. It was deduced that both retail and institutional investors experienced net selling pressure in December with a reversal in January resulting in an elevated January risk premium on equities. With most studies only considering institutional behaviour influencing prices, it was shown that retail investors order flow also has an effect on price returns with the magnitude in their January flow reversals being higher. Spanning both groups of participants, the direction change in order flow for January was stronger for undeforming shares, which is in line with the tax- loss selling hypothesis.

In recent years, some studies have shown that the presence of the January effect to be less prevalent, although Moller and Zilca (2008) maintain that the effect has not diminished in the U.S. equity market in more recent years. Other scholars posit that the existence of the January effect lies in the mining of data, which under certain hypotheses may encourage behaviours leading to spurious results. Eugene Fama is quoted on the matter of the January effect, saying “I think it was all chance to begin with. There are strange things in any body of data” (Andrade et al., 2013). Other scholars highlight that some of the theoretical approaches have only been adopted after the empirical discovery of these anomalies and that data driven methodologies should be favoured over pre- selected models (Boubaker et al., 2017). Identified in time series data, the January effect, which, because of its existence in many different markets, cannot be sufficiently explained by differences in settlement periods for trades occurring on different weekdays, recording errors in prices, or systematic patterns in the behaviour of market participants (Sun & Tong, 2010).

In identification of the size- effect, Banz (1981), was first to highlight its existence whereby smaller capitalisation firms exhibited higher anomalous returns in the month of January (Chaudhary, 2017). In the decades following the emergence of the size- effect, many studies initially concluded its overall disappearance from the markets, however ensuing literature revealed that knowledge of its existence caused the anomaly to be priced out of the market, its “disappearance” actually resulting in a reversal of the effect immediately following a published study of its existence within that country (De Moor & Sercu, 2013). Semenov (2015) highlights that, although the January effect is more pronounced for smaller capitalisation firms, their power as predictors of individual share returns, albeit more prominent than mid or large capitalisation shares, is no more pronounced during periods exhibiting anomalous returns.

2.7 South African Market

Literature investigating the prevalence of calendar effects on the JSE and African markets remains sparse and non- current. This is contrary to the notion that, due to the perceived higher inefficiencies and greater degree of information asymmetry in emerging markets, it would seem prudent that seasonal anomalies be more prevalent in these markets which warrants further research (Zaremba & Szyszka, 2016). Boako and Alagidede (2018) contend that African equity markets should not be viewed as an alternate asset class to western markets as global markets have a spill- over, or contagion effect, largely due to increased levels of market integration in endeavours to avoid vulnerabilities. According to Oberholzer and Boetticher (2015) the South African equities market is positively correlated with international markets both in terms of performance and levels of volatility, within the same time period.

In earlier studies, Alagidede (2008a) shows that the JSE All Share Index exhibits a significant positive Monday effect during the period of 1 March 2001 to 4 March 2006. This positive Monday effect is in the opposing direction to that documented in the U.S. and other developed markets. In testing the month of the year effect, Alagidede (2008b) confirms a positive February effect on the JSE All Share Index between July 1997 and October 2006, though in light of liquidity and trading expenses, there is no conclusive evidence that this presents an arbitrage opportunity. In testing for anomalous returns on the JSE for the month of January in more recent years, Auret and Cline (2011) compared median January returns to those of other months for the period of January 1988 to December 2006, and concluded that neither the January effect, nor the small firm effect, were evident. Their research sought only to uncover the existence of the January effect on the JSE and so, although this would not corrobate the existence of a February effect, as deduced by Alagidede (2008b), it reaffirms confirmation as to the non- existence of the January effect.

Mbululu and Chipeta (2012) sought to uncover the existence of the day of the week effect on the nine sector indices on the JSE. They used non- parametric tests on index returns between 3 July 1995 to 13 May 2011 and found the Monday effect to exist only in the basic materials sector, though no day of the week effects were uncovered otherwise. Plimsoll, Saban, Spheris, and Rajaratnam (2013) sought to uncover whether the day of the week effect was prevalent in the top individual 40 shares listed on the JSE from July 2002 until July 2012, as there was no evidence supporting a day of the week effect to be prevalent on the All Share Index. They deduced that ten of the Top 40 shares exhibited day of the week effects on at least one day of the week and so the prevalence thereof may be clearer at the firm level as opposed to the overall index.

Chinzara and Slyper, (2013)too sought to unveil the existence of day of the week effects on the JSE, at both All Share and sectoral index levels, using index data between June 1995 and December 2010. A significant positive Monday effect was found to exist at the All Share level, with the Industrial and Retail sectors exhibiting less significant positive Monday and negative Friday effects respectively. It was concluded that these effects were explained by corresponding excess time- varying probabilities during those periods and become less significant once volatility levels were allowed to vary across all days of the week. Contrary to portfolio theory, positive returns on Thursdays were found to exist in the absence of excessive volatility levels

Darrat, Li, and Chung (2013) explore the significance of calendar effects on the JSE by considering the extended time period of index price data spanning some forty years, from January 1973 to September 2013. In testing for the month of the year effect, only December and January months were considered wherein no significant anomalous returns were uncovered. In testing for the day of the week effect, and using Wednesday returns as a benchmark, Mondays and Tuesdays were shown to exhibit significantly lower returns, however this effect was no longer prominent post 2008 with the authors attributing this to possible higher levels of efficiency in the domestic market post global credit crisis.

Most recently, albeit on currency returns against the USD as opposed to equity returns, Kumar (2016) investigates the day of the week and January effect on a basket of developed market and emerging market currencies, including the South African Rand (ZAR) for the period extending from 1985 to 2014. The findings show that the ZAR exhibited the highest return against the USD on Mondays, out of all currencies considered. Furthermore, all emerging market currencies experienced positive gains against the USD in the January months, with most of these anomalies being priced out in more recent years, with the ZAR being one of the two exceptions to this. Consequentially, the potential influence this may have on equities listed on the JSE should be considered. At the end of 2016, 38% listed JSE equities were foreign owned, with a quarter of the listed companies having their primary listing domiciled in another country (Thomas, 2017).

2.8 Conclusion

The study of calendar effects has long been under scrutiny in developed market research studies in endeavours to uncover the causes pertaining to their existence. Prevalence of these anomalies raises concerns regarding the efficiency of markets, as predictable seasonal effects, that are exploitable, would constitute violation of the EMH. Notwithstanding, more studies conclude their prevalence and contrast this with the prevailing implications this may have on markets efficiency. The sparse literature pertaining to seasonal effects the South African market provides no recent support to validate the efficiency of the domestic market. Perceived efficiency within our market serves as justification regarding the transparency and competitiveness of the market. This is important, within the global context, as due considerations will be made to include domestic equities within global portfolios, for possible benefits from added diversification and more efficient allocation of capital. It is therefore imperative that recency is provided to literature to affirm our efficiency and competitiveness thereof.

3 Research questions and hypotheses

The main objective of this study is to investigate the prevalence of calendar effects on the JSE by employing a Markov regime switching model allowing for time varying transitional probabilities (TVTP) between regimes. In doing so, knowledge as to the prevalence of calendar effects will provide recency to existing literature, thus allowing deductions to be made concerning the levels of efficiency inherent in the domestic financial market. This may be achieved through an empirical study providing sufficient answers as evidence to three research questions

3.1 Research Question 1

Do certain days of the week exhibit consistent and predicable abnormal returns, whether positive or negative, on the JSE?

3.2 Research Question 2

Do certain months of the year exhibit consistent predictable abnormal returns, whether positive or negative, on the JSE?

3.3 Research Question 3

In considering firms of varying size based on market capitalisation, is size a significant predictor in assessing whether certain days of the week or months of the year exhibit consistent predictable abnormal returns, whether positive or negative, on the JSE?

4 Research methodology

4.1 Introduction

This research aimed to showcase a cause and effect relationship between share price returns and the day of the week or month of the year, by examining abnormal share price returns in certain periods. The researcher was independent of the data and maintained an objective stance. The problem in this research was well defined and readily quantifiable, therefore a deductive philosophy under a positivism approach was appropriate (Saunders, Lewis, & Thornhill, 2016, p150).

This empirical research lends itself to a quantitative study, which made use of secondary, archival data, longitudinal in nature as it was collected over an extended period, for consideration as measurement.

4.2 Proposed research methodology and design

The proposed approach was to analyse daily and monthly share index returns during specific calendar periods, specifically days of the week and months of the year. Calendar effects may be studied using observations of individual share returns, as was conducted in the by Plimsoll et al (2013) on individual shares on the JSE, or alternatively by examining a share index as used by French (1980), Chu et al. (2004) and Urqhuhart and McGroarty (2014).

Previous studies of calendar anomalies have calculated means and variances on daily or monthly share returns, and estimate a simple ordinary least squares (OLS) regression using dummy variables to account for the different days of the week or months of the year, using t and F tests as well as ANOVA to account for any significance and equality of means, which does not account for time series properties and non- linearity of the data (French, 1980). Furthermore, it does not account for non- normality in the data, which is most often the case in share returns, and dummy variables will wrongly attribute non- seasonal economic shocks to the dummy variables, which will lead to spurious results (Chu et al., 2004).

Firstly, it was proposed that descriptive statistics be calculated on the index returns. The Jarque- Bera test was conducted, using skewness and kurtosis measures of the underlying distribution in order to confirm that returns are non- normal, a characteristic which is commonly inherent in stock market returns. Confirmation of non- normal returns serves as justification to use a Markov- regime switching model, first proposed by Hamilton (1989) and found to be more accurate than OLS regressions using dummy variable (Agnani & Aray, 2011).

The methodology used is partially based on the seminal work proposed by Hamilton (1989), though greater allowances in terms of the number of regimes is made, as well as transition probabilities to be time varying. This method has a number benefits, allowing testing for multiple month or daily anomalies and accounting for multiple regimes such as, for example, a bear or bull market regime. The Markov switching models allows for multiple "unobserved" regimes as opposed to an *a priori* predetermined number of regimes, the number of which can be estimated depending on the data. Guidolin and Timmermann (2008) highlight the importance of regimes, noting that disregarding of regimes will lead to sub- optimal portfolio allocation weightings.

In this model, the number of regimes is not assumed or predetermined, but is rather estimated depending on the data set. The number of regimes will be determined independently by fitting that number of Markov- switching models and regimes which minimises the Bayesion Information Criterion (BIC) (Chu et al., 2004). Thereafter the data is modelled as an autoregressive process, with parameters being subject to regime switching determined by the outcome of a first order Markov process, which is a stochastic process.

The premise behind a variable following a first order- Markov chain is that, given that the variable is in a certain regime, we only need to know the probability that it will remain in that regime, or using a probability matrix, we will be able to ascertain the probability of it being in another regime in the next time period i.e. the conditional probability of the variable being in a certain regime in the next relies solely on the current regime and not distant past regimes. These regimes may be classified as "unobserved" as they are not predetermined by month, or day, but rather by the probability transition matrix determining regimes in consecutive periods. Once the number of regimes is determined, the frequency distribution of high return regimes is examined to discern the presence of relevant anomalies e.g. the frequency distribution of the month of January in high return regimes may be examined. An enhancement to the model employed by Chu et al (2004) is to allow the transition probabilities to be time varying at each point and not to be fixed. Allowance in the model of these time varying transfer probabilities (TVTP) offers greater flexibility, as they are partially determined by random shocks and fluctuations in market returns and are not entirely determined by external shocks throughout the entire time period (Amisano & Fagan, 2013). As the period under consideration encompasses significant fluctuations in volatility, such as the financial crisis in 2007, the of use time varying transfer probabilities caters to the robustness in the model. Additional flexibility in adopting the time varying specification is that it enables accurate inference in the increase or decline of a calendar effect over a subset of entire time period under consideration (Agnani & Aray, 2011).

To the researcher's knowledge, this methodology has not been conducted on the JSE in determining the presence of calendar effects. This study will also contribute by providing recent and robust findings as to the existence of calendar effects on the JSE, of which there are no recent studies.

4.2.1 Unit of Analysis

The unit of analysis is daily (weekday effect) and monthly (month effect) rate of change of index returns, which is computed in the form of a natural logarithm first difference of the daily or monthly closing index prices:

Equation 1: Unit of analysis

$$R_t = 100 \times (lnP_t - \ln P_{t-1})$$

Where P_t denotes the daily/ monthly index price at time t.

For daily return calculations whereby there is a holiday with no trading taking place, Singh (2014) suggests that the average of the share price of that specific weekday for the previous month will be used. During periods of high volatility this method could render unwanted estimations of weekday returns. It is for this reason, coupled with the large number of daily returns in the collected data, that the researcher has chosen to omit estimated daily returns during holidays. Should a holiday occur on the final day of a month, then the trading day preceding the holiday will be using for monthly return calculations.

4.2.2 Universe

The universe will encompass indices comprising the top 160 firms by market capitalisation listed on the main board of the JSE between 30 June 2002 and 31 December 2017.

4.2.3 Sampling method and size

The sample will include JSE index data of the top 160 shares listed on the JSE, market capitalisation, going back for a period of 16 years, from 30 June 2002 to 31 December 2017. Although there are typically more than 350 shares listed on the JSE, the J203 All Share Index encompasses the top 160 firms by market capitalisation, and represents 99% of the total market capitalisation (Muller & Ward, 2013). The indices are revised quarterly at the end of March, June, September and December in each year by the JSE.

4.2.4 Data gathering

Due to data availability, secondary share data used for the study was sourced from Thomson Reuters Datastream. Daily and monthly closing index values were collected for the J203 total return index for the period 30 June 2002 to 31 December 2017 in order to test for day of the week and month of years calendar effects. In order to test for the size effect, daily and monthly index values were collected for the J200 Top 40 Index, the J201 Mid Cap Index and the J202 Small Cap Index for the same period of time. Firm constituents in these indices are constituents of the J203 All Share Index, with the J200 Index comprising the top 40 shares by market capitalisation, The J201 the following 60 shares by market cap and the J202 the smallest 60 J203 constituent firms by market capitalisation.

4.3 Data Analysis

The approach adopted by Muller and Ward (2013) was to gather share data and backwards adjust it for share splits, consolidations and the reinvestment of dividends to total returns on share prices. Then, five equally weighted portfolios were created based on market capitalisation, the returns on which formed the unit of measurement and rebalanced quarterly in line with the JSE rebalancing of indices. Moller and Zilca (2008) construct ten equally weighted decile portfolios based on market capitalization in their study on the January effect. Due to the limited availability of share price data available for delisted firms for the period under consideration, the researcher opted to make use of the J203 All Share Total Return Index, which too accounts for dividend reinvestments, share splits and consolidations, and mitigates the inherent survivorship bias which would materialise by considering only shares which have not been delisted. The primary difference is that the index is weighted by market capitalisation and is not equally weighted.

Smaller capitalisation shares have been found to exhibit higher average returns than larger capitalisation shares (Fama & French, 2012). Making use of the J202 Small Cap, J201 Mid Cap and J200 Top 40 Indices will be able provide insight as to whether the day of the week effect or month of the year effect are more prevalent in lower capitalisation shares. Daily and monthly returns will be calculated based on these indices derived from these indices. These indices are rebalanced on a quarterly basis on the final days of March, June, September and December, by re- ranking all listed companies listed on the JSE by capitalisation and reassigning them to the indices on a quarterly basis.

In the calculation of model parameters, the MS_Regress toolbox for Markov Switching Models, initially developed in MATLAB by Marcelo Perlin (2015) was used. The initial package catered for constant transition probabilities although it was later updated by Ding (2012) to allow for specification of TVTP matrices. The log returns of the daily and monthly indices were calculated by the researcher in Microsoft Excel and the Matlab code was amended to appropriately retrieve the various returns from the Excel files. The initital log returns, or log differences, were tested for stationarity using the Augmented Dickey- Fuller unit root test, conducted in Matlab.

Hamilton (1989) posits that, under the assumption that index returns follow a Markov Switching Model, then

Equation 2: Hamilton's Markov switching model

$$R_t - \mu_t = \emptyset_1(R_{t-1} - \mu_{t-1}) + \emptyset_2(R_{t-2} - \mu_{t-2}) + \cdots + \emptyset_n(R_{t-n} - \mu_{t-n}) + \varepsilon_t$$

Where R_t is the index return at time t, n is the number of lags and ε_t is normally distributed with zero mean and finite variance σ^2. μ_t is regime dependent mean, the dynamics of which are determined by a k- state Markov chain.

$\mu_t = \beta_{S_t}$

Where S_t is the state process at time t, an unobserved variable with values $S = \{1,2, \dots, K\}$ being the possible states of the mean return. More directly, S_t represents the regime at time t i.e. suppose the regime at time t is equal to j ($S_t = j$), then the mean return at time t is equal to β_j and so $\mu_t = \beta_j$.

As S_t follows a first order Markov Chain, we have that

$Prob\big(c = j\big|S_{t-1} = i, S_{t-2} = k, \dots, R_{t-1,}R_{t-2,} \dots\big)$

$= Prob(S_t = j|S_{t-1} = i) \; \forall \, p_{ij} \;\; i,j = 1,2, \dots, k$

A property of this is that the conditional distribution of the following state, S_{t+1} relies only on information of the current state, S_t and not on any previous information $\{S_{t-1,}S_{t-2}, \dots, S_1, R_{t-1}, R_{t-2,} \dots, R_1\}$. We characterise the transition probability p_{ij} as the probability of the regime switching from i to j in time t given that the regime in the previous period was i. In any given period, the following state is governed by the current probability matrix, $P_t = \lfloor p_{ij} \rfloor$, a $k \times k$ matrix with the constraint that column probabilities sum to 1 i.e. $\sum_{i=1}^{k} p_{ij} = 1, \forall \, i \leq k$.

In order for the transition probability matrix to be time- varying by specification, Ding (2012) amended the Matlab code to adopt a recursive time- varying probability function for every probability matrix entry to account multiple regimes i.e. $k > 2$. With k states, there are $k(k-1)$ independent time- varying transition probabilities which need to be determined.

Define the $k \times k$ matrix Q_t:

$$Q_t = \begin{pmatrix} q_{11,t} & q_{12,t} & \cdots & q_{1k,t} \\ q_{21,t} & q_{22,t} & \cdots & q_{2k,t} \\ \vdots & \vdots & \ddots & \vdots \\ q_{k-1,1,t} & q_{k-1,2,t} & \cdots & q_{k-1,k,t} \\ 1 & 1 & \cdots & 1 \end{pmatrix}$$

Define the probability generating function, $q_{ij,t} = \Phi(\boldsymbol{X}_{ij,}\boldsymbol{b}_{ij})$ for each $q_{ij,t}$ with $i,j \in (1,2,\dots,k-1)$ where:

$\Phi(.)$ is the cumulative normal density function, $\boldsymbol{X}_{ij}$ is the regime variable vector for q_{ij} and $\boldsymbol{b}_{ij}$ the vector of parameters to be estimated. The auxiliary matrix U_t is generated based on Q_t:

$$U_t = \begin{pmatrix} 1 & 1 & \cdots & 1 \\ 1-q_{11,t} & 1-q_{12,t} & \cdots & 1-q_{1k,t} \\ \vdots & \vdots & \ddots & \vdots \\ \prod_{i=1}^{k-2}(1-q_{i1,t}) & \prod_{i=1}^{k-2}(1-q_{i2,t}) & \cdots & \prod_{i=1}^{k-2}(1-q_{ik,t}) \\ \prod_{i=1}^{k-1}(1-q_{i1,t}) & \prod_{i=1}^{k-1}(1-q_{i2,t}) & \cdots & \prod_{i=1}^{k-1}(1-q_{ik,t}) \end{pmatrix}$$

The final TVTP matrix, P_t at time t is created by using the Hadamard product:

$$P_t = Q_t \circ U_t = \begin{pmatrix} p_{11,t} & p_{12,t} & \cdots & p_{1k,t} \\ p_{21,t} & p_{22,t} & \cdots & p_{2k,t} \\ \vdots & \vdots & \ddots & \vdots \\ p_{k-1,1,t} & p_{k-1,2,t} & \cdots & p_{k-1,k,t} \\ p_{k1,t} & p_{k2,t} & \cdots & p_{kk,t} \end{pmatrix}$$

Or

$$p_{1j,t} = q_{1j,t}$$

$$p_{2j,t} = (1-q_{1j,t})q_{2j,t}$$

$$\vdots$$

$$p_{k-1,j,t} = \left(1-q_{1j,t}\right)\left(1-q_{2j,t}\right)\dots\left(1-q_{k-2,j,t}\right)q_{k-1,j,t}$$

$$p_{kj,t} = \left(1-q_{1j,t}\right)\left(1-q_{2j,t}\right)\dots\left(1-q_{k-2,j,t}\right)\left(1-q_{k-1,j,t}\right)$$

Where each column $j, j = 1,2,\dots,k$ will sum to 1. This is consistent with the initial code proposed by Perlin (2015), however it should be noted that P_t is the transpose of that originally proposed by Hamilton (1989) which allows for unconstrained optimisation algorithms to be used in Matlab (Ding, 2012).

Hamiltons (1989)'s model

Perlin (2015), highlighted a constraint in the MS_Regress package with regards to matching results to that proposed by Hamilton (1989). The Markov Switching model of Hamilton (1989) over n lags may be specified under the form:

Equation 3: Perlin augmentation

$$y_t - \mu_{S_t} = \sum_{1=i}^{n} \emptyset_i \left(y_{t-i} - \mu_{S_{t-i}}\right) + \varepsilon_t$$

$$\varepsilon_t \sim N(0, \sigma^2)$$

The package is not designed to cater directly to this kind of setup though Perlin (2015) does identify a two- step process in which the performance in the outcome of estimation is highly comparable. The initial step was to consider the equivalent model defined as a standard Markov Switching Model:

Consider $z_t = y_t - \mu_{S_t}$

and so equation 3 may be rewritten as $z_t = \sum_{1=i}^{n} \emptyset_i z_{t-i} + \varepsilon_t$

with $y_t = \mu_{S_t} + z_t$.

Step 1: Estimate MS_Regresss_Fit_TVTP within MS_Regress

$$y_t = \mu_{S_t} + z_t$$
$$\varepsilon_t \sim N(0, \sigma^2)$$

Step 2: Retrieve the vector $\hat{\varepsilon}_t$ and regress it on n lags:

$$\hat{\varepsilon}_t = \textstyle\sum_{1=i}^{n} \beta_i \hat{\varepsilon}_{t-i} + v_t$$
$$v_t \sim N(0, \sigma_{v_t}^2)$$

Where $\sigma_{v_t}^2$ closely approximates σ^2 of Hamilton's model.

The parameters of the Markov- Switching Model are estimated in the MS_Regress package through the maximum- likelihood method, the numerical optimisation of which is performed by the “fmincon” optimiser algorithm in Matlab. The model proposed by Hamilton (1989) is governed by dynamics of the condition mean, modelled by the autoregressive as well as the regime variable S_t, governed by the Markov Chain (Chu et al., 2004) and parameter estimation of Perlin’s two- step approach include lag coefficients $\{\emptyset_1, \emptyset_{2,\dots,}\emptyset_n\}$, mean returns of the unobserved regimes, $\{\beta_1, \beta_{2,\dots,}\beta_k\}$ and the TVTP matrices at each time period P_t.

Hamilton (1989) derived a smoothing filtering algorithm, the r- lag smoother (with r denoting the number of lags within the system), in order to draw probabilistic inferences against the unobserved regimes of S_t based on currently known information. The r- lag smoother is described as the inferential probability of S_t given observations up to $t + r$. MS_Regress applies this smoothing algorithm against filtered probability states for each time period.

The majority of Markov Switching Regime Models in the literature pertaining to calendar effects assign an *a priori* number of regimes, namely two (Chang, Choi, & Park, 2017) as was proposed in the initial literature by Hamilton (1989). An extension to this allows for more than two regimes to be considered and the optimum number of regimes be used in the analysis. In determining the optimal number of regimes or states and the optimal number of lags, two information criterions were considered, namely the Akaike information criterion (AIC) and the Bayesian information criteria (BIC) first proposed by Schwarz (Fabozzi, Focardi, Račev, Arshanapalli, & Höchstötter, 2014):

Equation 4: Information criteria

$$AIC = -2logL(\hat{\theta}) + 2k$$

$$BIC = -2logL(\hat{\theta}) + k\log n$$

Where

θ = the vector of model parameters.

$L(\hat{\theta})$ = the maximum likelihood of the model fit given parameters estimates of θ.

k = the number of estimated parameters in the candidate model.

n = the number of observations in the data set.

A Markov- switching model with multiple regimes and lags would typically have a large number of parameters to be estimated. The BIC, as a penalised- likelihood criterion, imposes a more severe penalty on having a larger number of parameters than does the AIC (Fabozzi et al., 2014). As such, the researcher opted to use the model which minimised the BIC and not the AIC, which was also the preferred option implemented by Chu et al (2004).

The BIC was compared on each index on to determine the optimal number of lags and regimes for each index under weekday and monthly return scenarios. This will determine the best model, the one that minimises the BIC, for each index the number of regimes and the order of auto regression for each. Perlin (2015) cautions the use of using more than three regimes using the MS_Regress package as Matlab's fmincon function may result in a solution which is a local maximum in estimating a large number of parameters. As such, models of regime orders limited to $k = 2,3$ were run against lag orders $n = 1,2,3$. This resulted in six different parameter estimations per index. The parameter set which best minimised the BIC per index was said to be the optimal fit in terms of the number of regimes and associated number of lags. The resulting residual vector was retrieved against each best fit parameter set and was re- regressed as per Perlin's (2015) two- step method, again with regime orders of $k = 2,3$ and number of lags $n = 1,2,3$, which closely approximates the results of Hamilton (1989). After the second iteration of regressing, the final model of regressed residual vectors which again minimised the newly calculated BIC on the second iteration was used.

4.3.1 Allocating daily and monthly returns to regimes

Once the optimal number of regimes and lags were determined per index, both daily and monthly, the smoothed probabilities were determined for each index point in time. In order to assign individual index monthly returns and daily returns with an associated regime, these smoothed inferential probabilities were considered. For an index, it would be assigned to a certain regime j at time t if it's inferential probability for regime j at time t was higher than all other inferential probabilities of other regimes at that same point in time. i.e. $P(S_t = j|.) > P(S_t = i|.)\ \forall\ i \neq j$.

Frequencies, under each regime, were matched to days of the week and months of the year. Their associated relative frequencies, based on the number of occurrences overall within a single regime provided evidence of the potential for a certain day of the week or month of the year to fall within a certain regime more or less often relatively, based on the data dependent inferential probabilities. The Chi-square goodness of fit test was conducted to detect any significant deviation from expectation in the allocated frequency distributions across regimes.

In testing the firm size effect within certain regimes against days of the week and months of the year, The J200 Top 40, J201 Mid Cap and J202 Small cap indices were considered. With the optimal number of regimes, lag order determined and associated inferential probabilities determined, months of the year and days of the week are compared between the indices based on relative frequencies i.e. for the January effect, the relative number of occurrences of the month of January within regime j for the J202 would be compared to the relative number of occurrences of the month of January within regime j for the J201 and that of the J200. Higher relative occurrences of the month of January being assigned to regime j for the J202 compared to the other indices would suggest existence of the size effect within the month of January.

4.4 Limitations

- This research aims to uncover the presence of anomalous returns caused by calendar effects. In the case of month of the year effects, the chosen methodology is only able to detect the occurrence of anomalous effects of the entire month and not uncover mean- reverting behaviour the latter subperiods within the month as described by Moller & Zilca (2008).
- Although the research covers 99% of shares listed on the JSE by market capitalisation, the large majority of listed shares, by number, were unaccounted for. In determining the existence of smaller capitalisation shares falling outside of the J203 All Share Index, further investigations would need to be undertaken.
- Transaction costs are ignored in the quarterly index rebalancing and so the feasibility of trading strategies based on the outcome of the research will have to be investigated further.

- Due to constraints in the ability to retrieve data for J203 All Share constituent firms having been delisted within the observed period under consideration, in an endeavour to avoid survivorship biases, the researcher opted to use total return Index values obtained from Thomson Reuters Datastream, which was readily available. The index is weighted by the market capitalisations of constituent firms, and as such, movements in those constituent firms with larger relative market capitalisations would hold more gravitas in influencing the overall index price. As such, results could deviate from constructing the index using firms with equal representation by weight, due to the influence of these larger capitalised firms.
- In determination of the firm- size effect, and again being constrained in acquiring delisted share data, the researcher opted to use the J200 Top 40, J201 Mid Cap and J202 Small Cap indices which were retrieved from Thomson Reuters Datastream. These indices, too, are weighted by market capitalisation which means they are price sensitive to fluctuations in the larger capitalised firm returns. A further caveat in testing the firm- size affect using the acquired data was that total return prices were only available for the J200 index for a period of five years, with no total return data being available for the J201 and J202 indices. As such, in testing for the firm size effect, this study only investigates the presence of the firm- size effect without consideration of dividends being reinvested i.e. returns are net of dividends and are not total returns.
- In making use of the MS_Regress package by Perlin (2015), the researcher is only able to consider the fitting of Markov Switching models with a maximum of three regimes, due to limitations in the accuracy in convergence of the fmincon numerical optimiser. Models in excess of three regimes may be a better fit, i.e. further minimising of the BIC, although, due to the constraint and concerns of accuracy, were not considered within this research study.

5 Results

5.1 Introduction

This research sought to uncover anomalous returns over certain calendar periods, namely, whether certain days of the week or months of the year exhibited abnormal returns by employing a Markov Switching Model regime with time varying transition probabilities. Furthermore, the researcher undertook to consider different sub-indices, namely the J200 Top 40, J201 Mid Cap and J202 Small Cap Indices, the constituents of which were also representative of the J203 All Share Index and are allocated to the sub- indices based on different groupings in market capitalisation size in order to uncover prevalence of a firm size effect. Markov Switching models were fitted with varying numbers of regimes ($k = 2,3$) and lag orders ($n = 1,2,3$) to all four indices, both daily and monthly, with the best fit determined for each index based on minimisation of the BIC. Due to a constraint in the MS_Regress package construct, the residual vectors on these eight best- fit models were re- regressed and again the optimal fit of the final models was attained by again assigning different regime and lag orders and adopting the ones that, once again, minimise the BIC.

To substantiate utilisation of the Markov Switching model, the Jarque- Bera test was conducted, using skewness and kurtosis measures of the underlying distribution, derived from the descriptive statistics, in order to confirm that returns are non- normal, a characteristic which is a commonly known facet of financial market index returns.

Table 1: Jargue- Bera Test for normality

		J203 All Share TR	J202 Small Cap	J201 Mid Cap	J200 Top 40
Daily returns	Jarque- Bera	47.36	6034.04	160.06	31.15
	P- value	0.000	0.000	0.000	0.000
Monthly returns	Jarque- Bera	38.49	36.53	52.76	37.87
	P- value	0.000	0.000	0.000	0.000

For both the daily and monthly returns over the four indices yielding low p- values well below a 0.01 level of significance, it may confidently be concluded, based on the Jarque- Bera test for normality that the daily and monthly returns on all indices differ significantly from a normal distribution. This warrants use of a Markov Switching model.

The empirical results that follow will discuss the findings as to the prevalence of the month of the year effect and the day of the week effect on the J203 All Share TR Index. Thereafter will follow an evidenced discussion as to the prevalence of the size effect, conducted on the J200 Top 40, J201 Mid Cap and J202 Small Cap Indices.

5.2 Month of the Year Effect

Table 2: Descriptive statistics of monthly returns by index

Monthly	J203	J202	J201	J200
Mean	0.0128	0.0135	0.0127	0.0100
Standard Error	0.0033	0.0029	0.0030	0.0036
Median	0.0145	0.0151	0.0138	0.0105
Standard Deviation	0.0454	0.0393	0.0413	0.0486
Sample Variance	0.0021	0.0015	0.0017	0.0024
Kurtosis	0.7823	1.0764	0.4811	0.7973
Skewness	-0.1373	-0.5097	-0.3533	-0.1232
Range	0.2731	0.2414	0.2604	0.2957
Minimum	-0.1324	-0.1268	-0.1458	-0.1491
Maximum	0.1407	0.1147	0.1146	0.1467
Sum	2.3793	2.5048	2.3617	1.8609
Count	186	186	186	186

Descriptive statistics are calculated, by index, for the monthly returns shown in Table 2. Table 3 highlights the mean and standard deviations monthly returns split by months of the year. A colour gradient scale is presented, showing the relation between risk and return. Notably, higher mean returns are generally associated with higher levels of volatility.

Table 3: Mean and standard deviation of returns by month

Monthly Index	J203 TR		J200 Top 40		J201 MC		J202 SC	
Month	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Jan	0.528%	4.519%	0.458%	4.551%	0.131%	5.941%	0.937%	5.233%
Feb	0.793%	5.135%	0.514%	5.583%	1.589%	3.708%	1.546%	3.809%
Mar	1.939%	5.005%	1.298%	5.364%	1.018%	4.154%	1.384%	3.674%
Apr	1.300%	2.980%	0.772%	3.366%	2.034%	2.989%	1.999%	3.285%
May	2.363%	5.829%	2.835%	6.254%	-0.810%	4.504%	-0.284%	4.332%
Jun	-1.367%	2.843%	-1.615%	3.288%	-1.093%	3.333%	-1.035%	3.585%
Jul	1.597%	6.047%	1.340%	6.512%	3.000%	4.160%	1.900%	2.611%
Aug	1.935%	3.275%	1.565%	3.544%	1.652%	3.072%	2.304%	2.928%
Sep	0.880%	5.558%	0.297%	5.930%	0.268%	4.254%	1.227%	3.582%
Oct	2.690%	5.399%	2.403%	5.746%	2.903%	4.236%	2.617%	5.334%
Nov	0.905%	2.593%	0.696%	2.599%	1.352%	4.025%	1.019%	3.639%
Dec	1.655%	3.592%	1.333%	3.825%	2.897%	3.178%	2.325%	3.976%

In an attempt to bring to surface any conclusive evidence that calendar effects are present in certain months of the year on the JSE overall, a variety of Markov Switching models were fitted to the J203 All Share TR Index with regime and lag orders of $k = 2,3$ and $n = 1,2,3$ respectively. The same approach was taken on the three sub- indices, namely the J200 Top 40, J201 Mid Cap and J202 Small Cap Indices.

Table 4 highlights these results with the AIC and BIC. Bold letter indicated minimisation of the BIC.

Table 4: Optimal model fit on initial regression for monthly returns

Index (Monthly)	Regimes, Lags	AIC	BIC
J203 All Share TR	**k = 2, AR(1)**	1063.2627	**1089.0687**
	k = 2, AR(2)	1063.9715	1096.2290
	k = 2, AR(3)	1055.6860	1094.3950
	k = 3, AR(1)	1070.4393	1118.8255
	k = 3, AR(2)	1043.7550	1101.8184
	k = 3, AR(3)	1057.7556	1125.4963
J202 Small Cap	**k = 2, AR(1)**	1015.9498	**1041.7557**
	k = 2, AR(2)	1022.9601	1055.2175
	k = 2, AR(3)	1039.8925	1078.6014
	k = 3, AR(1)	1029.4507	1077.8369
	k = 3, AR(2)	1011.6064	1069.6699
	k = 3, AR(3)	997.9427	1065.6833
J201 Mid Cap	k = 2, AR(1)	1054.6753	1080.4812
	k = 2, AR(2)	1048.0840	**1080.3415**
	k = 2, AR(3)	1051.8281	1090.5371
	k = 3, AR(1)	1058.3882	1106.7744
	k = 3, AR(2)	1040.6080	1098.6714
	k = 3, AR(3)	1050.6981	1118.4387
J200 Top 40	k = 2, AR(1)	1083.9964	1109.8024
	k = 2, AR(2)	1069.8007	**1102.0582**
	k = 2, AR(3)	1070.0386	1108.7476
	k = 3, AR(1)	1090.3738	1138.7600
	k = 3, AR(2)	1070.8821	1128.9456
	k = 3, AR(3)	1102.6732	1170.4139

For monthly returns it was identified the all four indices had optimal parameter fits, by minimisation of the BIC, with two regimes. Optimal lags for the J203 and J202 were one lag, and for the J201 and J200 were two lags. The residual vectors were then regressed, as per the advice of Perlin (2015) to conform with the model proposed by Hamilton (1989). Re-regression of the residual vectors yielded the final model parameters with optimal numbers of regimes and lag orders shown in Table 5.

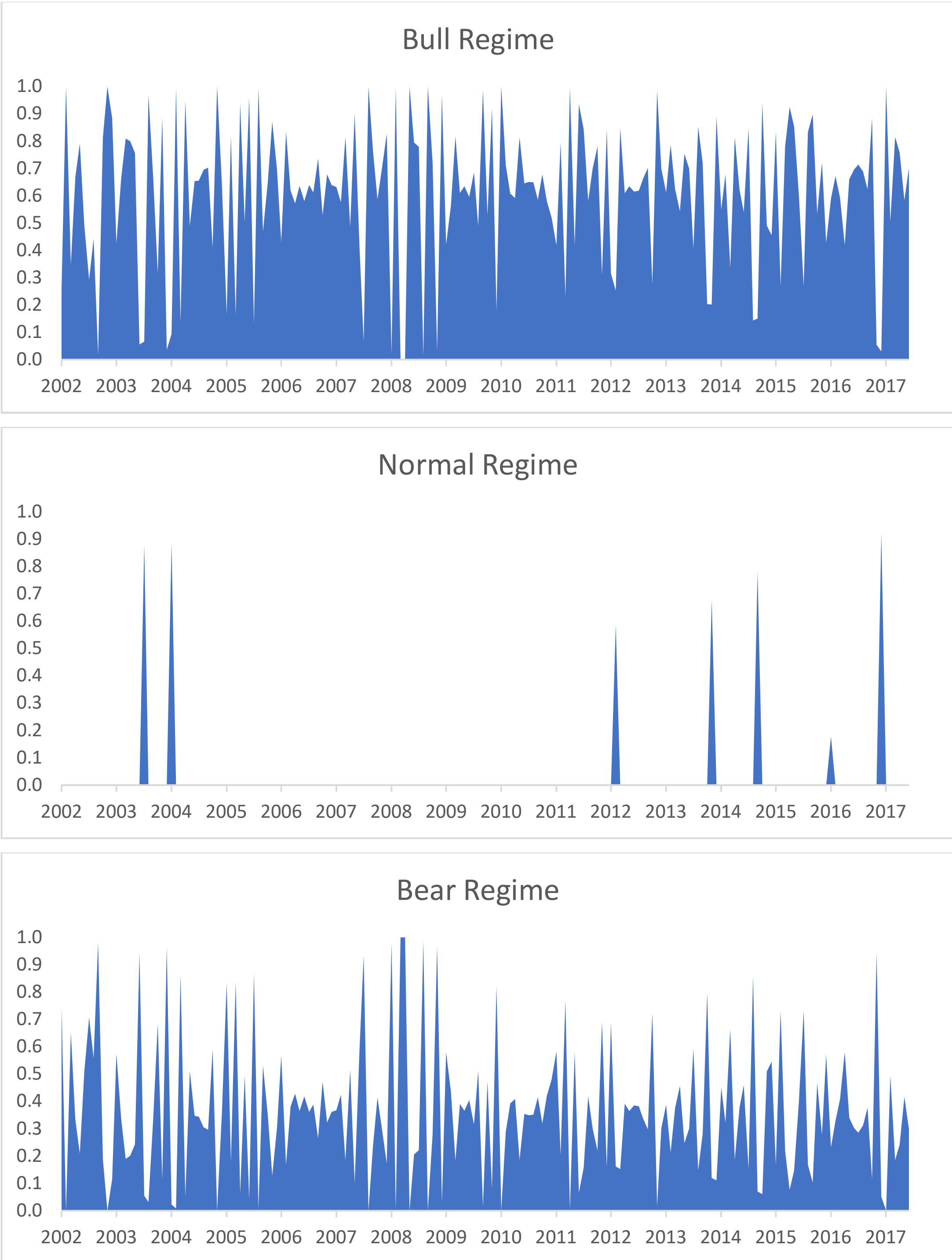
Table 5: Optimal fit on regressed residual for monthly returns

Index	Regimes (k)	Lags	BIC
J203 All Share TR	3	2	1130.094763
J202 Small Cap	3	1	1055.89184
J201 Mid Cap	3	2	1083.512505
J200 Top 40	3	3	1154.279285

Consequently, the optimal number of regimes, as governed by minimisation of the BIC, yielded three regimes for each index. The same number of regimes in each index is a fortunate consequence for comparison purposes. In light of this, and in order to better facilitate understanding of the output, regimes will be referred to as (1) the bull regime, (2) the normal regime and (3) the bear regime. The bull regime may be characterised as one exhibiting positive anomalous returns i.e. Index prices are increasing. The bear regime, in contrast, is one whereby anomalous negative returns are characteristic and the normal regime exhibits neither positive or negative abnormal returns.

Months in each year were classified into regimes based on the smoothed inferential probabilities calculated as per the r- lag smoothing algorithm devised by Hamilton (1989) i.e. if for a certain month in a certain year it was shown that $P(S_t = 1) > P(S_t = 2), P(S_t = 3)$, then that particular month in that year was assigned to the bull regime. These smoothed inferential probabilities are presented in Figure 1.:

Figure 1: J203 All Share Index smoothed probability regimes



It must be noted that the smoothed inferential probabilities sum to one vertically i.e. the sum of the smoothed inferential probabilities for the month of January in 2008 for the bull, normal and bear regimes will equal one, as will every other month.

As is evidenced by the smoothed inferential probabilities attributed to the J203 All Share TR Index, most of the activity, probabilistically, is attributed to the bull regime, followed by the bear regime, with there being very little probabilistic chance of returns being attributed to the normal regime. This corroborates with the descriptive statics in table X, whereby the J203 has a positive mean monthly return of 1.28%, with significant levels of volatility when compared to the sub- indices. Its standard deviation is significantly higher than the J202 Small Cap and the J201 Mid Cap Indices, at 4.54%, outdone marginally, in terms of volatility, only by the J200 Top 40 Index with a standard deviation of 4.86%. With a positive mean return and comparably higher fluctuations in returns, it can be expected that it would alternate probabilistically between these two regimes. As such, it can be expected, based on the time varying transfer probabilities, that the expected number of periods to be spent in the bull regime, too, would be higher.

Table 6: Expected regime duration for J203 monthly returns

Monthly Returns	*J203 All Share TR Expected Duration*
Bull Regime	2.09
Normal Regime	1.00
Bear Regime	1.25

Although this too corroborates with the smoothed inferential probabilities, the expected duration within in each state is short, owing to the high level of volatility in returns. In assigning months to certain regimes, the frequency of occurrence in each state is obtained:

Table 7: J203 regime frequencies by month

State	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Tot
Bull	9	11	12	11	10	10	7	14	10	13	14	13	134
Normal	1	0	1	0	1	1	1	1	0	0	0	0	6
Bear	5	4	2	4	4	4	8	1	6	3	2	3	46

Notable deviations from uniformity by frequency include July, exhibiting the lowest probabilistic occurrence in the bull regime and the highest in the bear regime and, in contrast, August, exhibiting the lowest probabilistic occurrence in the bear regime with high bull regime frequency. In order to understand the statistical significance thereof, a Chi-Square Goodness of fit test was performed on each month's frequency distribution across regimes against the expected frequency distribution across regimes. Under the assumption that investors are rational and that markets are efficient, it should be expected that, given the total number of frequencies in each regime across all months, the expected number of frequencies in each regime by month would be uniformly distributed e.g. If there were 120 total observed frequencies in a certain regime, then each of the twelve months would be observed to be within this regime ten times. Under this assumption, the observed frequency against the expected frequency in regime distribution.

Table 8: J203 Chi-square goodness of fit test by month

Month	p- value
Jan	0.5285
Feb	0.7750
Mar	0.4870
Apr	0.7750
May	0.7301
Jun	0.7301
Jul	**0.0372**
Aug	0.1908
Sep	0.3972
Oct	0.6120

Nov	0.3507
Dec	0.6120

At a 5% level of significance, the only statistically significant deviation in frequency distribution across regimes is July. Although not statistically significant at a 5% level, August does exhibit some deviation from expectation. One interesting insight is that August naturally follows July, and their deviations from expectation are in opposing directions in terms of regime frequencies

5.3 Month of the year size effect

In testing for the prevalence of monthly anomalies and size effect, the same approach was applied to the J200 Top 40, J201 Mid Cap and J202 Small Cap Indices. Smooth inferential probabilities were plotted by regime preference probabilistically based on months of the year. These are shown in Figure 2, Figure 3 and Figure 4.

Figure 2: J200 Top 40 Index smoothed probability regimes monthly

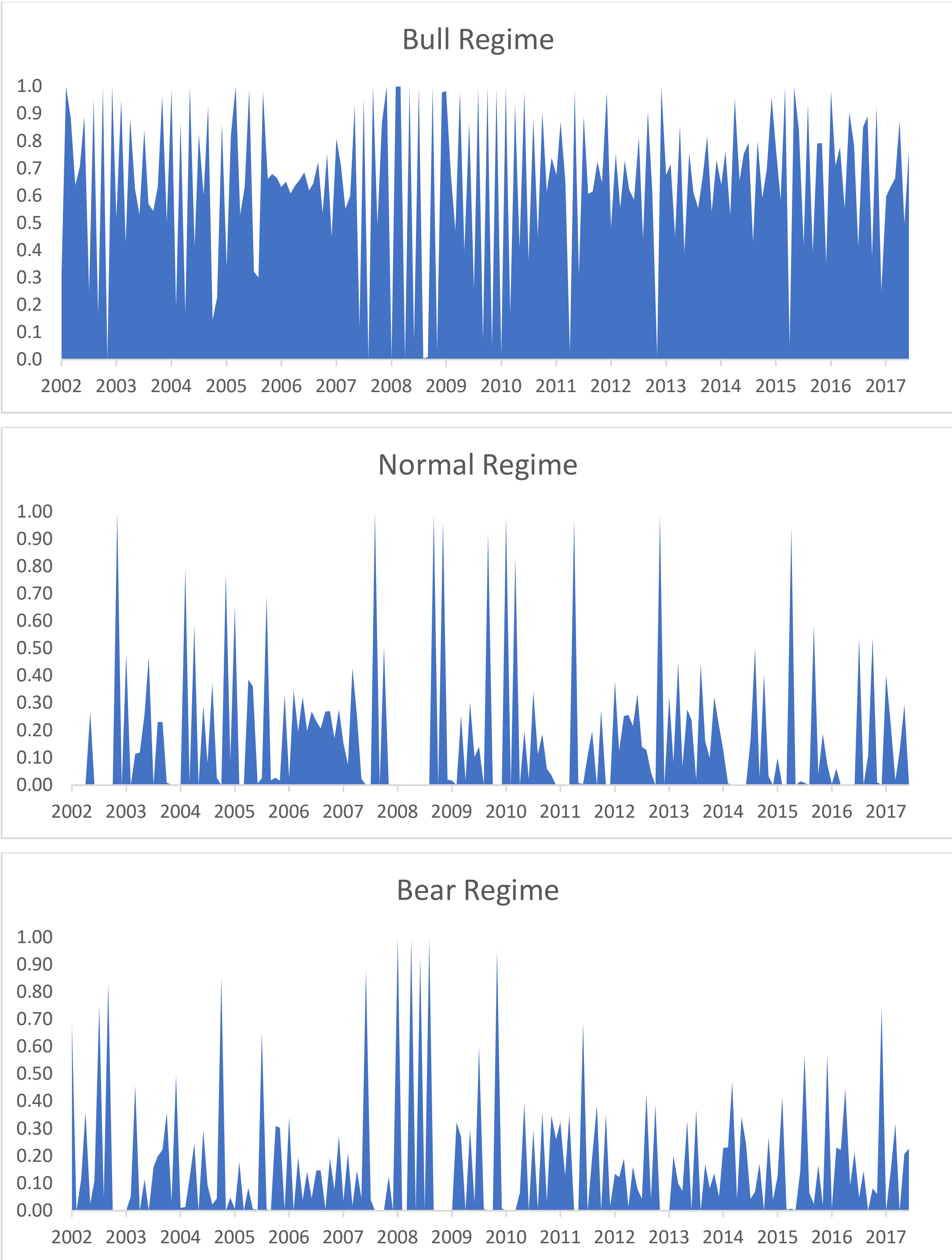


Figure 3: J201 Mid Cap Index smoothed probability regimes monthly

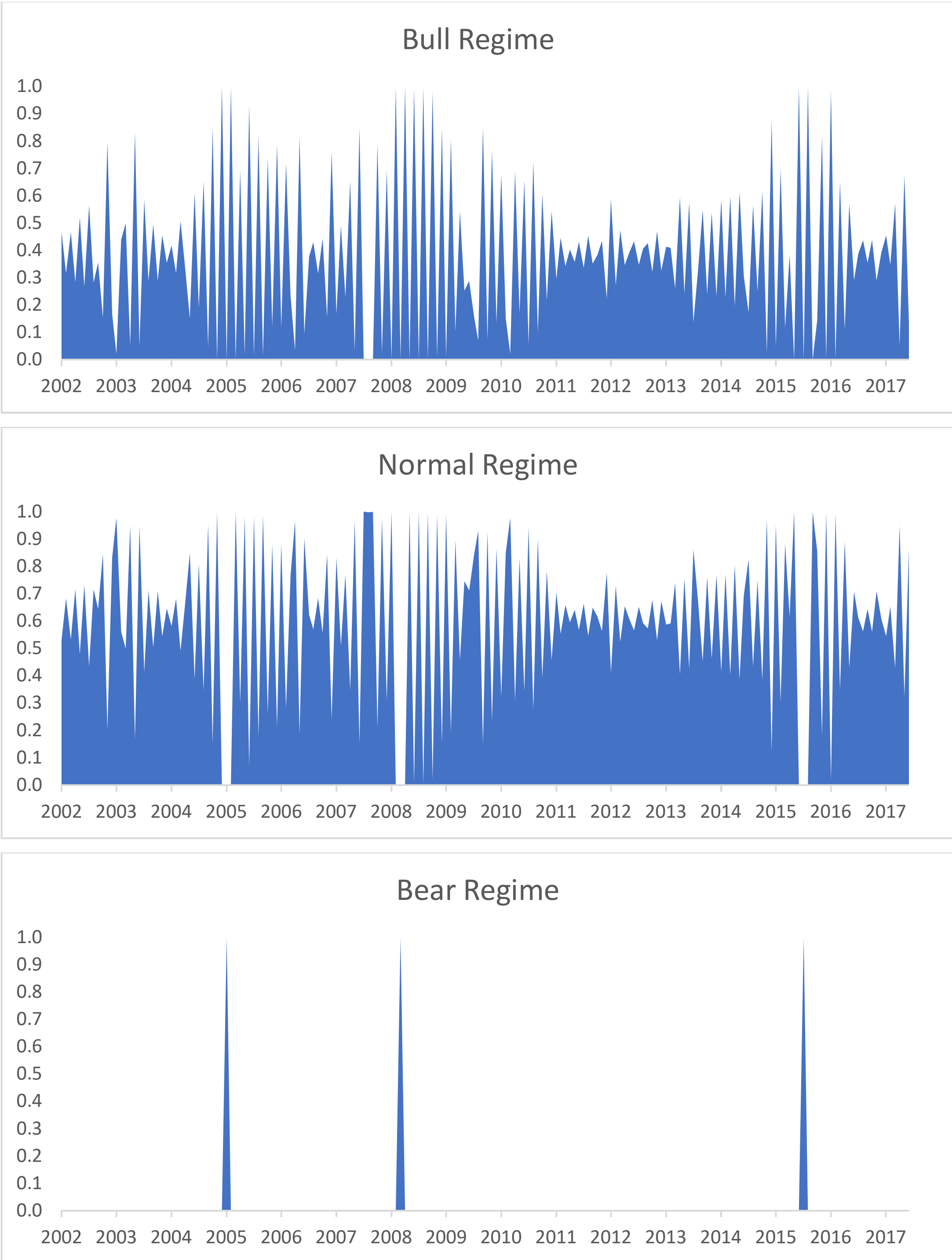
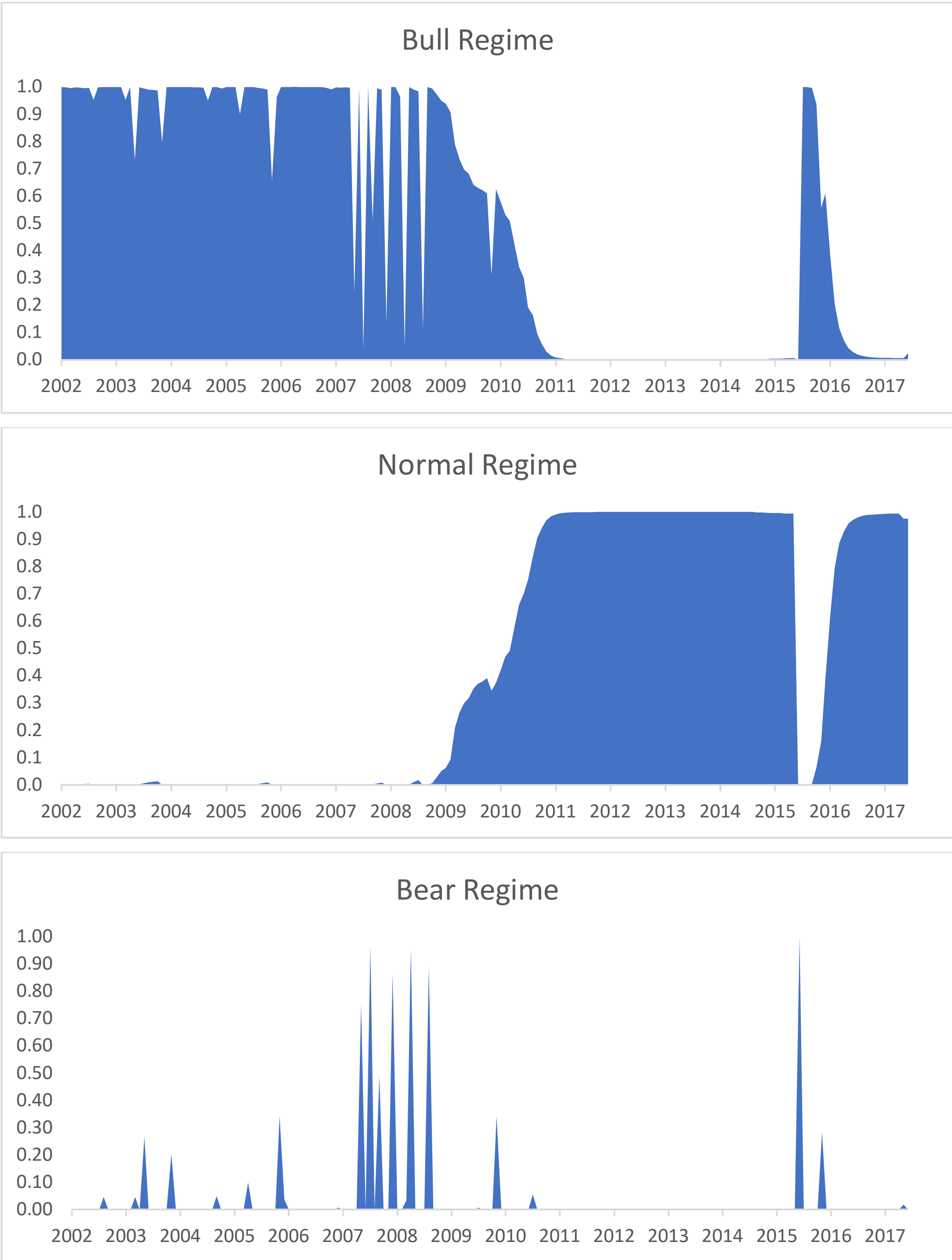


Figure 4: J202 Small Cap Index smoothed probability regimes monthly



The J200 Top 40 Index shows similar traits to the J203 All Share TR Index with the bull market exhibiting the highest area under the curve signifying larger bull regime prevalence.

It did however exhibit more probabilistic frequency within the normal regime, almost equally as much as the bear regime. With the lowest mean return, albeit still positive, at 1.0% and the highest standard deviation of all the monthly return indices, at 4.85%, transitions between regimes are expected to be volatile and expected durations within a given regime short.

The J202 Mid Cap Index exhibits far more probabilistic adherence to the normal regime, with transitions favouring the bull regime and sparse bear regime conformity. The J202 Small Cap Index, in contrast, exhibits absorptive transition probability tendencies during the period leading up until the Global Financial Crisis i.e. p_{11}, the probability of staying in regime 1, given it is in regime 1 is close to or is 1. Post 2009 the normal regime exhibits these absorptive properties which signifies stable market behaviour in the normal regime. The bear regime smoothed inferential probabilities are most prominent during the Global Financial Crisis period, between December 2007 and June 2009.

Table 9: Expected monthly durations by index

Monthly Returns	J200 Top40	J201 Mid Cap	J202 Small Cap
Bull Regime	1.98	1.00	10.87
Normal Regime	1.00	1.60	72.19
Bear Regime	1.00	1.00	1.00

The expected durations based on transition probabilities, as per the smoothed inferential probabilities, are as expected with short duration periods exhibited by the J200 Top 40 and J201 Mid Cap indices. The J202 Small Cap Index experiences longer expected durations which is in line the notion of absorptive transition probabilities for certain states over different periods. For each index, months are assigned to regimes in each year based on the highest smoothed inferential probability observed within that period:

Table 10: Monthly regime frequency by index

Index	State	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Tot
J202	Bull	8	8	9	9	8	8	9	9	9	7	7	8	99
Small	Normal	6	6	6	6	7	6	7	7	7	8	8	7	81
Cap	Bear	1	1	0	0	0	1	0	0	0	1	1	1	6
J201	Bull	2	6	2	6	4	7	4	5	4	6	6	7	59
Mid	Normal	12	9	13	9	11	8	11	11	11	10	10	9	124
Cap	Bear	1	0	0	0	0	0	1	0	1	0	0	0	3
J200	Bull	10	11	11	12	10	13	12	15	14	12	16	13	149
Top 40	Normal	1	3	3	2	4	0	2	1	1	3	0	0	20
	Bear	4	1	1	1	1	2	2	0	1	1	0	3	17

In observing regime frequencies for the J200 Top 40 Index, the most notable frequency distribution of regime frequencies is that of November talk more, with all observed November returns falling within the bull regime. August, too, exhibits bull regime tendencies having all but one observed returns falling within the bull regime with one exception falling within the normal regime. This is in line with the findings observed within in the J203 All Share Index, however there is no discernible evidence of July exhibiting bear regime tendencies. January exhibits the highest probabilistic tendency to fall within the bear regime. This negative January effect is significant at the 10% level according to the Chi- square goodness of fit test, with the November bear regime marginally falling to reject the null that there is no significant deviation.

Table 11: Chi-square test on monthly returns by index

	J202 Small Cap	J201 Mid Cap	J200 Top 40
Jan	0.7442	0.1195	**0.0656**
Feb	0.7442	0.7187	0.5089
Mar	0.7220	0.2634	0.5089
Apr	0.7220	0.7187	0.9034
May	0.7723	0.7930	0.1452
Jun	0.7442	0.4361	0.3802
Jul	0.7492	0.2917	0.8518
Aug	0.7492	0.8631	0.3294
Sep	0.7492	0.2917	0.7441
Oct	0.6310	0.7790	0.5479
Nov	0.6310	0.7790	0.1276
Dec	0.7723	0.5208	0.1770

January, in the J201 Mid Cap Index, also demonstrates the highest frequency distribution skewed away from the bull regime, followed closely by March. January frequency distribution across regimes marginally fails to be statistically significant at the 10% level. Although frequencies across all months favour the normal regime, July and December exhibit the highest bull market frequencies.

There are no highly discernible anomalous frequencies observed in the J202 Small Cap Index, with frequencies, for the most part, being uniformly distributed across months. This corroborates with the descriptive statistics, with the J202 having the highest mean return of 13.47% per month and the lowest standard deviation of 3.93% out of the four monthly indices. This index favours the bull market, though only marginally, with little fluctuation in frequency distribution across the months of the year.

In terms of the firm size effects across months of the year, there is no discernible evidence to support such an effect.

5.4 Day of the week effect

In order to determine the existence of the day of the week effect, the same methodology was conducted on the same indices using daily returns as opposed to monthly returns. Descriptive statistics were run in the same fashion

Table 12: Descriptive statistics of daily returns by index

Daily Returns	J203	J202	J201	J200
Mean	0.0006289	0.0006231	0.0005978	0.0005068
Median	0.0007913	0.0008723	0.0008392	0.0008645
Standard Deviation	0.0118574	0.0058356	0.0080018	0.0130141
Sample Variance	0.0001406	3.405E-05	6.403E-05	0.0001694
Kurtosis	3.5282613	8.9904615	3.5414628	3.4392426
Skewness	-0.056152	-0.613549	-0.417934	0.0011446
Range	0.1423574	0.1093045	0.1030145	0.1566256
Minimum	-0.071165	-0.044828	-0.054768	-0.076509
Maximum	0.0711925	0.0644764	0.0482467	0.0801167
Sum	2.4515636	2.4137643	2.3156921	1.9642708
Count	3898	3874	3874	3876

Table 13: Mean returns and standard deviations by day of the week

Daily Index	J203 TR		J200 Top 40		J201 MC		J202 SC	
Day	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Mon	0.123%	1.249%	0.085%	1.370%	0.002%	0.858%	0.000%	0.622%
Tue	0.025%	1.155%	0.021%	1.269%	0.067%	0.756%	0.043%	0.524%
Wed	0.042%	1.170%	0.036%	1.291%	0.060%	0.778%	0.057%	0.534%
Thu	0.100%	1.223%	0.096%	1.335%	0.107%	0.846%	0.110%	0.634%
Fri	0.026%	1.129%	0.015%	1.242%	0.060%	0.756%	0.099%	0.593%

Similarly, a variety of Markov Switching models were again fitted to the J203 All Share TR Index with regime and lag orders of $k = 2{,}3$ and $n = 1{,}2{,}3$ respectively. The same approach was taken on the three sub- indices: the J200 Top 40, J201 Mid Cap and J202 Small Cap Indices.

Table 14: Optimal model fit on initial regression daily returns

Daily	Regimes, Lags	AIC	BIC
J203 All Share TR	k = 2, AR(1)	4946.1103	4996.2560
	k = 2, AR(2)	4947.4496	5010.1318
	k = 2, AR(2)	4943.2769	5018.4955
	k = 3, AR(1)	4804.2127	**4898.2359**
	k = 3, AR(2)	4905.2756	5018.1035
	k = 3, AR(3)	4897.7363	5029.3689
J202 Small Cap	k = 2, AR(1)	5844.5645	5894.6608
	k = 2, AR(2)	5838.8395	5901.4599
	k = 2, AR(3)	5832.6069	5907.7514
	k = 3, AR(1)	5791.9110	5885.8417
	k = 3, AR(2)	5798.0763	5910.7931
	k = 3, AR(3)	5724.0688	**5855.5717**
J201 Mid Cap	k = 2, AR(1)	8330.2759	8380.3723
	k = 2, AR(2)	8332.0987	8394.7191
	k = 2, AR(3)	8332.5584	8407.7029
	k = 3, AR(1)	8243.6607	**8337.5913**
	k = 3, AR(2)	8285.9803	8398.6970
	k = 3, AR(3)	8250.0319	8381.5348
J200 Top 40	k = 2, AR(1)	12117.7179	12167.8143
	k = 2, AR(2)	12117.9433	12180.5638
	k = 2, AR(3)	12113.7928	12188.9373
	k = 3, AR(1)	12112.2050	12206.1357
	k = 3, AR(2)	11983.2606	**12095.9774**
	k = 3, AR(3)	12071.2257	12202.7286

The initial model fitting resulted in all indices being optimally suited to a three regime Markov model with varying lag orders, as governed by minimisation of the BIC. Once the residual vectors were retrieved and re- regressed, the resultant optimal regime and lag orders were obtained

Table 15: Optimal model fit for daily returns on residual regression

	Index	Regimes (k)	Lags	BIC
Daily	J203 All Share TR	3	2	1130.094763
	J202 Small Cap	3	1	1055.89184
	J201 Mid Cap	3	2	1083.512505
	J200 Top 40	3	3	1154.279285

Similarly, the optimal number of regimes for all four indices is three, a favourable outcome facilitating ease of comparison. Under the optimal Markov Switching models, the smoothed inferential probabilities were retrieved and are presented.

Figure 5: J203 All Share TR Index smoothed probability regimes daily

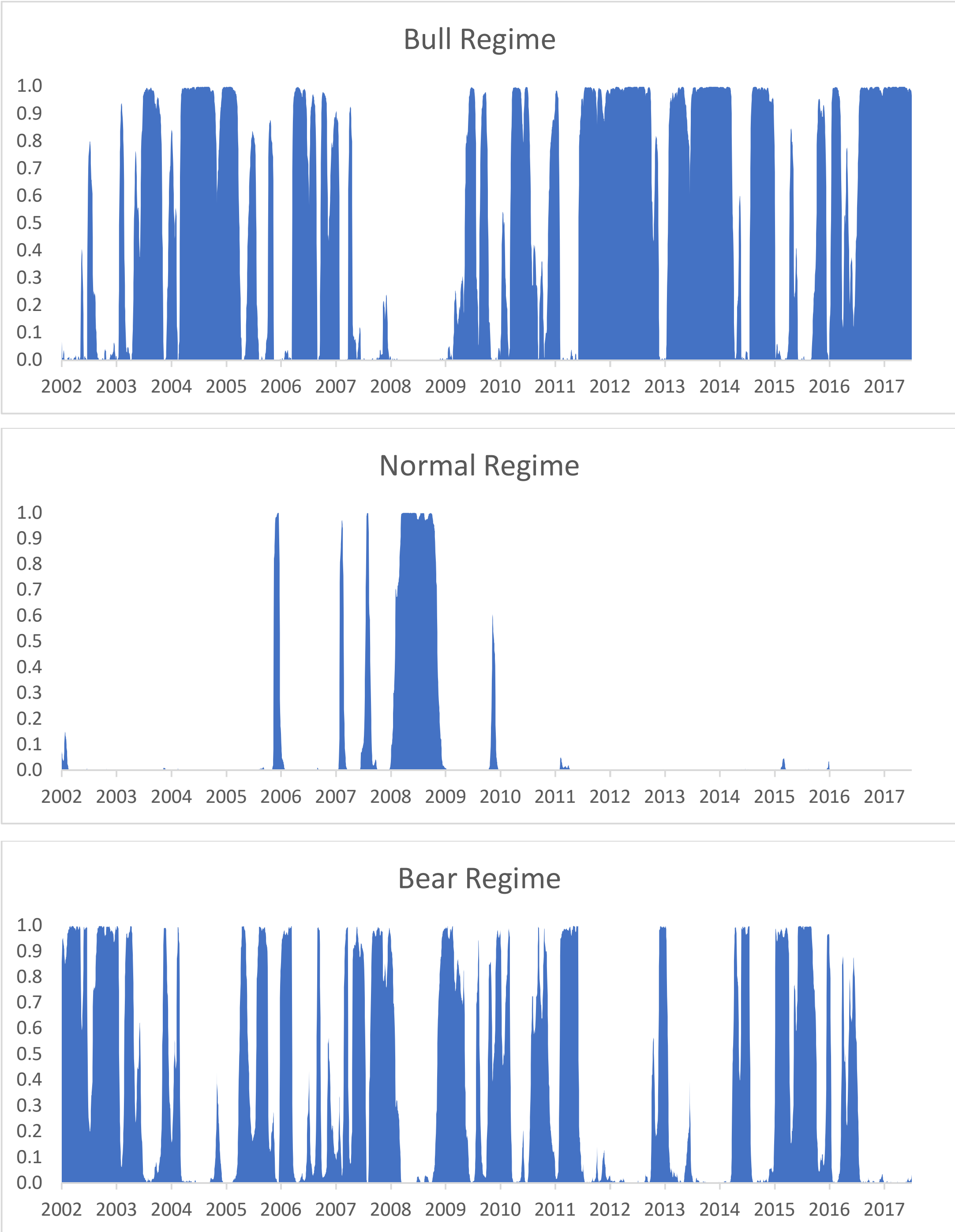


Figure 6: J200 All Top 40 Index smoothed probability regimes daily

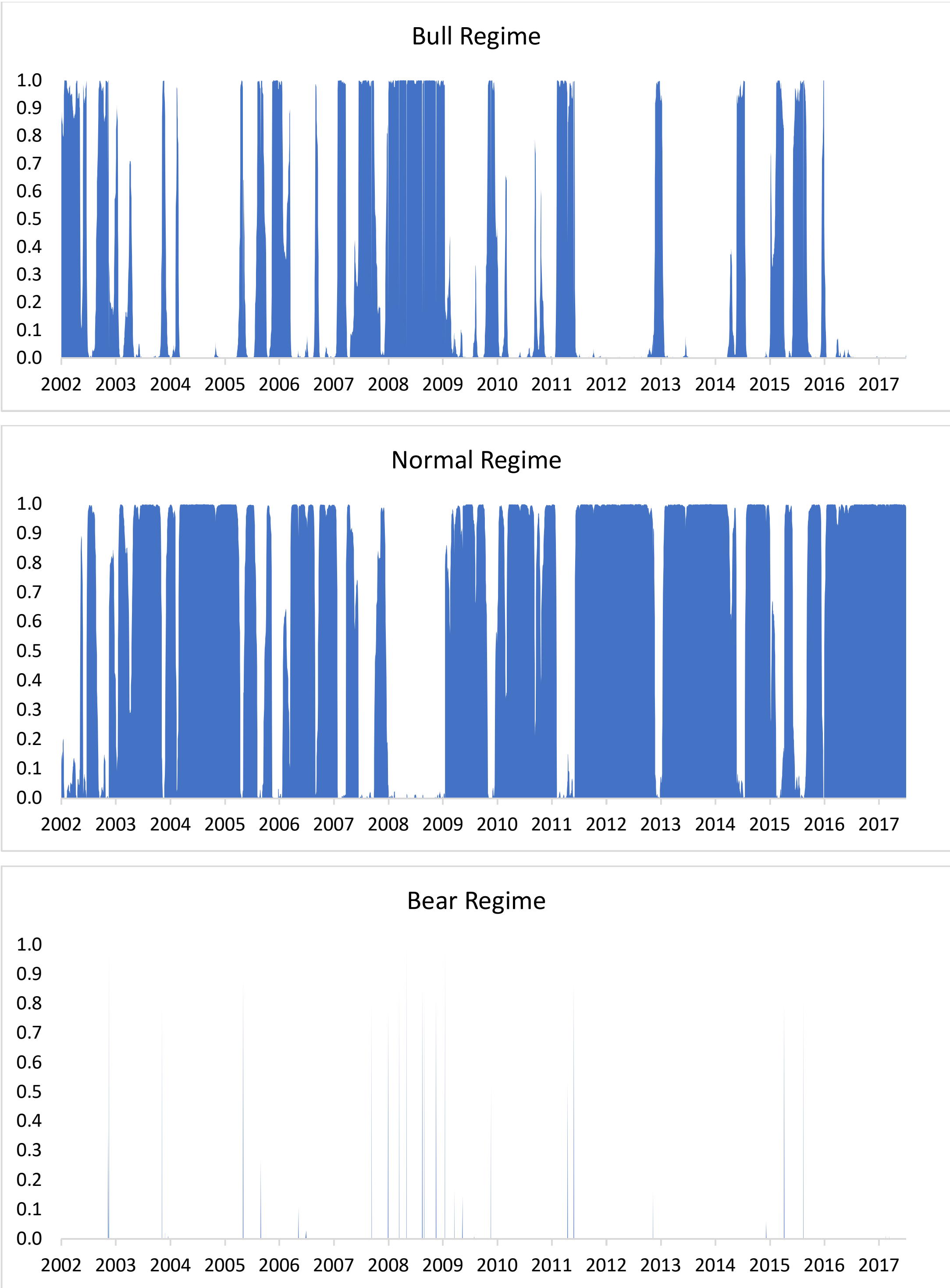


Figure 7: J201 Mid Cap Index smoothed probability regimes daily

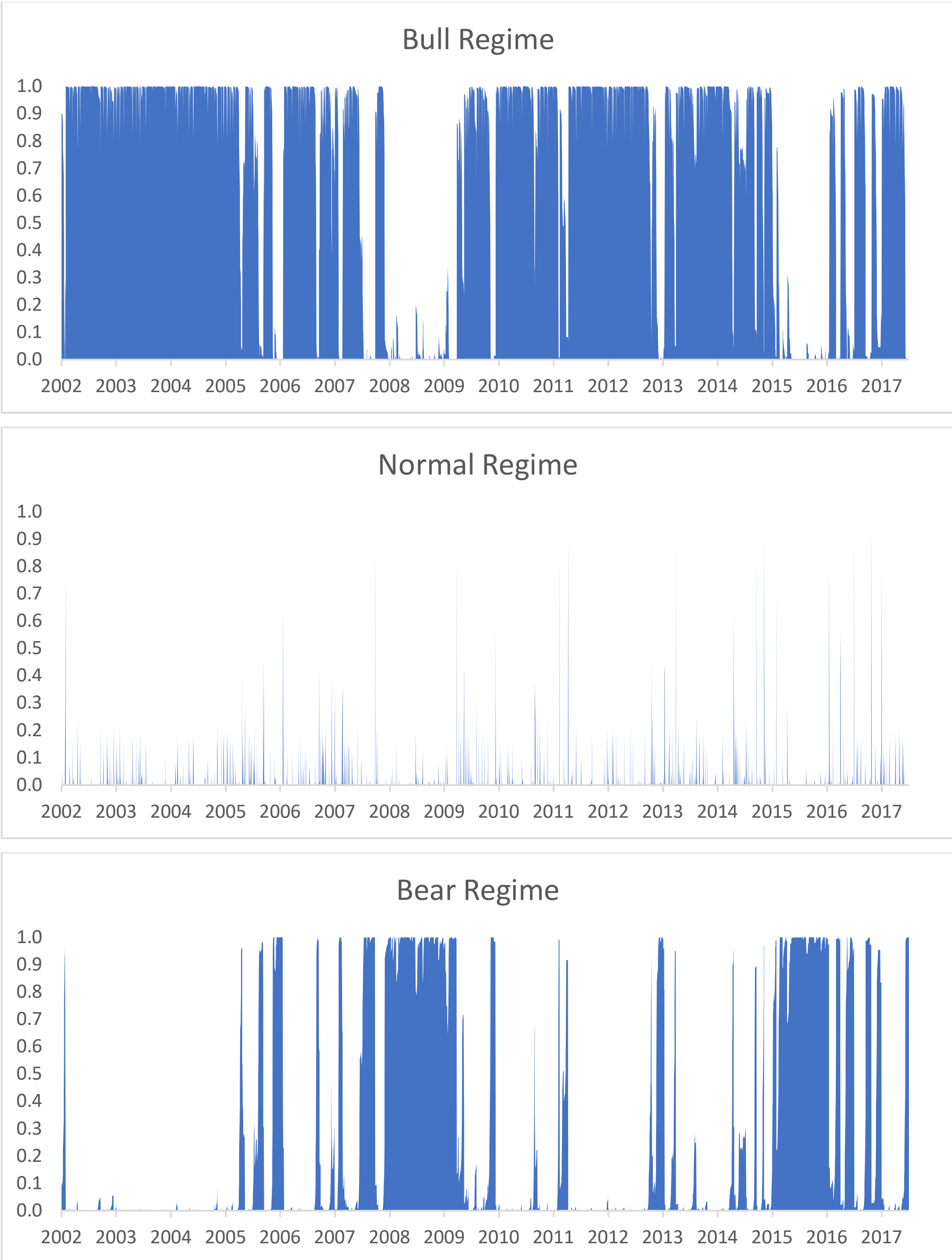
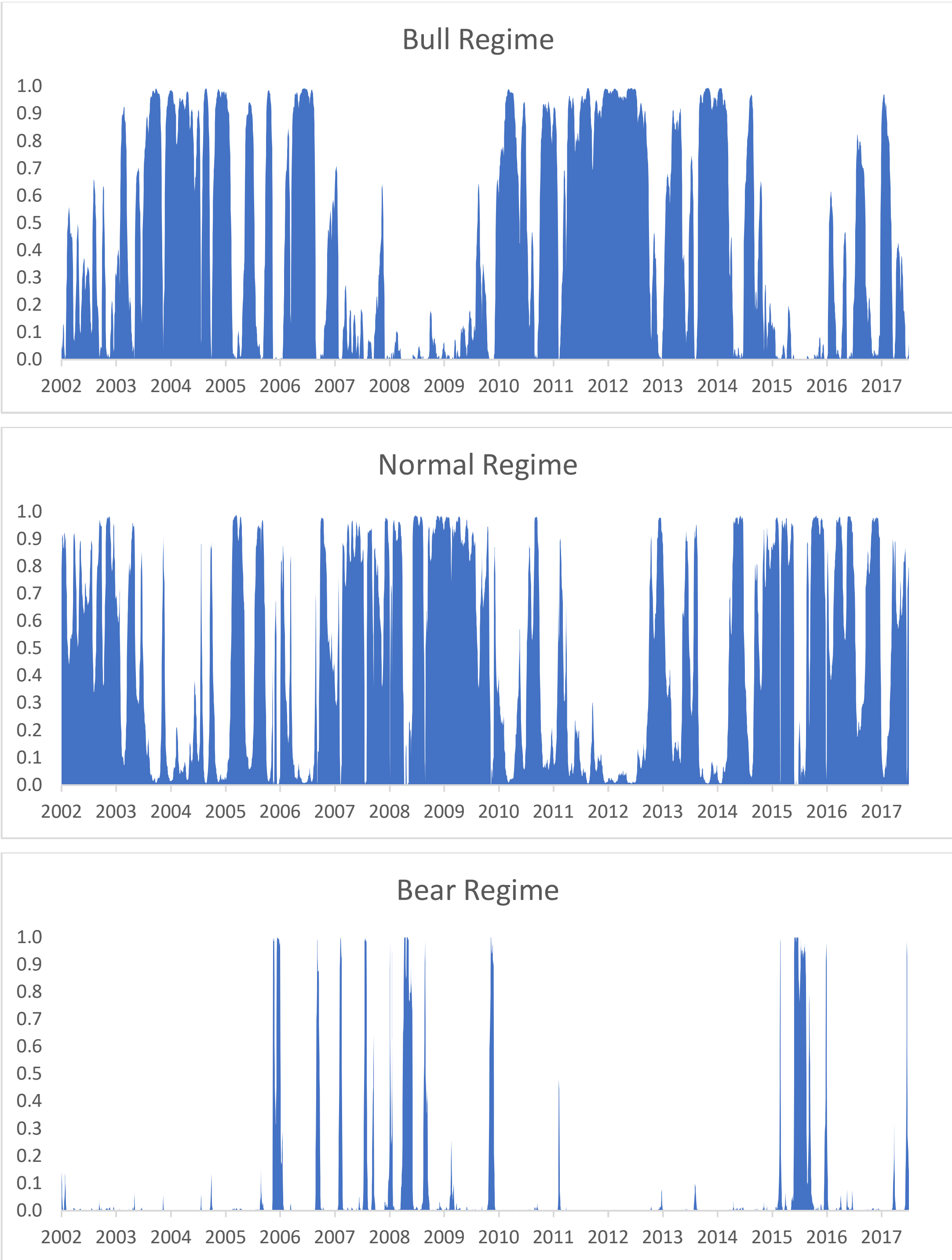


Figure 8: J202 Small Cap Index smoothed probability regimes daily



Smoothed inferential probabilities for the J203 All Share and the J201 Mid Cap Indices showcase significant preference within the bull regime with transitions favouring the bear regimes. Transitions to the bear regime, for both indices, is highly prominent during the periods including the global financial crisis between December 2007 and June 2009 as well as the Asian crisis between June 2015 and Feb 2016.The J200 Top 40 and J202 Small Cap indices favour the normal regime with preferred transitions to the bull regime. Posterior probabilities within these indices related to the bear regime are sparse, yet they also showcase the periods relating to the global financial crisis and the Asian crisis.
Time varying transition probabilities result in the following expected number of periods, in days, for an index to remain within a certain regime:

Table 16: Expected daily regime duration by index

Daily	*J203*	*J200*	*J201*	*J202*
Bull Regime	65.58	27.39	47.22	66.97
Normal Regime	49.35	92.27	1.00	1.17
Bear Regime	39.81	1.00	34.29	2.61

Assigning days of the week to regimes, based on the maximum smoothed inferential probability at that point in time, yields the frequency distribution of regimes by day, for each index.

Table 17: Regime frequency distribution by day of the week

Index	State	Mon	Tue	Wed	Thu	Fri	Tot
	Bull Regime	424	435	438	435	429	2161
J203 All Share TR	Normal Regime	54	56	55	51	52	268
	Bear Regime	279	297	296	303	294	1469
	Bull Regime	212	218	219	212	205	1066
J200 Top 40	Normal Regime	538	565	557	570	562	2792
	Bear Regime	2	3	4	3	4	16
	Bull Regime	549	577	566	569	564	2825
J201 Mid Cap	Normal Regime	4	3	6	4	7	24

	Bear Regime	199	206	209	212	199	1025
	Bull Regime	341	357	347	353	353	1751
J202 Small Cap	Normal Regime	368	383	385	385	374	1895
	Bear Regime	43	46	49	47	43	228

For clarity, these frequencies are easier read in relative terms, with rows summing to one, shown in Table 18.

Table 18: Regime relative frequency distribution by day of the week

Index	State	Mon	Tue	Wed	Thu	Fri
	Bull Regime	19.62%	20.13%	20.27%	20.13%	19.85%
J203 All Share TR	Normal Regime	20.15%	20.90%	20.52%	19.03%	19.40%
	Bear Regime	18.99%	20.22%	20.15%	20.63%	20.01%
	Bull Regime	19.89%	20.45%	20.54%	19.89%	19.23%
J200 Top 40	Normal Regime	19.27%	20.24%	19.95%	20.42%	20.13%
	Bear Regime	12.50%	18.75%	25.00%	18.75%	25.00%
	Bull Regime	19.43%	20.42%	20.04%	20.14%	19.96%
J201 Mid Cap	Normal Regime	16.67%	12.50%	25.00%	16.67%	29.17%
	Bear Regime	19.41%	20.10%	20.39%	20.68%	19.41%
	Bull Regime	19.47%	20.39%	19.82%	20.16%	20.16%
J202 Small Cap	Normal Regime	19.42%	20.21%	20.32%	20.32%	19.74%
	Bear Regime	18.86%	20.18%	21.49%	20.61%	18.86%

Frequency distributions across regimes, for all indices, appear uniformly distributed. Slight deviations from uniformity occur, with Mondays and Fridays exhibiting less bull regime tendencies than their midweek counterparts, though this is not statistically significant. The Chi- Squared Goodness of fit test yields no statistically significant deviation distributionally across regimes from expectation in any of the indices.

Table 19: Chi-square goodness of fit test by day of the week

	Mon	Tue	Wed	Thu	Fri
J203 All Share TR	0.6363	0.9229	0.9367	0.8056	0.9648
J200 Top 40	0.5483	0.9055	0.8347	0.8780	0.7639
J201 Mid Cap	0.6832	0.6266	0.8270	0.8185	0.5527
J202 Small Cap	0.7015	0.9150	0.8279	0.9230	0.8884

In conclusion, although there are slight deviations, there does not appear to be any conclusive evidence of any day of the week exhibiting abnormal returns throughout the period under consideration.

6 Discussion

6.1 Introduction

The aim of this research was to uncover the prevalence of calendar effects on the JSE using a Markov-switching model, incorporating time varying transfer probabilities and catering for more than two distinct regimes, from the period between 1 July 2002 and 31 December 2017. To the best of the researcher's knowledge, this methodology has not been performed on JSE index returns, and provides more recent insight into the domestic markets level of efficiency, with the most recent investigation only considering index data up until September 2013.

6.2 Day of the week

In testing for anomalies associated with market returns on certain days of the week, of which the Monday effect is the most prominent, extensive international research has been conducted. The U.S, being the most thoroughly researched financial market, is known to exhibit a significant and persistent negative Monday effect: Lakonishok and Smidt (1988) found persistence of the negative Monday effect in all periods on the DJIA Index for a ninety year period from 1987 to 1986. Lakonishok and Maberly (1990) attribute this effect, for the period between 1962 and 1986, to relatively thin overall trade on Mondays, with retail investors exhibiting dominant sell transactions on Mondays. Chelley-Steeley et al. (2016) confirm the persistence of the Monday effect in the U.S. AMEX Index in the subsequent period extending from 1997 to 2007 as well as on the German DAX. Over a more thorough and recent time period, J. Zhang et al. (2017) showcase the persistence of the Monday effect in both pre and post financial crisis periods, with the Monday effect being significant during the sample period of 1990 to 2016 in both the U.S. as well as in China. They also uncovered that at least one day of the week effect was present in each of the 25 countries included in the study. It could be inferred that, due to the existence of the Monday effect in the U.S., and due to increased levels of global integration in financial markets, that both developed markets such as the German financial market, and a primarily emerging market given the time frame, such as China, would exhibit similar correlated return movements at similar times.

The findings in this research show no significant day of the week effect or Monday effect, positive or negative, for the period under consideration. Although not significant, Mondays on the J203 All Share TR Index, by way of relative frequency within the bull regime, appear to exhibit marginally less favour of the dominant regime, having the lowest relative frequency out of all the days of the week being ,19.62% followed by Friday with a relative frequency of 19.85% with Wednesdays exhibiting the highest relative frequency at 20.27%. Daily risk-return measures show that Mondays, although exhibiting the highest mean in daily returns of all the days of the week on the J203 All Share TR Index, also have the highest volatility levels by way of standard deviation. Wednesday daily returns, in contrast, are characterised by moderate mean returns and a lower relative standard deviation. These findings, although not statistically significant, show a partial tendency for the domestic market to move in line with the developed markets on certain days of the week, potentially due to heightened levels of global integration amongst global financial markets. In light of such findings, and seemingly marginal deviations from uniformity by days of the week, the potential for exploiting any perceived arbitrage opportunity based on day of the week trades is not feasible. Perhaps not the preferred outcome to be considered by arbitrageurs, the inconclusivity of evidence to support day of the week effects does speak to the high levels of efficiency within the South African financial market. This would be contrary to the assumption that all emerging market financial systems are less efficient than their developed counterparts and supports our competitive prowess as a transparent and efficient financial system (Zaremba & Szyszka, 2016). Positive risk- adjusted daily returns and efficiency in the J203 All Share TR Index also warrants consideration in a global equity asset portfolios for diversification purposes (Ngene et al., 2017).

In contrast, the findings of this research do not, for the most part, corroborate with research conducted on the JSE regarding day of the week effects. The research findings in this study suggest that all days of the week exhibit uniformly distributed preferences of being in the bull regime, with marginal and statistically insignificant deviations translating into Mondays being least in favour of the bull regime, potentially owing to higher levels of volatility in daily returns, and Wednesdays most favouring the bull regime on the J203 All Share TR Index. Alagidede (2008a), considered 1 March 2001 to 4 March 2006, a subperiod of the one employed by this study, in endeavours to uncover the day of the week effect on the JSE. The study catered to inherent market risk with the results of that study revealing the existence of a positive Monday effect which is contrary to the findings in this research and contradicts any assertions that the JSE is highly correlated to developed markets on Mondays. It may be inferred that Monday volatility levels have increased in subsequent years leading to lower risk adjusted returns. Mbululu and Chipeta (2012) and Chinzara and Slyper (2013), in considering a very similar period of time in their studies to uncover the day of the week effect on the JSE, have differing results. Mbululu and Chipeta (2012) employ a non- parametric test, using measures of skewness and kurtosis, to cater to the non-normality observed in the returns on the J203 All Share index and nine sectoral indices for the period 3 July 1995 to 13 May 2011. The concluding findings yield no conclusive day of the week effect on the J203 All Share index, with the basic materials sector being the only sectoral index to exhibit a day of the week effect, a positive Monday effect. Chinzara and Slyper (2013), over the similar period from June 1995 to December 2010, using a GARCH (1,1) model, find a contrasting significant positive Monday effect for the J203 All Share Index. Further to this, in their sectoral index analysis, the Industrials and Retail sectors exhibited positive Monday effects and negative Friday effects respectively, attributing these results to time- varying volatilities. Although the scope of this research excluded the consideration of sectoral indices, in which no comparison therein may be drawn, the opposing results in non- existence of a positive Monday effect made by this study cannot solely be attributed to the later time period considered. Chinzara and Slyper (2013) do highlight the disappearance of these effects under conditions of excessive volatility, a condition for which the Markov switching model is able to cater adequately for, which serves as a possible reason for the discrepancies in findings.

Darrat et al. (2013), in a study spanning forty years from June 1973 to September 2013, tested Monday and Tuesday returns on the All Share Index using Wednesday returns as a benchmark and found them to be significantly lower than the Wednesday returns. The results of this research partially corroborate these findings, with J203 All Share Index returns on Mondays and Tuesday being marginally less than Wednesday returns, though this result is not supported with any statistical significance.

Plimsoll et al. (2013), in a subset of the period considered within this study, from July 2002 until July 2012, found no prevalence of any day of the week effect on the J203 All Share Index, in line with this research. In considering the individual share constituents of the J200 Top 40 Index, which is beyond the scope of this research, they found that ten of the forty firms exhibited a significant day of the effect.

6.2.1 Month of the year

Most notable of all the month of the year effects, the January effect, was first unveiled on the DJIA in a study by Wachtel in 1942 on the relatively short sample period between 1928 and 1940 (C. Y. Zhang & Jacobsen, 2013). Studies pertaining to calendar effects, and the January effect, received little attention by scholars in subsequent years until 1976, wherein they were popularised by the extended period seminal study by Rozeff and Kinney, covering a period between 1904 and 1974, showing that equites in January months on the NYSE exhibited an average return of 3.5% compared to an average monthly return of 0,5% (Beladi et al., 2016).

Agnani and Aray (2011) employ a Markov Switching Model with two volatility regimes to investigate the January effect on the NYSE between January 1940 and December 2006. They find evidence in support of its existence throughout the period though its prominence is diminishing, highlighting that the magnitude of the effect is more pronounced during periods of increased volatility.

In a more recent study over the extended time frame between 1900 and 2013, Urquhart and McGroarty (2014) investigate the prevalence of the January effect on the DJIA Index by splitting the period into six subsamples to gain insight into the seasonality characteristics regarding the effects prominence during certain time periods and migration patterns. They found that, although not statistically significant, there are time varying characteristics associated with the January effect being prevalent in half of the subsamples as well as higher average returns in January. The effect appears to have been most prominent in the period following the published article by Rozeff and Kinney in 1976, though they conclude the effect has diminished somewhat in recent years.

Looking towards European Markets, Rossi and Gunardi, (2018) conduct a study analysing a shorter time period, between 2001 and 2010 covering market in four countries, France, Germany, Italy and Spain. They find a significantly positive January effect to be present in Spain, a positive April effect in Italy as well as a negative September effect in Germany.

The findings in this study are very interesting regarding the month of the year effect on the J203 All share TR Index. The Month of July, by means of distribution of regime preference, exhibits a statistically significant negative effect at the 5% level. In fact, it is the only month to have a higher probabilistic regime preference for the bear regime than the dominant bull regime, which is favoured by all other months of the year. The expected duration, by number of months, for probabilistic preference to fall within the bull regime is 2.09 months compared to 1.25 month in the bear regime and one month in the normal regime, and yet the month of July still considerably favours the bear regime against the probabilistic odds. It must be noted that the mean monthly returns in July on the J203 All Share TR Index are moderate when compared to other month, though it has the highest level of volatility in monthly returns which would suggest more frequent shifts in regime. In turn, the following month, being August, although only somewhat less significant, exhibits the highest propensity in favour of the bull regime, with the least prone to being the bear regime. This is not surprising with August benefitting from comparatively high mean monthly returns coupled with lower levels of relative volatility. As a seemingly favourable consequence with August naturally following on from July and exhibiting opposing preferences in terms of regime favour, we note a significant inflection point in probabilistic regime preference, being the last trading day in July. It is at this point that probabilistic preferences between the bull and the bear regime are likely to reverse on the J203 All Share TR Index.

As a trading strategy this won't necessarily lend to consistent selling of the J203 All Share TR Index on the last trading day in June and repurchasing the index at the end of July in the hopes of avoiding a potential initial and profiting from a perceived subsequent positive move in the market for August. The actual regime for the month of July, at the beginning of July, would be unknown and although July favours the bear regime marginally over the bull regime, the bull regime remains the dominant regime within the J203 All Share Index. July, as a month, exhibits the highest bear regime tendency probabilistically, though this preference is marginal over bull regime preference which means that this effect cannot be consistently exploited. This means that in order to potentially profit from the higher probability of July being within the bear regime, one would need to take a speculative *a priori* view of the expected regime at the turn of the month, which would be seemingly irrational given its higher levels of volatility. Speculative profits made do not contradict the conditions for no arbitrage, but are rather contrary to the rationale that market participants are rational and utility maximising and as such, the effect does not necessarily contravene conditions of the EMH until such time as they become more predictable. What may be inferred, regardless of any observed regime in July, is that the subsequent August month is most likely to exhibit bull regime preference probabilistically.

One less prominent effect on the J203 All Share TR Index is that of January, exhibiting the second highest bear regime preference, after July, a negative effect which is in contrast to the January effect experienced by some developed financial markets. The existence of the negative January effect on the domestic market, albeit less prominent, does not necessarily oppose that notion that the local market is uncorrelated with that of developed markets as it still exhibits a predominantly bull regime preference. It does however, support the notion that incorporation of the J203 All Share TR Index will add diversification benefits in the context of a global equity portfolio. Furthermore, the existence of a negative January effect on the JSE may be as result of it already being adequately considered within global market portfolios, the resultant potential decline in January returns locally being as result of perceived efficient reallocation of capital from the JSE or other emerging markets to financial markets with higher risk adjusted return expectations over the period. Inference of the tax-loss selling hypothesis as a cause of month of the year effects on the JSE extends only to the context of local equities being held in a global equity portfolio and being subjected to tax- regimes in other markets affecting the reallocation of capital. Unlike other developed financial markets, firms listed on the JSE are not required to adhere to a specific annual period, like a calendar year for U.S. firms, for financial reporting reasons and as such, firm financial years will vary locally.

The findings in this research pertaining to month of the year effects on the JSE do not fully corroborate with previous studies on the local market. Alagidede (2008b), in examining month of the year effects on African financial markets spanning the period from July 1997 to October 2006, found no January effect, though a positive February effect was identified on the JSE ALL Share Index. The findings in this research show that February and April are the months which deviate least of all from expectation i.e. in relative terms they are the most impartial in terms of preference between the bull and bear regimes.

Auret & Cline (2011), in testing for the sole existence of the January effect, and not considering other months of the year, consider two subperiods on the JSE All Share Index, the first being January 1988 to December 1995, and the second being from January 1996

to December 2006. They find no significant prevalence of the January effect during either period. Considering there is only a partial overlap between the second subperiod considered in their study and the one considered in this research, no meaningful comparative inference may be drawn. It is however possible that the emergence of a negative January effect on the JSE occurred in subsequent years, possibly owing to increased volatility spill over from international markets through greater efficiencies and global integration endeavours.
Darrat et al. (2013) consider monthly returns on the JSE All Share Index over an extended period, between June 1973 and September 2012. In their research in testing for only anomalous returns they conclude no notable December or January effect.

Literature pertaining to month of the year effects appear to be rather fragmented, by approach in methodology and by choice of period. It's not unlikely that, should the prominence of an effect be significant, the level of significance varies with time. The scarcity of research in the local landscape also limits the extent to which comparisons may be drawn and the validity thereof. Overlapping time periods allow for comparisons to be contrasted if subperiods are tested separately. Alternatively, studies considering longer time periods without smaller subperiod tests are open to dilution of any significant findings which may only be prevalent for a shortened period. Furthermore, should the time periods under consideration cover a similar period, then inferences may be drawn, however certain studies are restricted by testing for only certain month of the year effects, such as the January effect, and do not always cater for the prevalence of other migratory or emerging month of the year effects.

6.2.2 Size effect

In a seminal paper by Banz (1981), using firms listed on the NYSE for a minimum of five years, over the period spanning 1926 to 1975, it was revealed that smaller capitalisation firms were shown to yield higher risk adjusted returns than mid and large capitalisation firms, the quantified excess risk adjusted return being 0.40% higher per month in the lower quintile portfolio. It has also been shown that the January effect is more pronounced in smaller capitalised shares than larger ones on the U.S Markets, with smaller firms being more prone to usable tax- losses in December as returns are smaller compared to returns of larger firms (Beladi et al., 2016). Semenov (2015) posits that smaller firms are susceptible to higher

levels of systematic or market risk at the beginning of the year, and thus command higher risk adjusted returns during the month of January than larger capitalised firms, thus exhibiting higher mean monthly returns. (Chu et al., 2004) in an extended study on the NYSE investigate the prevalence of the January effect and the January size effect over the period 1926 to 1992. Employing a Markov switching model with allowance for multiple regimes they find no discernible evidence of an overall presiding January effect on the market, however there is significant evidence of a January effect to be found in smaller capitalised shares.
In a thorough global study pertaining to the size effect spanning 39 countries, both emerging (inclusive of South Africa) and developed financial markets, De Moor and Sercu (2013) consider monthly USD returns on shares for each market over the period from January 1980 to May 2009. They find a significant size effect to be present across a global small capitalisation portfolio which are unexplained by risk factors associated with smaller firms such as liquidity, financial distress risk, information asymmetries and understated betas in pricing models (CAPM). They do not however investigate the prevalence of individual size effects by country.

On the domestic front, Muller and Ward (2013) test for the size effect on the majority of firms listed on the main board of the JSE over the period 1985 to 2011. Share prices are adjusted to include dividend payments, yielding total returns per firm, and both delisted and surviving firms are included in the sample to avoid survivorship bias. Thirty equally weighted portfolios of ten shares each were created and rebalanced quarterly. No discernible size effect was found, though the smallest capitalisation firms seemed to exhibit inferior returns comparatively, contrary to findings in the literature pertaining to developed markets.
Literature on the size effect related to calendar effects on the JSE is considerably sparse. A large number of studies seeking to establish existence of calendar effects on the South African market usually do so in the context of international comparison e.g. testing the prevalence of calendar effects across the African continent and use broad level index data which doesn't cater to establishment of the presence of a size effect. Auret and Cline (2011) did investigate the presence of the January and size effects on the JSE between January 1988 and December 2006, though the significance of either effect held any gravitas.

In an endeavour to uncover the existence of the size effect, and ascertain whether it has any considerable bearing on day of the week and month of the year effects, Sub- indices were considered, namely the J200 Top 40, J201 Mid Cap and J202 Small Cap indices, with constituent shares being the constituent shares of the J203 All Share Index. In line with Banz' (1981) proposition that smaller capitalisation firms exhibit larger risk adjusted returns than their larger firm counterparts, we find conclusive evidence in support of this on the JSE in more recent years by considering the descriptive statistics of returns across the indices. For monthly returns, the mean return of the J202 Small Cap Index, at 1.347%, is significantly higher than that of J200 Top 40, J201 Mid Cap and even the J203 All Share TR Index, even though it itself is not a total return index i.e. a return which does not consider the reinvestment of dividends. Remarkably, the J202 Small Cap Index also exhibits the lowest standard deviation out of all four indices at 0.288%. Prevalence of the size effect holds true on daily index returns too. The mean daily return on the J202 Small Cap Index is 0.062%, marginally lower than that of the J203 All Share TR Index, being 0.063%, however when taking daily volatility of returns into consideration, the J202 Small Cap Index standard deviation of 0.009% is roughly half that of the J203 All Share being 0.019%. This affirms the notion that smaller capitalised shares exhibit higher risk adjusted monthly and daily returns during the period under consideration.

6.2.3 Month of the year size effects

Prevalent negative January effects exist on the J200 Top 40 and J201 Mid Cap Indices, by means of observed preference of relative frequency, probabilistically. The month of January, for both indices, displays the highest favour of the bear regime. It must be noted that preference is in relative terms compared to other months. The J200 Top 40 Index is characterised by dominant bull regime tendency, whereas the J201 Mid Cap Index favours the normal regime. January within both indices exhibits the lowest frequency of probabilistically falling within the bull regime compared to other months, however both are more prone to falling within the normal regime otherwise. In consulting the monthly means and standard deviations of returns of January within the two indices, the propensity for January to find the bear regime more favourable may be attributed to a considerably lower relative mean and the highest standard deviation in the J201 Mid Cap Index, with a combination of a low and high mean and standard deviation respectively in the J200 Top 40 Index. Although the J202 Small Cap Index shows similar mean monthly return and volatility traits for the month of January, probabilistically it does not deviate significantly from other months across frequency distribution of regimes. This highlights the propensity for the negative January effect to be less prevalent in smaller capitalisation firms as opposed to larger ones. This may seem contrary to literature pertaining to the U.S. smaller firms exhibiting a higher positive January effect, however the direction of the effect is in the opposing direction and as such, no inference will be made.

Other monthly effects include a negative March effect on the J201 Mid Cap Index, exhibiting very similar traits to that of January within the same index. Positive effects present themselves on the J200 Top 40 Index in the months of August and November. November exhibits a bull regime preference in every single instance, with August preferring the bull regime in all instances but one. From a mean- variance standpoint, November monthly returns are characterised by a comparably low mean return in November, though with the lowest volatility of all the months. August exhibits a rather favourable mean monthly return comparably with relatively neutral levels of volatility.

The J202 Small Cap Index portrays similar mean- variance characteristics in terms of returns by months of the year when compared to the other indices. In consulting the smoothed inferential probabilities, it is highly evident that the bull regime was favoured in the years leading up until the global financial crisis with the normal regime being highly favoured thereafter. Furthermore, as a result of it's lower relative volatility, the expected duration, in months, in which it is expected to remain within these two regimes is far greater than that of the other indices. The J202 Small Cap Index has an expected duration of remaining within the bull regime for 10.87 months, as opposed to that of 1.98 months and a single month for the J200 Top 40 Index and J201 Mid Cap Indices respectively. It's expected duration within the normal regime is 72.19 months as opposed to the single month expected duration within the J200 Top 40 index, and 1.6 months within the J201 Mid Cap Index, with all three indices having an expected duration within the bear regime of a single month. As such, the frequency distributions by regime within the J202 Small Cap Index are seemingly uniformly distributed, with no untoward deviations suggesting that any anomalous monthly effects exist within the index.

In consideration of the monthly mean returns and standard deviations thereof, it must be noted the June is the only month which yields consistent negative returns, in excess of 1%, across all four indices. This would suggest the prevalence of a persistent negative June effect spanning firms of all sizes. No notable probabilistic deviation in frequency distribution of regime preference presents itself as an outcome of the Markov Switching model. In consideration of the monthly return volatilities within the month of June across the four indices, it is shown to exhibit far less volatility when compared to other months of the year. Due to the four indices having higher preference to be in the bull or normal regime, as opposed to the bear regime, and owing to considerably less relative volatility through which to prompt deviation in regime, it may be concluded that no significant support in favour of a negative June effect may adequately deduced.

6.2.4 Day of the week size effect

In testing for day of the week effects across the four local indices, the same rigorous Markov switching methodology was conducted and smoothed inferential probabilities deduced. Preference of regime, by way of probabilistic relative frequency, were married to days of the week in line with the highest smoothed inferential probabilities observed. Performing the Chi- squared Goodness of fit test comparing actual frequency distribution by regime against the expected distribution, split by days of the week, yielded no significant deviation from expectation. This is also evidenced by there being only slight deviations from uniformity for each day in relative frequency terms.

Conclusions drawn solely on the basis of mean daily returns by day of the week would suggest prevalence of a positive Thursday effect spanning all four indices, as well as a positive Monday effect on the J203 All Share TR and J200 Top 40 Indices. Similarly, by considering mean daily returns in isolation, it could be inferred that a negative Monday effect is prevalent on the J201 Mid Cap and J202 Small Indices, with mean daily returns close zero being the lowest observed. Prudential consideration of volatility levels associated with these daily returns renders the higher Thursday daily returns to be inconsequential on a risk adjust basis, as the higher means are coupled with significantly higher volatility levels across all indices. The same may be said of the perceived positive Monday effect on the J203 All Share TR and J200 Top 40 Indices which also exhibit substantially higher associated levels of volatility.

A notable observation concerning the potential negative Monday effect on the J201 Mid Cap and J202 Small Cap Indices is that, although their mean daily returns are the lowest observed, the associated levels of volatility remain the highest, or marginally second highest, observed. This is corroborated by the relative frequencies, assigned probabilistically, whereby the observed bull regime relative frequency observed on Mondays within the two indices deviate the most from expectation i.e. if we expect bull regime frequencies to be uniformly distributed across the five trading days of the week, then it should be expected that 20% of the observed frequencies would fall within the bull regime in both indices. Monday return relative frequencies observed in the bull regime for the J201 Mid Cap and J202 Small Cap Indices are 19.43% and 19.47% respectively. Although not defiantly aberrant, it does illustrate the higher propensity for Monday returns to deviate from the bull regime, which is the dominant regime for both indices, due to increased volatility levels.

In the absence of any definitive evidence to support the existence of day of the week size effects on the indices under consideration, we may draw a number of interesting conclusions pertaining to return behaviour on certain days. Thursday returns, across all four indices, are characterised by higher levels of volatility and higher associated mean daily returns, the benefits of which may be potentially disregarded under risk adjusted terms. Monday returns across all four indices are also characterised by higher levels of volatility, yet additional mean return, in compensation for the higher levels of volatility, is not rewarded on the J201 Mid Cap and J202 Small Cap Indices. Unexpectedly, the mean Monday returns are the lowest observed. Friday mean returns are considerably low, with the lowest levels of associated volatility for all indices with exception to the J202 Small Cap index which exhibits higher relative Friday mean returns and higher levels of volatility.

This corroborates highly with the findings set forward by Michaely et al. (2016) whom assert that market participants are preoccupied with the weekend on a Friday, which leads to subdued market reactions and a more corrective response being observed the following Monday. It may be inferred that the corrective response on a Monday leads to the resultant excess volatility observed in Monday returns, an outcome in which additional mean return, as compensation, is not materially guaranteed. The research by Yuan (2015) provides some insight into the perceived lack of additional return in light of increased volatility levels: he posits that when higher attention is paid to the markets by investors, especially when market indices are high, it will lead to abnormal selling behaviours, which would be the case on a Monday following a relatively high Friday announcement. Given that volatility levels on a Monday are considerably high across all indices, the researcher makes reference to Monday mean returns within an index relative to its Friday mean return. The J203 All Share TR Index and the J200 Top 40 Index both exhibit considerably high average Monday returns, with considerably low mean Friday returns. In contrast, the J201 Mid Cap and J202 Small Cap Indices with comparatively higher Friday mean returns exhibit the lowest Monday returns observed. In light of this, it does not seem untoward to assume that, given the high levels of volatility in Monday returns following subdued Friday reactions and lower levels of volatility, the endeavours undertaken by investors on a Monday are corrective in response to the previous Friday mean return. By implication the mean Monday return would be a function of the Friday mean return, and the risk adjusted return on a Monday should not be observed in isolation.

6.2.5 Conclusion

This study sought to uncover the existence of anomalous seasonal effects pertaining to days of the week and months of the year. Certain months have been shown to exhibit higher a higher propensity to switch regimes, and so would exhibit anomalous returns. No days of the week were shown to exhibit anomalous returns consistently, though it has been shown that, due to differing volatility levels on certain days, there are deviations in the expected associated risk- adjusted returns. A negative January effect, present in the J201 Mid Cap and J200 Top 40 Indices, is not present in the J202 Small Cap Index negating the prevalence of a size effect leading to more prominent anomalous returns. The findings in this research provides no evidence as to the existence of arbitrage opportunities or strategies that may be conducted in a speculative manner. Given these conditions and through the findings in this study, the researcher posits that the JSE adheres to efficiency levels associated with that of the weak form of the EMH, whereby market participants stand to gain through fundamental research given certain market conditions.

7 Conclusion

7.1 Introduction

The existence of calendar anomalies infers violation of the levels of efficiency within the market, provided they are both adequately predictable and exploitable (Floros & Salvador, 2014). By implication this asserts that, should an anomaly be predictable, though not adequately exploitable by a rational investor seeking to gain from an arbitrage opportunity, then the conditions of the EMH are not compromised.

This study made use of a Markov switching model, allowing for up to three regimes and TVTP to cater to time varying inordinate levels of volatility throughout the period, to gain an empirical understanding into the prevalence of calendar anomalies on the JSE in recent years. The findings within this research do not necessarily corroborate with studies concerning international financial markets on the same topic, if it's assumed that calendar anomalies locally are positively correlated with those abroad. The scant literature surrounding calendar anomalies on the JSE consider varying, and less recent time- periods with restricted considerations in testing for only certain calendar effects, which compromises the comparative validity thereof. There are, however, some valuable and important insights which have been brought to light by this research. Firstly, it highlights the unobserved probabilistic preference of daily or monthly returns within a certain index over a period of time. The additional clarity gained in this regard does not constitute grounds upon which one may consistently predict market returns, however it adds considerable probabilistic inference capabilities when used in conjunction with other predictive measure such as descriptive statistics. Secondly, it sheds light on the level of efficiency of our markets, which forms the basis upon which the transparency of the financial market is gauged and speaks to the level of the markets overall competitive stance in the global financial system. Thirdly, it highlights observed traits inherent in the financial market, the risk- reward components of which, under certain known market conditions, showcase the level to which local equity investments should be considered for inclusion within the context of a global equity portfolio. Greater levels of transparency coupled with additional diversification benefits facilitate optimal allocation of capital in a global equity portfolio context, rather than being classified as a separate investible asset class (Ngene et al., 2017).

7.2 Principal findings

Concerning month of the year effects on the J203 All Share Index, the monthly returns exhibit preference, probabilistically, in favour of the bull regime followed by the bear regime. July is the only the month of the year exhibiting more favour towards the bear regime, signifying the prevalence of a negative July effect on the index. This is followed by an almost probable preference of the bull regime in August signifying a positive August effect. The negative July effect coincides with the highest volatility levels in monthly returns, signalling higher probability of transitioning from the preferred bull regime to another regime. August returns, on the other hand, are characterised by higher mean returns in a low volatility period and so it is not easily dissuaded from the bull regime. The index also showcases a possible negative January effect, which is contrary to the positive January effect experienced in the U.S. (Chelley-Steeley et al., 2016). Low mean returns for January in, conjunction with significantly high volatility levels, form a basis upon which January may more easily deviate from the dominant bull regime.

In testing for day of the week effects on the JSE, there initially appeared to be no discernible evidence of any effect on the J203 All Share index. Daily returns on the index again favoured the bull regime, followed by the bear regime, as was the case with monthly returns on the index. Relative frequencies in each regime observed by days of the week appeared seemingly equal with only minor deviation. In investigating the potential existence of a day of the week size effect, similar evenly distributed results were shown with seemingly more pronounced deviations appearing in the Monday returns on the J201 Mid Cap and J202 Small Cap Indices. In inspecting the mean returns and standard deviations across the days of the week, it was evident that Mondays and Thursdays exhibited persistent high levels of volatility across all of the four indices under consideration. Mean Thursday returns were also high, prompting the view that, on a risk adjusted basis, the higher mean returns, in compensation, were as result of higher levels of volatility. The mean Monday returns on the J201 Mid Cap and J202 Small Cap indices, however, were the lowest observed, despite the associated high levels of volatility. Under further scrutiny it was evident that indices exhibiting lower mean Monday returns also exhibited higher mean Friday returns, despite the propensity for Friday returns to be significantly less volatile. This warrants consideration of Friday mean returns relative to mean Monday returns in determination of this effect, and that risk adjusted Monday returns should not be viewed in isolation. It must be noted that this effect differs from the turn of the week effect observed in the U.S., whereby Monday returns are lower following higher Friday returns in the previous week (Rossi, 2015). This effect the is based on mean returns spanning the entire period under consideration, the prominence of which falls out of the scope of this study.

Other observed month of the year effects include a negative January effect on the J200 Top 40 and J201 Mid Cap Indices. The month of January, for both indices, displays the highest preference in favour of the bear regime. The J200 Top 40 Index is characterised by dominant bull regime tendency, whereas the J201 Mid Cap Index favours the normal regime. January within both indices exhibits the lowest frequency, probabilistically, of falling within the bull regime compared to other months, however both are more prone to falling within the normal regime otherwise. A very similar negative March effect is also observed on the J201 Mid Cap Index.

No notable negative January effect was observed on the J202 Small Cap Index. Although more prominent in the larger capitalisation indices, it is not found that smaller firms amplify its effect. This is in contrast to the positive January effect observed in the U.S. and other markets, whereby the effect is more pronounced in smaller capitalised firms (Beladi et al., 2016). Owing to the opposing direction in the effect observed in the study, no direct inferences are drawn comparatively. Consistent with Banz' (1981) proposition that smaller firms exhibit higher risk adjusted returns than mid- sized and larger firms, this study finds significant evidence of this at index level. Aside from the diminishing negative January effect observed, there is no evidence to support to the notion that calendar effects are more pronounced in smaller firms on the JSE at index level.

7.3 Implications for market participants

The prevalence of calendar effects on the JSE is of significant importance to market participants, regardless of their individual investment mandates. Arbitrageurs will naturally seek to gain risk free returns from mispriced assets. Wealth managers, in endeavours to preserve future returns under the lowest possible volatility conditions, would actively seek to hedge against adverse market movements which cause marked fluctuations in expected returns. Active fund managers will, as best as is possible, seek to beat the market benchmark by achieving the highest possible return given a certain level of risk through optimal capital allocation and diversification. Foreign investors too will seek, in the context of a global equity portfolio, the optimal allocation of capital through improved diversification benefits obtained by including suitably correlated equities exhibiting appropriate risk adjusted returns.

The findings in this research suggest the prevalence of certain calendar effects. In order for these effects to be in contravention of the laws governing the EMH, they would have to be consistently exploitable, which, by default would mean they are consistently predictable. The findings in this research do not support the existence of any definitive effects that may be adequately exploited without risk. Rather, in conjunction with other predictors of returns, it adds gravitas and provides insight into market movements from a probabilistic standpoint. Descriptive statistics concerning market returns may, in isolation, point towards the existence of a certain anomaly, however coupled with a view of the regime preference inherent in an index and presiding market conditions, such as varying volatility, it allows for more holistic inferences to be drawn as to the likelihood in direction the market may take

Knowledge of the preferred regime order observed by an index provides substantial informational properties under varying market conditions. If an index, such as the J203 All Share Index, has a known preference of being in the bull regime, followed by the bear regime instead of the normal regime, then under periods of higher volatility, it can appropriately be expected that a shift in regime will occur more swiftly, from the bull regime in favour of the bear regime. This provides more insight into expected behaviour in returns compared to using descriptive statistics in isolation. Furthermore, a permanent shift in regime preference may be observed. This is evident in the monthly returns on the J202 Small Cap Index whereby it exhibited significant semi- permanent preference of the bull regime prior to the global financial crisis, with a permanent significant shift to the normal regime thereafter.

It may be conjectured that the prevalence of calendar anomalies contravenes the laws governing the level of efficiency within the domestic financial markets. The findings in this research point towards having a more holistic view of the expected outcome probabilistically, given certain market conditions and observed preferences of the market under those conditions, and taking an *a priori* view on its direction in light of this. It is not speculative, nor is it an irrational stance to assume, given that the *a priori* view maximises utility probabilistically through the expected outcome. As such, no strategy may be suggested to gain risk free arbitrage returns, nor do the views taken contravene the rationale that market participants are rational investors. Given these conditions and through the findings in this study, the researcher posits that the JSE adheres to efficiency levels associated with that of the weak form of the EMH, whereby market participants stand to gain through fundamental research given certain market conditions.

7.4 Limitations of the research

This research undertook to investigate the prevalence of calendar effects within the JSE, and by so doing, gain a better understanding as to the level of efficiency inherent in the domestic financial market. The findings in this study have shown that calendar effects are inherently existent, albeit not directly exploitable.

This research confirms their existence, though the prevailing reasons behind their existence was beyond the scope of this study. Research was conducted at index level, with the only isolative metric employed being tests based on market capitalisation, to deduce whether calendar effects appear more prominently in smaller firms, which has shown to have no significant merit.

At a sectoral level, these effects would possibly appear more prominently as result of seasonality in the nature of industry earnings, varying degrees of correlations with economic cycles, advances in technology, susceptibility to foreign exchange fluctuations and stages within the industry life cycle. More granularly, at a firm level, these effects may be more pronounced as result of changes in demand preferences, by market participants, pertaining to investment styles such as growth, value and momentum investment philosophies. In this research, it has been shown that certain market conditions, such as excess volatility, have a significant impact on the on the regime preferences adopted by the market, though the prevailing causes prompting market conditions to change is not clear.

7.5 Suggestions for future research

The prevalence of anomalies, in isolation, serves as an effect without a notable cause. Further research at sectoral and firm specific levels assists in isolating the root of these anomalies and facilitates better understanding as to the reasons underpinning the emergence of such seasonal effects. Should a more granular cause be determined, the potential impact this may have may be better understood, and in turn, assist in contributing to the levels of transparency and efficiency within the domestic financial market.

Market conditions have a significant impact on the regime preferences exhibited by market participants and are well researched. Empirical studies which are able to provide evidence supporting the extent to which changes in these conditions are attributable, quantifiably, to the level in prominence exhibited by seasonal effects, will contribute significantly to the predictive power of these studies.

This research has shown that Monday returns on the JSE exhibit higher relative levels of volatility across all four of the indices considered, yet in some instances the mean returns are significantly lower in relative terms, which contradicts the notion that return premiums should be adjusted upwards in periods exhibiting higher volatility. Indices exhibiting this behaviour are characterised by higher relative Friday mean returns. It may arguably be inferred that mean Monday returns, on a risk adjusted basis, should not be considered in isolation. An empirical study providing conclusive evidence to support that mean Monday risk adjusted returns are a function of mean Friday risk adjusted returns, within an index, would contribute significantly to the body of knowledge.

Any researcher conducting studies pertaining to financial markets, and employing a Markov switching model, should be cognisant of the possible permanent or semi- permanent shift in regime. The findings in this research provides evidence of semi- permanent bull regime Preference exhibited by the J202 Small Index in the years leading up to the global financial crisis. Post financial crisis there was a semi- permanent shift in preference of the normal regime. In this light, researchers should remain current in observing any permanent shifts that may occur. This also facilitates in providing recency to the literature.

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9 Appendices

9.1 Ethical Clearance

Gordon Institute of Business Science
University of Pretoria

09 November 2017

Rich Sean

Dear Sean

Please be advised that your application for Ethical Clearance has been approved.

You are therefore allowed to continue collecting your data.

We wish you everything of the best for the rest of the project.

Kind Regards

GIBS MBA Research Ethical Clearance Committee