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The South African Volatility Index (SAVI) as a tool for market timing on the Johannesburg Stock Exchange (JSE)

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By

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Abstract

This study tests the viability of using the South African Volatility Index (SAVI) as a tool to time equity trades on the Johannesburg Stock Exchange (JSE), and uses technical analysis in the application of selected market timing trading strategies. This study therefore has very real practical relevance to investors on the JSE, who wish to take an active approach to investing. Using the JSE Top 40 Index for the period May 2007 to March 2018 as a sample, this investigation firstly considers whether the technical trading rules developed for the CBOE VIX, as used in the United States market, can be applied to the South African market using the SAVI as a market timing tool in order to outperform a passive buy-and-hold strategy. This involved switching the portfolio between the Top 40 equity index and the STeFI money market index, depending on the nature of the timing signals generated by the SAVI-based strategies. Secondly, this study considers the viability of using the SAVI in a market timing rule to take advantage of the documented size (small-capitalisation versus large-capitalisation) and style (value versus growth) anomalies on the JSE. In the first part of this study, it was found that three of the eleven market timing trading strategies outperformed the buy-and-hold strategy before the inclusion of transaction costs. When compared to the results found by the researchers in the U.S context, it appears that these strategies are more successful in the U.S context using the VIX, as the majority of the trading strategies yielded positive excess returns over their respective sample periods. Additionally, in the second part of this study, it was found that the returns of the style strategy were not significant enough to deem it a profitable market timing strategy. However, the returns of the size strategy were significant enough to make it a profitable strategy. Transaction costs, applied at different levels, had a significant impact on the results of all strategies, with only one of the market timing strategies, namely the simple moving average strategy, beating the buy-and-hold strategy after transaction costs of up to 0.2% and 0.45% (for sales and purchases respectively) have been taken into account.

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Chapter 1 Introduction and Background

Volatility is defined as a measure of dispersion around the average return of a security. A volatile market can be described by the tendency of a security's price to increase or decrease sharply within a small period of time (Gabriel and Ugochukwu, 2012).

Volatility can be a result of the disclosure of new, unanticipated information in the market which, in turn, alters expected returns on a stock. Volatility can also be caused by changes in trading volume, practices or patterns, which in turn are driven by factors such as modifications in macroeconomic policies, shift in investors' tolerance of risk and increased uncertainty. Other factors that influence the significant movement in stock prices include demand and supply forces, investor psychology, economic strength of the market and uncertainty about the future economic outlook (Gabriel and Ugochukwu, 2012).

The common way to define volatility is through the standard deviation of historical returns. However, this definition relates to historic volatility, which differs from implied volatility (Poon and Granger, 2003). The historic volatility is calculated from historic returns of stocks. Implied volatility is the volatility that is derived from an option's price, and shows what the market implies about the stock's volatility in the future (Poon and Granger, 2003). In 1993, the Chicago Board Options Exchange (CBOE) launched the VIX index, which originally was calculated with options based on the S&P 100, one of the main US stock indices. The VIX is a measure of the level of implied volatility in the stock market for the next 30 days, and therefore represents the expectation of stock market volatility during the following month (Fleming et al., 1995). In 2003, the CBOE made some changes to the VIX in order to improve its ability to better reflect markets expectations; one of these changes resulted in the VIX being based on the option prices of the S&P 500 Index as opposed to the S&P 100 Index (CBOE website).

In 2007 the Johannesburg Stock Exchange (JSE) introduced an index similar to the CBOE's VIX, called the South African Volatility Index (SAVI). The SAVI was launched as an index designed to measure the market's expectation of the 3-month implied stock market volatility. The SAVI is based on the JSE Top 40, which is a capitalization index comprising of the forty largest stocks by market capitalisation. These forty stocks are therefore also among the most liquid stocks (and hence constitute the basis for the most traded equity index option) in the South African market, and is determined using at-the-money option prices (Phiri, 2015).

Using a volatility index calculated from option prices to predict movements in the equity market implies that there is some form of contagion between equity markets and option markets, where information travels from option markets to equity markets. Despite the fact that these two markets form distinct entities which consist of separate securities that trade at different locations and times, the markets are extremely integrated, therefore information that is exposed in the option market should be reflected in the equity market, and vice versa. The information that is reflected in the prices of options has implications for both the volatility and returns of the equity markets. Using the option market as a way to provide information about future equity returns relies on the assumption that information starts in the option market and spills over to the equity market (Doran and Krieger, 2010). In practice, some investors believe that by understanding the relationship between volatility and equity returns they potentially can take advantage of investment opportunities resulting from volatile markets.

Every day equity traders are faced with the decision of when to invest and when to exit the stock market. Market timing is a strategy which involves moving in and out of the market by predicting the future direction of the market, and attempts to outperform the passive buy-and-hold approach (Johannes et al., 2002). In order for an investor to benefit from market timing, the stock market needs to exhibit characteristics of mean reversion which are evident in an inefficient market. This means that periods of high returns should be followed by periods of low returns, and vice versa.

The review of the literature in the section to follow describes numerous studies which use regression analysis in which the level of the volatility index or the change in the volatility index is used as a predictor of movements in the stock market. However, this study avoids the more traditional regression analysis approach, and instead tests whether future movements of the JSE Top 40 can be predicted using technical analysis as applied to movements of the SAVI.

Technical analysis focuses on the analysis of historical movements in the prices and trade volumes of securities (Zhu and Zhou, 2009). Technical analysis therefore attempts to understand or predict the market sentiment behind price trends. Technical analysts believe that past trading activity and price changes of a stock are good indicators of the stock's probable future price movements. Technical analysis was largely influenced by concepts that stem from Dow Theory, a theory developed by Charles Dow, which focused on trading market movements. Dow Theory has two assumptions that form the basis of technical analysis. The first assumption is that market price discounts all factors that may have an effect on a stock's price, and the second assumption is that market price movements are not completely random, but move in identifiable trends that repeat over time (Zhu and Zhou, 2009).

Many investors in the U.S investment market are implementing trading strategies which combine technical analysis with the VIX, on the assumption that this may result in a predictive model that has the potential to beat the buy-and-hold strategy on the S&P 500 index. Thus, the claim is that technical analysts can use the VIX to assess whether or not the current market sentiment is either excessively bullish or bearish, in order to plot the market's next move.

It is assumed that because both technical analysis and the VIX are forward-looking, combining them together could create a more powerful forward-looking signal (Kozyra and Lento, 2011). This study tests the use of the deviation of the volatility index from its moving average to predict future stock market returns on the JSE. The reason behind using the method of moving averages of the volatility index stems from the fact that the volatility index is a dynamic indicator, which means that volatility is always adjusting. Therefore, since volatility is always adjusting, the volatility indicators should continuously adjust as well (Connors and Alvarez, 2009).

The CBOE VIX has in recent times become a popular tool used to time the US stock market. Whilst the body of research surrounding market timing using the CBOE VIX is growing, there is limited research on using the SAVI as a tool to time the South African stock market. This study is aimed at testing the viability of using the SAVI as a tool to time the market. This will be done in two ways. Firstly, this study, using the JSE Top 40 Index for the period May 2007 to March 2018 as sample, considers whether the technical trading rules developed for the CBOE VIX as used in the United States market, can be applied to the South African market using the SAVI as a market timing tool, in order to outperform a passive buy-and-hold strategy. Secondly, this study considers the viability of using the SAVI in a market timing rule to take advantage of the documented size (small-capitalisation versus large-capitalisation) and style (value versus growth) anomalies on the JSE. This study adds a different element to the existing body of research relating to market timing on the JSE, by using the SAVI, which is traditionally viewed as an investor fear gauge and is a relatively new indicator in the South African market, as tool. Furthermore, this study aims to determine whether the SAVI is an accurate indicator of stock market volatility and investor fear. It is further important to note that this study, unlike most studies of this nature, investigates the above questions both gross and net of transaction costs. This study therefore has very real practical relevance to investors on the JSE, who wish to take an active approach to investing.

The main objectives of this study are:

i. To test the SAVI as a market timing tool to determine when to optimally enter and exit the JSE, specifically against the passive buy-and-hold strategy (both before and after transaction costs).
ii. To determine whether the SAVI can be used as a signal to shift between portfolio strategies, specifically style (value versus growth) or size (large-cap versus small-cap), in order to generate positive excess returns.

Chapter 2 will start the remainder of this document with a review of the literature on market efficiency, market timing, and the profitability of using technical analysis in trading strategies. After in Chapter 3 discussing the data used in this study, the study is broken down into two parts: the first part (Chapter 4) involves testing SAVI based technical trading strategies on the JSE, and the second part (Chapter 5) relates to testing SAVI based style and size rotation strategies on the JSE. The data, methodology, and results and analysis for each of these two separate but related investigations will be discussed in their associated chapters. Lastly, in Chapter 6 the conclusions reached will be discussed, followed by considering the limitations to the study as well as recommendations for future research.

Chapter 2 Literature review

This review of the relevant literature starts by looking at the empirical evidence relating to market efficiency. Next the relationship between volatility and stock returns is examined, followed by the empirical evidence on the feasibility of timing the market using an implied volatility index. Additional literature on timing the market using size and value styles is examined. Lastly, the literature on empirical evidence relating to the use of technical analysis when implementing trading rules is examined in this chapter.

2.1 The role of market efficiency

The efficient market hypothesis (EMH) is a market theory that states that security prices fully reflect all available information at any given time, given that the market is liquid (Fama, 1965). The EMH exists in three different forms, namely the weak form, the semi-strong form and the strong form. The assumption behind the weak form of the EMH is that current stock prices reflect all the data of past prices, and that past price and volume data have no relationship with the future direction of security prices. The semi-strong form refers to the case where publically available information is fully reflected in market prices; whereas strong-form efficiency is the case where market prices fully reflect all information (including insider information) and therefore there is no extra return achieved by any additional analysis of the stocks. It follows that if financial markets are efficient in any of the three forms, implied volatility cannot provide relevant information, which indicates the future direction of the stock market and the use of technical analysis in trading strategies should not be able to earn any excess returns.

In contrast, some researchers have found that significantly large implied volatility levels are a signal to take a long position in the market (Giot, 2005). The possible rationale behind this is that very high implied volatility levels are observed during periods of financial uncertainty, where investors are perceived to be over-reacting as they frantically sell-off their financial assets to limit their losses or raise cash. It is therefore believed that these are short-term time periods where investors do not act rationally but engage in ‘herding’ behaviours which cause a decrease in asset prices (Giot, 2005).

In an efficient market it is believed that stock prices follow a random walk. The random walk theory assumes that stock price changes are independent of each other and have the same distribution. An inefficient market on the other hand is characterised by stock returns that do not follow a random walk, for example the mean reversion of stock returns (Grater and Struweg, 2015). If mean reversion in the market exists, it is possible to use past stock returns to predict future returns, since it is expected that periods of high returns should be followed by periods of low returns and vice versa. The ability to use technical analysis to beat a passive buy-and-hold strategy is therefore reliant on the inefficiency of the market, which in the case of this study is the JSE.

However, the evidence on whether the JSE is an efficient in the various forms of the EMH is still very mixed. A recent example of an empirical study that tests whether the JSE follows a random walk is that of Grater and Struweg (2015), which covers the period 1999 to 2014. This study finds that the returns of the JSE for the period of analysis are stationary, meaning that when a shock occurred the series did not deviate from its average value in future periods. Based on the finding of mean reversion (i.e. non-randomness) of the JSE returns, it further suggests that the prediction of future prices is possible based on historical price movement, and concludes that the JSE is not weak-form efficient.

The findings by Grater and Struweg (2015) of the JSE returns being non-random are somewhat confirmed by Kruger (2011), who finds that there is serial dependence in the JSE's return generating process, when testing for this result over the period February 2000 to December 2009 (using the JSE All Share Index), thereby indicating return predictability on the JSE. Kruger (2011), however does note that the serial dependence is episodic in nature, meaning that periods of return predictability can be intersected by periods of white noise. These findings suggest the possibility that the profitability/outperformance of a market timing strategy may therefore also be episodic.

Seetharam (2016) tests the occurrence of the random walk hypothesis on JSE ALSI returns for the period during 1997 to 2014; in addition to using the ALSI returns, the study included the returns of 50 other South African securities in the analysis and different frequencies of this data was tested. It was discovered that the frequency of data chosen by the researcher has a major impact on the results. The overall trend in the findings indicates that the random walk hypothesis is proved to be true when using higher frequency data such as daily returns. However, when lower frequency data such as semi-annual returns is used, it is found that returns do not follow a random walk process.

While Seetharam (2016) associates the type of results found (i.e. whether the results are characteristic of an inefficient or an efficient market) with the frequency of the data used in the analysis, Phiri (2015) associates the type of results found with the linearity of the testing procedures as well as the type of market index used. Phiri (2015) tests the weak-form EMH using six generalised market indices (the All Share Index, the JSE Top 40 Index, the industrials index, the financial index, the mining index and the gold index) on the JSE over the period January 2000 to December 2014. The results indicate that when linear unit root tests are used to test for market efficiency, the JSE stock indices are found to be weak-form efficient, however, when nonlinearities are accounted for in the unit root testing procedures, it is found that the JSE stock indices are not weak-form efficient. Furthermore, when observing the results from the non-linear unit root tests, it was found that the All Share Index, the JSE Top 40 Index, the industrials index and the financial index reject the weak-form EMH, whereas the mining index and the gold index are found to be weak-form market efficient. Phiri (2015) lends insight into this study, as this study will be testing the possibility of market timing using the JSE Top 40 Index. As this index was found by Phiri (2015) to reject the weak-form EMH, the implication is that there is possible potential to time the market when the JSE Top 40 is used as the market's proxy.

Phiri (2015) found that the JSE Top 40 returns exhibit market inefficiency of the weak-form, however, Noakes and Rajaratnam (2016) find conflicting results. Noakes and Rajaratnam (2016) test the efficiency of small (Small Cap index), mid (Mid Cap index) and large cap (JSE Top 40) indices on the JSE using a random number generator test. They find that most of the small cap stocks, at an individual share level, exhibit price movements that are non-random, whereas price movements of the large cap stocks were found to be random. This study shows that there is a positive relationship between efficiency and company size as measured by its market capitalisation. They also found that the JSE appeared to be less efficient during the financial crisis period when compared to a more stable period. However using a random number generator test, which may not take into account the complexity of the return generating process such as the non-linearity of returns, may be the cause of the contrasting findings with Phiri (2015). While producing conflicting results, Noakes and Rajaratnam (2016) suggest that the phenomenon of market efficiency may be unique to specific groups of stocks which exhibit similar attributes on the JSE. Noakes and Rajaratnam (2016) make an important conclusion in that considering that the JSE is a concentrated market, it may not be correct to generalise about the market efficiency of the JSE as a whole.

The review of the literature on market efficiency on the JSE shows that the extent or evidence of market efficiency is not consistent across all stocks, and when using different forms of data. Grater and Struweg (2015) confirm that the JSE is inefficient in the weak-form, however, the remaining literature showed that this result depends on numerous attributes such as the size of the stock, the time period under analysis, and the frequency of the data used. While the literature on market efficiency on the JSE has been mixed, any finding of non-randomness in JSE stock returns lends support to the possibility of market timing on the JSE.

2.2 The relationship between stock volatility and stock returns

This section of the literature review will examine current empirical evidence on the relationship between share price volatility and share returns, both contemporaneous, and on a lagged (predictive) basis.

2.2.1 The relationship between stock volatility and contemporaneous stock returns

Low stock prices are associated with high discount rates; this therefore predicts that future stock returns will be high. High stock price volatility levels and low stock prices are associated with high risk, thus, the future stock returns are expected to be high due to the high risk premiums involved (Ang, 2014). In summary, high stock price volatilities are theoretically accompanied by low contemporaneous stock returns, and should correspond to high future stock returns; the research referenced in this section uses various proxies for stock market/price volatility. Before discussing literature on the relationship between stock market volatility and *future* stock returns, this first part of this section will begin by looking at the empirical evidence relating to the relationship between stock market volatility and *contemporaneous* stock returns; it follows that for any relationship to exist between stock market volatility and future stock returns, there must first be a relationship found between stock market volatility and contemporaneous stock returns. This section will end off by examining empirical findings on these relationships in the South African context.

Thielen (2016) confirms the theoretical relationship between stock market volatility and contemporaneous stock returns, he finds an inverse relationship between the contemporaneous S&P 500 returns and the VIX (implied volatility), but notes that this relationship is only valuable to investors when the changes of the VIX are of a large magnitude. Sarwar (2012) conducts a regression analysis to test the relationship between the VIX and the daily returns of the S&P 500 Index for the period 1992 to 2011, and confirms the findings of Thielen (2016) that there is a strong negative relationship between the contemporaneous stock market returns and the VIX.

Sarwar (2012) further breaks down the period under analysis into three sub-periods, and finds that the relationship between the two variables is more significant in the high-volatility sub-period (2004 to 2011), as compared to the low-volatility period (1992 to 1997). These findings therefore suggest that the significance of the relationship between the VIX and stock market returns depends on the average level of the VIX, as well as the trend of the VIX for a given period. Furthermore, this study found an asymmetric relationship between the two variables, in which the VIX reacts more aggressively to negative stock market returns as opposed to positive returns, indicating that the VIX functions more as a gauge of investor fear than of positive investor sentiment.

Since the CBOE's introduction of the VIX, other markets have started to launch their own implied volatility index - for example, in India the India VIX was introduced in April 2008. Dhanaiah et al. (2012) perform a regression analysis to test the relationship between the India VIX and the Indian Nifty Index. The study confirms similar findings to what the majority of the studies have found in the U.S. market, namely that movements in the contemporaneous Nifty Index returns are significantly inversely related to movements in the India VIX. Mall et al. (2011) similarly conduct a statistical analysis to test for granger causality between the India VIX and the Nifty Index, and find that changes in the India VIX cause changes in the Nifty Index. This result only applies to the long run but not to the short run. In addition to India, stock markets in Europe have also introduced an implied volatility index. Emna and Myriam (2017) therefore test the relationship between implied volatility indices and the associated stock price indices in the case of France, Germany, Switzerland, and the United Kingdom, and their findings confirm the negative contemporaneous relationship found in other markets. Emna and Myriam (2017) also find an asymmetric relationship between the implied volatility index and the associated stock market index for all markets except for the German market.

The empirical evidence above indicates that there is a relationship between the volatility index and contemporaneous stock market returns. However, Vermeij (2012) finds that the VIX does not explain much of the movement in the S&P 500 index, since the regression analysis yielded a very low R-square. It is noteworthy to point out that the explanatory variable used in this regression is the difference between the closing of the VIX index of the day before subtracting the moving average VIX index (calculated for a period of one year). The use of the moving average of the VIX is indicative of the use of technical analysis, which will be discussed in later sections of this chapter.

The majority of the empirical evidence discussed above found a negative relationship between contemporaneous stock returns and the implied volatility index, indicating that high volatility levels (and high risk) are associated with low stock prices. However, this may not be the case when taking a forward looking view. The following section therefore examines the empirical evidence relating to the relationship between future stock returns and current volatility.

2.2.2 The relationship between stock volatility and future stock returns

Giot (2005) investigates the relationship between implied volatility and forward looking stock index returns. It is generally accepted that high levels of implied volatility indicate that markets are oversold; according to Giot (2005), if this is true, high levels of implied volatility can be viewed as a short term to medium term buy signal. His study therefore tests the relationship between the level of the VIX at a given time (time t) and the forward looking (1, 5, 20, and 60 day-ahead) relative changes in the S&P100. The results confirm the hypothesis by finding that there is a positive relationship between the current VIX level and the forward looking returns on the S&P100, at very high levels of the VIX. Similar to Giot (2005), Banerjee et al. (2007) regress the S&P 500 returns on the VIX. Banerjee et al. (2007) use 30-day and 60-

day compounded S&P 500 future holding period excess returns. It is found that there is a positive relationship between the S&P 500 future holding period excess returns and the VIX, with a stronger relationship found when using 60-day excess returns as opposed to 30-day excess returns. Banerjee et al. (2007) suggest that the reason behind this is that the VIX takes approximately 60 days to revert to its mean.

Guo (2003) examines whether realised volatility can be used to forecast excess returns of the S&P 500 index. The study regresses the quarterly excess returns of the S&P 500 index against the measure of quarterly realised volatility (measured by the sum of the squared daily stock market returns in a quarter) and finds that volatility accounts for only about 1% of the variation of the one-quarter-ahead excess stock market return. Guo (2003) then adds the consumption-to-wealth ratio (a proxy for the liquidity premium) as an additional explanatory variable; with the inclusion of this variable it is found that past volatility explains a significant portion of excess stock returns. The motive behind adding in a variable that approximates the liquidity premium comes from the idea that investors may still hold stocks when expected return is low (and expected volatility is high) if they have excess liquidity. The results of the regression indicate that an increase in volatility leads to an increase in stock market returns, and that this result is more significant when the effect of liquidity is controlled for.

Hsiao and Li (2010) find a non-linear relationship between future weekly market returns of the S&P 100 index and implied volatility; the study was performed over the period 1996 to 2008. Implied volatility in this case is calculated as the weighted average implied volatility of at-the-money and near-the-money calls and puts. The study uses a dynamic factor model to determine whether the weighted average implied volatility can predict the following week's stock market returns. It is found that a high implied volatility predicts a potential future market reversal when the current weekly return on the S&P 100 is below -2%. However, it is found that a high implied volatility predicts a continuing future market loss when the current weekly return on the S&P 100 is between -1% and -2%. This implies that under specific conditions reducing market exposure when the market volatility increases, could be detrimental to investors. Hsiao and Li (2010) conclude that a smart investor should in fact add exposure to the market when it has just experienced a big loss, even though the volatility is high. They find that traders, who desire to explore temperate market inefficiency, could benefit from a trading signal provided by high levels of the implied volatility.

Most of the empirical evidence above finds a positive relationship between future stock returns and volatility, indicating that when volatility levels are high, future stock returns are expected to be high as investors demand higher rates of return on stocks due to their high risk premiums. Apart from the common trend of the positive relationship found between the two variables, Guo (2003) and Hsiao and Li (2010) add slightly different elements to their analysis. Guo (2003) finds that this positive relationship is more significant when the effect of liquidity is controlled for. Additionally, Hsiao and Li (2010) suggest that there is no uniform relationship between the future market return and the implied volatility across all market conditions. Thus far this literature study has focused mainly on empirical evidence in the U.S. market. Although there is little empirical evidence relating to this topic in African markets, the following section examines whether the same relationship that is found in the U.S. market holds true for African, and in particular the South African, markets.

2.2.3 The relationship between stock volatility and stock returns in the African context

There are very few studies in the African market context that tests the relationship between a volatility measure and stock returns. One of the few example's is the study by Gabriel and Ugochukwu (2012), which examines the relationship between the level of volatility and stock price prediction in Nigeria. This relationship is tested at the individual firm level, with the measure of volatility being calculated using an ARCH model. The study tests this relationship using four major companies (First Bank, Nigerian Breweries, Nestle Foods and Mobil Petroleum). The findings are that the current stock prices of First Bank and Nestle Food is significantly related to the volatility of these stocks, thereby indicating a positive relationship. However, it was found that the current stock prices of Mobil and Nigerian Brewery could not be predicted by their respective stock price volatility. Gabriel and Ugochukwu (2012) conclude that investors can apply their own investment strategy by analysing the trend of volatility in the market over time, in order to be able to predict the movement in stock price and achieve superior advantage when actively trading on the Nigerian Stock Exchange.

A study conducted in the South African market by Chan (2012) examines whether the SAVI is a close approximation of the cross-sectional standard deviation of the returns of domestic general equity funds by testing for the correlation between the two variables. The results show that there is a positive correlation between the two variables, concluding that the SAVI is an acceptable proxy for the volatility of returns.

Kenmoe and Tafou (2014) adopt a regression analysis to test the relationship between the SAVI and the JSE Top 40 Index. The findings are consistent with those of other markets where there is a statistically significant inverse relationship between the contemporaneous JSE Top 40 returns and the SAVI. Additionally, the study finds an asymmetric relationship between these two variables. When conducting the analysis, the period under observation is further broken down into sub-periods and it is noteworthy that the significant negative relationship between the SAVI and the contemporaneous returns of the JSE Top 40 exists in all sub-periods. Kenmoe and Tafou (2014) conclude that the SAVI can be used as an investor's fear gauge.

Section 2.2 examined the empirical evidence on the relationship between stock market returns and volatility. Although there is very little empirical evidence on this topic in the South African context, the research found appears to be consistent with the findings in other equity markets. The main theme of this study is the feasibility of using the South African Volatility Index (SAVI) to time the JSE; it therefore follows that the use of the volatility index as a market timing tool is only possible if both contemporaneous stock returns and future stock returns have some relationship with stock market volatility.

2.3 Timing the market using an implied volatility index

Market timing involves moving in and out of a stock market or rotating between different asset classes by using economic and technical indicators to predict the future direction of the stock market. While the VIX has become widely used by traders in the marketplace as a tool for timing the market, using the VIX as a market timing tool is a relatively new concept in the body of academic research. This part of the literature chapter will look at academic research relating to the VIX as a market timing indicator.

Ferson (2012) investigates whether the performance of portfolio managers is dependent on volatility timing. This study makes use of a Stochastic Discount Factor Model that includes a volatility timing component, and uses data from the Center for Research in Security Prices Mutual Fund database focusing on active, U.S. equity fund data. It is found that the better performing mutual funds are the ones with more active responses to volatility. Additionally, when the funds are sorted according to their R-squares (the regression R-squares of their returns in standard factor models) it is found that the more active funds are the better performers.

Timing the market using the VIX can be done in different ways. Ang (2014) uses the VIX as a tool to determine the optimal weight of leverage in a portfolio (consisting of equity and T-bills) at any given point in time. He compares this market timing strategy to a static weight strategy where 60% of the portfolio is invested in equity and 40% is invested in T-bills throughout the entire period. The results show that the market timing strategy decisively beat the static strategy and was less prone to draw-downs during the early 2000s and the 2008 financial crisis. During these periods the VIX was high and the market timing strategy shifted into T-bills; therefore the market timing strategy partly avoided the low returns that occurred when volatility increased.

A moving average strategy that shifts between NYSE AMEX stocks and a risk-free asset (30-day T-bill), depending on what the equity price is compared to its moving average, is tested by Han et al. (2013) for the period 1993 to 2009. The study considers 10, 20, 50, 100 and 200 day equity price moving averages. The results show that the moving average strategy outperforms the buy-and-hold strategy. Similarly, Connors and Alvarez (2009) implement a moving average trading strategy using the VIX and confirm that the VIX can identify overbought markets and investors can therefore use it as a tool to determine when they should be aggressive in locking in gains and/or avoiding long purchases.

Ding et al. (2017) examine whether short term cross-sectional trading strategies using the VIX are profitable. The sample of data includes common stocks in the NYSE, AMEX and NASDAQ for the period 1988 to 2016. Portfolios are constructed that separate the stocks according to how sentiment-prone they are. To assess which portfolios are more prone to investor sentiment, the portfolios are based on characteristics such as return volatility, firm size and earnings ratio, amongst other factors. The trading strategy involves holding the sentiment-prone stocks when the VIX is low, and holding sentiment-immune stocks when the VIX is high. Ding et al. (2017) construct a long-short benchmark portfolio that is long the most sentiment-prone portfolio and short the most sentiment-immune portfolio over the entire period. The findings show that these trading strategies yield significantly greater excess returns than the benchmark long-short portfolio strategy which does not condition on the VIX.

It is a common theory that investors should enter the market when the VIX is high and exit the market when the VIX is low (Connors, 2012). Unlike previous studies, Lubnau and Todorova (2015) are of the view that it is a good time to enter the market during significantly low periods of volatility, thus their trading strategy generates a buy signal when volatility is relatively low. They therefore test the idea of using an implied volatility index as a market timing tool in various markets, namely the U.S (S&P 500), France (CAC 40), Germany (DAX 30) and Japan (Nikkei 225). The results of the market timing strategies for the CAC, DAX and Nikkei show outperformance of the buy-and-hold strategy in these markets, whereas the results in the U.S market were inconclusive and were less significant than the results in the other markets. A possible reason for this finding is that historical information may not be fully incorporated into the equity markets of France, Germany and Japan, whereas the U.S market exhibits a greater degree of market efficiency.

The studies above show that the VIX can be used in different ways to time the market, and furthermore indicate that active investment may be profitable when using the VIX. However, other studies were found to be against the VIX as a useful indicator. Vermeij (2012), for example, employs a model where the average implied volatility is calculated using a daily moving average of the VIX index over a 12 month period. If the actual VIX level is higher than the average implied volatility, investors are expected to be bearish, and therefore SPDRs (an ETF on the S&P 500) on the S&P 500 are sold (short position). Conversely, if the actual VIX level is lower than the average implied volatility, investors are expected to be bullish, and therefore SPDRs on the S&P 500 are bought (long position). Although the theory was that these positions should deliver a better performance than the S&P 500 market performance, the study in fact found that the trading strategy caused a loss, and the performance of the S&P 500 index proved to be far better. This result was expected, since the first part of the study indicated that the VIX has very little predictive power on the S&P 500 index. However, the use of an ETF on the S&P 500 to gain exposure to the S&P 500 index may not be optimal due to short selling restrictions, higher transaction costs, as well as it not being as liquid compared to S&P 500 futures. Thus, a superior choice of gaining exposure to the S&P 500 index would be through S&P 500 futures.

Cacia and Tzvetkov (2008) assess the capability of the VIX as a sentiment indicator which is used to generate signals in a short term trading strategy which involves trading the S&P 500 Index; a long position is taken when the VIX is relatively high and a short position is opened when the VIX is relatively low. The results show that the trading strategy outperforms the buy-and-hold strategy even after transaction costs of 0.1% are accounted for. Cacia and Tzvetkov (2008) conclude that volatility based indicators can be used as a successful tool for timing the market, measuring investors' sentiment and implementing short term trading strategies. However, they caution that due to the fact that the VIX contains an autoregressive volatility forecast as well as the expectations of option traders, the VIX cannot be considered to be a pure sentiment indicator; they elaborate that spikes in the VIX could be due to emotional reactions to the market, or due to the volatility properties itself; this conclusion may provide some explanation to the unprofitable results found by some researchers who attempt to use the VIX as a market timing tool.

The empirical evidence above was based on the U.S market, and the various findings indicate that the VIX can be used as a market timing tool. However, the profitability of the results depend on the model, as well as on the data that is used. Furthermore, it was observed that the VIX should not be considered as a pure investor sentiment indicator. In the South African context, limited research relating to the SAVI as a market timing tool exists. The following part of the literature will document previous findings in the South African market.

Adamson (2017) applies momentum trading strategies using shares from the JSE All Share Index over the period 2009 to 2017. The study aims to test whether the SAVI is a reliable tool for timing the market by observing the SAVI's correlation with the returns earned from the momentum trading strategies (the momentum trading strategy involves buying past "winner" shares and selling past "loser" shares, using predetermined holding periods). It is found that the SAVI is only correlated to the returns of the momentum strategies when the trading strategies performed poorly, *i.e.* during the periods where the momentum strategies performs poorly, the SAVI serves as a predictor of the rise in volatility.

While Adamson (2017) tests whether the SAVI is a reliable tool for timing the market, De Kock (2015) uses the application of the SAVI as a market timing tool as he uses daily moving averages (ranging from a 10-day to a 150-day) of the SAVI to determine when to switch between the JSE All Share Index (ALSI) and the JSE All Bond Index (ALBI). This analysis tests the theory that when the market is volatile investors will switch from an equity portfolio into a bond portfolio. Before transaction costs are included, the market timing strategy outperforms the simple buy-and-hold strategy. However when transactions costs of levels between 0.5% and 1% are applied, the buy-and-hold strategy beats the market timing strategy. De Kock's (2015) study provides evidence that market timing using the SAVI is possible, however, transaction costs have a negative impact on the market timing strategy's outperformance over market returns.

2.4 Timing the market using size and value styles

Theoretically, when volatility is expected to increase, increasing uncertainty about the future leads to a shift into value stocks as investors lose confidence in growth stocks (Copeland and Copeland, 1999). Conversely, when volatility is expected to decrease, this signals an increasing confidence in the future, which is a condition that favours growth stocks. Therefore, in theory investors should shift between value and growth stocks depending on the volatility of the market.

Similarly, using implied market volatility in a signal to shift between large cap and small cap stocks is based on the notion that large cap stocks perform better in periods of uncertainty (i.e. in periods of high volatility) and small cap stocks perform relatively better in periods when stock market volatility is low (Copeland and Copeland, 1999).

There are several studies that have used the VIX as a market timing signal to switch between size (large cap vs. small cap) and style (value vs. growth) portfolio strategies. Copeland and Copeland (1999) examine these strategies, and their findings show that portfolios of large-capitalisation stocks outperform portfolios of small-capitalisation stocks on days after the VIX has increased (i.e. on the days where the VIX is expected to reverse downwards), similarly, on these days value-based portfolios outperform growth-based portfolios. On days that follow a decrease in the VIX, the opposites occur. It is also noteworthy that Copeland and Copeland (1999) made use of the one-day percentage change in the VIX from its 75-day moving average as the signal to switch between portfolios. Boscaljon et al. (2011) conducted a similar study, and the findings were consistent with those of Copeland and Copeland (1999). However, these findings are only statistically significant for longer holding periods of 30 days or more. Therefore, it is suggested that for longer holding periods investors may be able to gain economically significant returns by rebalancing their portfolios between value and growth stocks based on changes in the VIX index.

Keränen (2017) uses a different portfolio construction method, by constructing long-short portfolios based on the Fama-French three factor model, using the so-called SMB and HML factors. The return on the SMB-portfolio is equal to the average return on the small stock portfolios minus the average return on the large stock portfolios, and the return on the HML portfolio is equal to the average return on the value portfolios minus the average return on the growth portfolios. The trading strategy involves taking a long position in the SMB portfolio when the VIX is relatively low, and taking a short position in the SMB portfolio when the VIX is relatively high. Similarly, a long position in the HML portfolio is taken when the VIX is relatively low and a short position is taken when the VIX is relatively high. The results show that the SMB portfolio generates positive returns when VIX levels are low. However the SMB portfolio generates negative returns when VIX levels are high - findings which are consistent with Copeland and Copeland (1999). An unexpected finding (inconsistent with Copeland and Copeland, 1999) is that it is more profitable to invest in growth stocks when the VIX is high, and value stocks when the VIX is low.

Efremidze et al. (2014) argue that while the VIX may indicate the expected size of the volatility changes, it does not inform investors about the level of randomness within the VIX time series; this could be a possible explanation to the unusual result found by Keränen (2017). Efremidze et al. (2014) therefore replicate the similar style and size rotation strategies using the VIX as discussed above, but in addition employ entropy indicators calculated from the VIX time series, which measures the level of uncertainty independently from predictable parts of the volatility changes, which could impact the market risk premium and discount rates of value and growth stocks. They find that the strategy that includes the entropy indicators outperforms the rotation strategy without the use of entropy indicators.

Style rotation is widely tested in numerous studies on the U.S market, as well as in a few international studies, including those of Basu (1983), Rosenberg et al. (1998), Graham and Dodd (1934), De Bondt and Thaler (1987) and Van Rensburq and Robertson (2003). The focus of this part of the literature chapter was to describe evidence on market timing through rotation between size and value styles, using the VIX (or analogous volatility indices) as a rotation signal.

2.5 The profitability of using technical analysis and moving averages in trading strategies

Technical analysis is a trading tool that is used to identify trading opportunities and evaluate stock price movement by examining statistics that are gathered from trading activity.

While it is traditional for technical analysis to rely on the historical price and volume data of a security in order to generate buy and sell signals for the security, Kozyra and Lento (2011) determine technical trading rules using VIX price data in the U.S market, over the period 1999 to 2009. Three different technical trading rules are used in this study, namely the moving average crossover rule, the trading range breakout rule and the filter rule. These three rules are first tested using historical stock price data (the traditional technical trading rules) and then these same three rules are tested using VIX data instead of historical stock price data. This study compared the returns from the traditional technical trading rules using security price data to the technical trading rules using VIX price data, and find that overall the trading rules using VIX price data outperformed the traditional technical trading rules for 63% of the cases. Kozyra and Lento (2011) suggest that there is a relationship between the profitability of technical analysis and the level of market volatility.

Whilst most previous studies used moving averages up to a 200 day period, Isakov and Marti (2011) use moving averages on periods as long as four years. On this basis, they test the ability to time the U.S market by using trading strategies based on the moving averages of the S&P 500, and conclude that moving average rules are able to identify and take advantage of long-term market movements. It can also be noted that trading strategies that identify short-term market movements imply trading that occurs less frequently. However investors may still want higher returns even in bull markets and may not be as patient as to wait for trend reversals. In addition to these findings, Isakov and Marti (2011) also find that their trading signals correspond to bull and bear markets, indicating that the trading rules produced accurate signals.

Marshall et al. (2017) make use of moving average as well as time-series momentum trading rules in the U.S context, using value-weighted size quintile portfolios from Ken French's website for the period 1963 to 2013. Time-series momentum trading rules are slightly different from moving average trading rules, in that they generate a buy signal when the share price moves above a historical price at a certain historical point. The trading rules make use of look-back periods of 10, 50, 100 and 200 days. The signals generated from the trading strategies involve a re-allocation between the value-weighted portfolio and a risk-free asset. The study finds that both trading rules yield profits after transaction costs are accounted for. When comparing the moving average trading rules to the time-series momentum rules, it is found that moving average rules are more likely to generate a buy signal earlier, and exit long positions quicker, than time-series momentum rules, which leads to superior returns when using moving average trading rules. Additionally, these authors find that both trading rules are profitable on the small and mid-cap portfolios, but not on the large-cap portfolio. Marshall et al. (2017)'s explanation as to why technical trading rules are popular among investors but are rejected by some academic studies, is that technical trading rules are most profitable on small and mid-cap stocks, whereas it is common for academic studies to make use of market indices consisting of large-cap stocks.

Brock et al. (1992) test two popular trading rules, namely moving average and trading range break, by using the Dow Jones Index from 1897 to 1986. They found that the returns from the buy signals were higher than market returns, whereas the returns from sell signals were lower than market returns. These results indicate that technical rules have predictive power, however this study notes the absence of transaction costs in its analysis. Furthermore, the authors suggest that the return generating process of stocks is more complex than what is suggested by studies that use linear models, and note that technical rules may pick up on some of the hidden patterns that linear models do not take into account.

Overall the trend in the empirical findings suggests that it is profitable to use technical analysis and moving averages when implementing trading strategies. However there are no definite answers as to what length of the moving average works best and whether the size of a stock affects the profitability of the trading strategy.

2.6 Conclusion on literature findings

The review of the literature began with studies on market efficiency on the JSE. Grater and Struweg (2015) confirm that the JSE is inefficient in the weak-form, however, the remaining literature showed that this result depends on the size of the stock, the time period under analysis, and the frequency of the data used. The finding of the JSE to be inefficient in the weak-form (whether this finding relates to some stocks or the entire market) and therefore exhibiting some behaviour of mean reversion, opens up the possibility of using trends in the market to time the market.

Since this study is aimed at using an implied volatility index (a proxy for stock market volatility) as a tool to time the market, a relationship must first exist between stock market volatility and contemporaneous stock market returns. The majority of the empirical evidence found a negative relationship between contemporaneous stock returns and the implied volatility index, indicating that high volatility levels (and high risk) are associated with low stock prices and low contemporaneous returns. Furthermore, when examining the relationship between stock market volatility and future stock returns, most of the empirical evidence finds a positive relationship between future stock returns and volatility, indicating that when volatility levels are high, future stock returns are expected to be high as investors demand higher rates of return on stocks due to their high risk premiums. In the South African context, Chan (2012) found that there is a positive correlation between the SAVI and the cross-sectional standard deviation of the returns of domestic general equity funds, this suggests that the SAVI is an acceptable proxy for the volatility of returns and may therefore serve as a useful market timing tool. Additionally, Kenmoe and Tafou (2014) found a significant negative relationship between the SAVI and the contemporaneous returns of the JSE Top 40 which indicates that the SAVI can be used as an investor's fear gauge.

As the majority of this literature suggests that a relationship exists between stock market volatility (determined by an implied volatility index) and both contemporaneous and future stock returns, the next part of the literature adds some practicality to this relationship by examining the empirical evidence relating to using an implied volatility index to time the market. The empirical evidence based on the U.S market indicated that the VIX can be used as a market timing tool. However, it was observed that the VIX should not be considered as a pure investor sentiment indicator. In the South African context, limited research relating to the SAVI as a market timing tool exists. However, a study by De Kock (2015) showed that the applied market timing strategy outperformed the simple buy-and-hold strategy in the absence of transaction costs, indicating the possibility of market timing on the JSE. Furthermore, the findings by Adamson (2017) suggest that market timing on the JSE using the SAVI may only be useful during certain types of market conditions (more specifically during significant market downturns). This study not only aims to use an implied volatility index as a tool to time the market, but also involves the use of technical analysis when implementing the market timing strategies. The last part of the literature therefore showed literature relating to the profitability of using technical analysis and moving averages in trading strategies; it was found that in most cases it was useful to apply technical analysis and moving averages when implementing trading strategies, as the literature showed that accurate trading signals were produced when implementing these strategies.

In summary, the literature provided some evidence that firstly, the JSE (or some stock listed on the JSE) exhibits returns that follow a non-random process which opens up the possibility of market timing on the JSE. Secondly, it was found that there is a relationship between stock market volatility and both contemporaneous and future stock returns, which justifies the potential for using an implied volatility index as the market timing tool. Lastly, it was evidenced that when implementing technical analysis in trading rules, for the most part, accurate trading signals and positive strategy returns were produced. This lends support for Chapter 4, which tests whether the technical trading rules (using the CBOE VIX) used in the United States market can be applied to the South African market using the SAVI as a market timing tool, in order to outperform a passive buy-and-hold strategy. Before moving on to Chapter 4, the data and descriptive statistics used for this study will be discussed in Chapter 3.

Chapter 3 Data and descriptive statistics

This chapter discusses and describes the data on which this study was based, starting with an overview of the data, followed by some brief descriptive statistics.

3.1 Data

The SAVI was introduced in 2007, and the first data point available is that of 2 May 2007. The first part of this study (Chapter 4) therefore covers a sample period from 2 May 2007 until 9 March 2018. The frequency of the data used in this study is daily due to the thin-trading that exists in the South African options market, and since it is important to account for trading activity, the use of daily data is the smallest practical interval to use which avoids overlooking movements or events that occur on a specific day.

There are different measures used when determining the expected volatility of the stock market. Some researchers believe that the standard deviation of returns not only provides information about past market movements, but also provides some information about the future, as there is a high correlation between short-term standard deviation in the stock market and future standard deviation (Cusatis, 2011). Other studies have use the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model, which generates volatility forecasts. Giot (2002), however, suggests that GARCH-type forecasts provide a small amount of incremental information when compared to the information provided by implied volatility indices. This study uses the SAVI, an implied volatility index, calculated by the JSE as the weighted average price of call options and put options over a wide range of strike prices that expire in 3-months' time, and therefore constructs a forward-looking index that provides a daily prediction of market volatility in three months' time.

Since the SAVI is calculated using implied volatilities obtained daily from specific Top 40 options, the associated equity index used in this study is the JSE Top 40 share price Index (Top 40). Both the Top 40 index and the SAVI were sourced from McGregor BFA. This study makes use of the Composite Short-Term Fixed Interest Index (STeFI) as the risk-free asset, as it is an industry-wide used benchmark since it is a short-term index which is investable and hence relatively liquid. The STeFI data was sourced from Morningstar.

The second part of this study (Chapter 5) covers a sample period from 2 May 2007 to 24 May 2018, and uses three additional indices in conjunction with the SAVI and the Top 40. The three additional indices used here are the JSE's Value Index (J330), the Growth Index (J331), and the JSE's Small Cap Index (J202), which were all sourced from Mcgregor BFA. The Value and Growth Index on the JSE serves as proxies for value and growth portfolios, respectively. Similarly, the JSE Top 40 Index and the Small Cap Index serves as proxies for large-capitalisation and small-capitalisation portfolios respectively.

3.2 Descriptive statistics for the SAVI and the Top 40

Firstly, descriptive statistical tests were performed on the returns of the Top 40 index, the Small Cap Index, the Value Index and the Growth Index. The statistics included here are the mean, skewness and kurtosis. The purpose of this section is to examine the distributional properties of the return series.

The average Top 40 return over the entire sample period of 2 598 days was approximately 0.04% per day. The Top 40 returns had a range of 15.66%, with a minimum return of -7.65% and a maximum return of 8.01%. The Small Cap Index, the Value Index and the Growth Index each had an average return, per day, over the sample period of 0.02%, 0.02% and 0.04%, respectively.

Skewness measures the degree to which a distribution is asymmetric about its mean value (Brooks, 2008). A normal distribution is symmetric about its mean and has a skewness coefficient of zero. The skewness coefficient of the returns of the Top 40 index was 0.12, meaning that the return series was positively skewed with most of the returns being greater than the average return of 0.04% (see Figure 1). The skewness coefficient of the returns of the Small Cap Index, the Value Index and the Growth Index was -0.38, -0.04 and 0.07 respectively, which shows that both the return series for the Small Cap Index and the Value Index were negatively skewed, while the return series for the Growth Index was positively skewed.

Kurtosis measures the thickness of the tails of the distribution (Brooks, 2008). A kurtosis coefficient of three is representative of a normal distribution. The kurtosis coefficient for the Top 40 return series was 4.01. Since this coefficient is slightly greater than three, it means that the Top 40 returns are slightly peaked around their average value (see Figure 1), this is expected of a distribution which characterises a financial time series (Brooks, 2008). The kurtosis coefficient for the Small Cap Index, the Value Index and the Growth Index return series was 9.37, 2.70 and 4.61 respectively. The Small Cap Index and the Growth Index represent a distribution which is peaked around the average value with relatively more outliers in the return series, while the Value Index has fewer outliers in the return series with the returns clustering around the average value (see Figures 2, 3 and 4). A graphical representation of the return series for each of the indices is shown below.

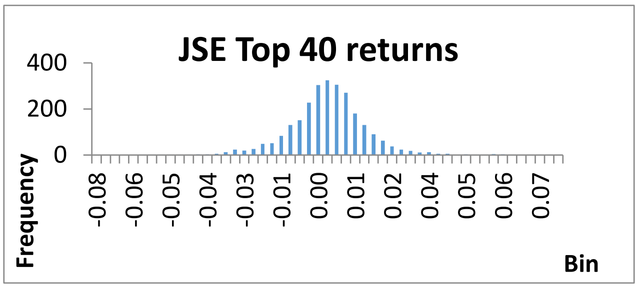

Figure 1: Distribution of JSE Top 40 returns

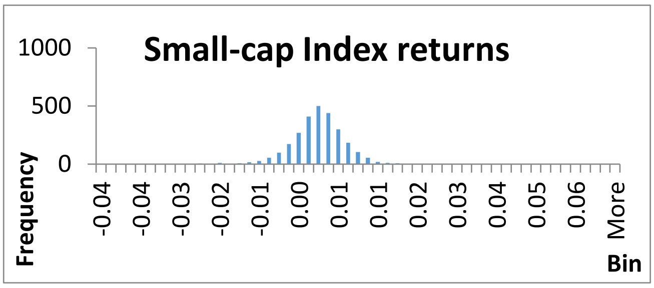

Figure 2: Distribution of Small Cap Index returns

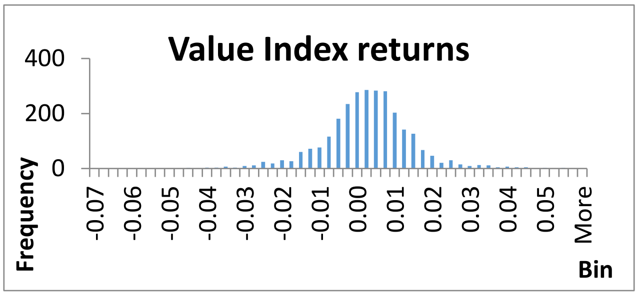

Figure 3: Distribution of Value Index returns

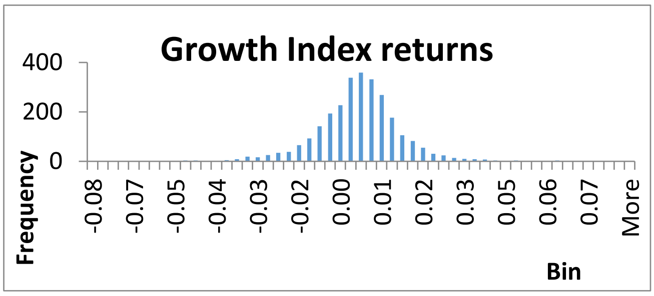

Figure 4: Distribution of Growth Index returns

Similar to the descriptive statistical tests that were performed on the Top 40 index, this section will discuss the statistics that relate to the SAVI. The average SAVI level was approximately 22.33% over the entire sample period. The volatility of the Top 40 returns according to the SAVI ranged from a minimum SAVI level of 11.88% to a maximum SAVI level of 57.97%. The high maximum value of 57.97% is related to the financial crisis that occurred towards the end of 2008. The skewness coefficient of 1.72 and kurtosis coefficient of 4.34 shows that the SAVI is non-normally distributed with positive skewness. A graphical representation of the SAVI level is shown in Figure 5 below. A further analysis of the SAVI and Top 40 returns according to distinct time periods will be discussed in section 4.3.

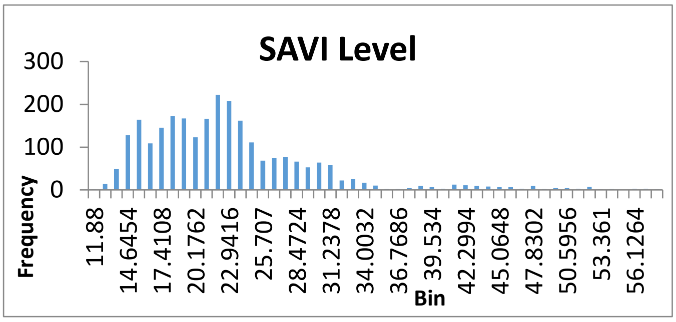

Figure 5: Distribution of SAVI level

Chapter 4 Testing SAVI-based technical trading strategies on the JSE

This chapter tests whether the technical trading rules (using the CBOE VIX) used in the United States market can be applied to the South African market using the SAVI as a market timing tool in order to outperform a passive buy-and-hold strategy, using the JSE Top 40 Index and STeFI as proxies for equities and short-term interest-bearing investments, respectively. The chapter will start off by discussing the methodology applied in the analysis, and finally ending off with a discussion on the results and analysis found in this section.

4.1 Methodology

In this section, the SAVI was used in various technical-based market timing strategies to generate buy and sell signals, which were then used to determine the timing of the shifting of theoretical funds from the Top 40 index into the STeFI, and vice versa. The total cumulative return achieved with the various market timing technical strategies were then compared to the return of the Top 40 index (the buy-and-hold strategy) over the period May 2007 to March 2018.

The majority of academic studies test for the relationship between the VIX and future stock returns by regressing future holding period excess returns of the S&P 500 on the VIX (see, for example, Giot, 2005, and Banerjee et al., 2007). This form of regression tests the theory that high levels of implied volatility indicate that markets are oversold. However, the regression does not provide a timing signal which indicates when to be invested in the stock market and when to exit.

More recent research makes use of simple moving averages, a form of technical analysis, in order to determine trading signals (see, for example, Han et al., 2013; Connors and Alvarez, 2009; Ding et al. (2017); and De Kock, 2015). It is assumed that because both technical analysis and the VIX are forward-looking, combining them together could create a more powerful forward-looking signal (Kozyra and Lento, 2011). The reason behind using the method of moving averages of the volatility index stems from the fact that the volatility index is a dynamic indicator which means that volatility is always adjusting. Therefore, since volatility is always adjusting, the volatility indicators should continuously adjust as well (Connors and Alvarez, 2009). Furthermore, since the return-generating process of stocks is more dynamic than what is suggested by the various studies that use linear models, it can be debated that technical rules pick up some of the hidden patterns that linear models do not.

The moving average smooths out price data by creating a constantly updated average price, with the average price being calculated over a specific period of time. While a moving average is the most commonly used method in technical analysis, it is not the only form of technical analysis that exists. This study makes use of several different forms of technical analysis in arriving at the trading strategies. The five technical rules applied in the analysis are (1) the simple moving average rule, (2) the relative-strength index (RSI) strategy, (3) the moving average crossover rule, (4) the trading-range breakout rule, and (5) the filter rule.

As a first step, at the start of the period of analysis for that particular strategy, a nominal investment of R100 was hypothetically made into the Top 40 Index. The ultimate objective was to determine whether the final amount obtained by applying the market timing strategies over the entire period would be greater than the final amount obtained if an investor had remained invested in the Top 40 index over the entire sample period (the so-called "buy-and-hold" strategy).

Each of the five technical rules and selected variants of them were separately used over the period of analysis to generate ongoing timing signals as either a daily buy- or a daily sell-signal; if there was a buy-signal 100% of the nominal investment amount was theoretically "invested" in the Top 40 index, and if there was a sell-signal 100% of the investment was theoretically "invested" in the STeFI. Since the current day's closing value of the SAVI was used in determining the trading signal, a change from a buy to a sell signal (or vice versa) for the current day would be a trading signal to shift into a position in the alternate asset class the following day. In other words, the strategy involved remaining in one of the two asset classes until there was a change in signal. The returns obtained over the sample period were defined as the returns generated from the switch in asset class, and were calculated from the period where there was a previous change in signal to the period where the next change in signal occurred. The value of the nominal investment is thereby updated every time a switch was made between the two asset classes. The total returns for each of the trading strategies were compared to the total return generated when simply buying and holding the Top 40 index, over the period May 2007 to March 2018.

It must be noted that since the aim of these market timing strategies was to beat the returns of buying-and-holding the Top 40 index, the periods where the market timing strategy aimed to outperform the buy-and-hold strategy would be defined as a period when there is a change in signal from a buy signal to a sell signal, i.e. the signal that prompts the investor to exit the Top 40. In other words, the objective of using the trading strategies as opposed to a buy-and-hold approach, was to attempt to avoid being exposed to the periods of poor market performance.

The trading rules that were used as market timing signals in this study were as follows:

a) The *simple moving average rule* - this is the most commonly used technical rule. A buy-signal was generated when the value of the SAVI was 5% or more above its 10-day moving average; conversely a sell-signal was generated when the SAVI was 5% or more below its moving average.

b) The *RSI strategy* - this strategy was originally developed by Connors and Alvarez (2009) using the VIX. The RSI is a commonly used momentum oscillator that compares the magnitude of a security's recent gains to the magnitude of its recent losses. Connors and Alvarez (2009) suggest that more robust results are found when the time frame of the RSI is shorter, and hence a 2-period (i.e. 2-day) RSI was used. The formula for the RSI is as follows:

$$RSI = 100 - \frac{100}{1+RS} \qquad \text{Equation 1.1}$$

$$\text{Where } RS = \frac{Average\ of\ X\ days\ up\ closes}{Average\ of\ X\ days\ down\ closes} \qquad \text{Equation 1.2}$$

A buy-signal was generated when the 2-period RSI of the SAVI was above 90, and a sell-signal was generated when the 2-period RSI of the Top 40 was above 65.

c) The *moving average crossover rule* - according to this rule, buy and sell signals are generated by two moving averages, a long-period average and a short-period average. A buy (sell) signal was generated when the short-period moving average of the SAVI rose above (fell below) the long-period moving average. Several variations of this rule were applied to this study, namely 1-50 day, 5-150 day, and 1-200 day moving average crossover rules, where the first number indicated the short period average, and the second umber the long-period average.

d) The *trading-range breakout rule* - a buy signal was generated when the SAVI level broke through a resistance level, defined as the local maximum SAVI level. A sell signal was generated when the SAVI level broke through the support level (*i.e.* the local minimum SAVI level, which is the minimum level over an x -day rolling period). Different maximum and minimum SAVI levels were determined, based on the number of days used, namely x = 5, 10 and 50 days.

e) The *filter rule* - a buy signal was generated when the SAVI rose x% above a given level, and a sell signal was generated when the SAVI fell x% below a given level. It is suggested that a SAVI level below 22 is indicative of a bearish market, and a SAVI level above 28 is indicative of a bullish market from a contrarian point of view; therefore the range of 22 and 28 was applied for this strategy in the present study. Numerous variations were tested using a magnitude of 1%, 2%, and 5% both above 28 and below 22, respectively.

Section 4.3 that follows will first discuss the results before transaction costs are taken into account, and then follow with a discussion relating to the inclusion of transaction costs. Most previous studies have assumed the transaction costs to be an arbitrary value or range of values and have assumed that the transaction costs for sales are equivalent to the transaction costs of purchases (e.g. Cacia and Tzvetkov, 2008 and De Kock, 2015). Since the inclusion of transaction costs have a major impact on net investment returns, this study aims to apply transaction costs that are a more accurate representation of the actual transaction costs that an investor would incur. Moneyweb Investor performs a regular analysis that compares fees charged by online stockbrokers in South Africa (Tarrant, 2017); according to this analysis it is a reasonable assumption that a transaction cost of about 0.1% is incurred by large institutions and a transaction cost of about 0.7% is incurred by a retail investor when trading in equities on the JSE. These costs apply to both on purchase and sale transactions. Therefore, the range of transaction costs that were applied to each trade in the various tests in this study were 0.10%, 0.20%, 0.50%, and 0.75%. In addition to this range of transaction costs, a Securities Transfer Tax cost of 0.25% was added in the case of all stock purchases (but not sales, to which this tax does not apply). The applicable transaction costs were applied at every point where there is a change in signal – in other words, at points where a hypothetical trade is made by shifting the investment into, or out of, the Top 40 Index. However, it must be noted that the transaction costs that were taken into account were only the costs incurred when buying and selling the Top 40 index, but not the costs incurred when buying and selling the STeFI. The costs of investing or withdrawing funds from the latter is not nearly as significant as equity trades, and were thus deemed low enough to be ignored in this study, given the dominance of equity transaction costs in the strategies used.

4.2 Results and analysis

In the sections to follow, the results and analysis of the first part of the study are presented gross of transaction costs, and thereafter net of transaction costs.

4.2.1 Results and analysis (without the effect of transaction costs)

The table below (Table 1) shows the results for the different trading strategies; column A shows the results of buying and holding the Top 40 (the buy-and-hold strategy), while column B shows the results of the trading strategies when no transaction costs are taken into account. Three of the trading strategies outperformed the buy-and-hold strategy over the test period: the simple moving average (MA) strategy, the RSI strategy, and the MA crossover (5, 150) strategy. These three outperforming trading strategies are highlighted in green, while the underperforming trading strategies (in the absence of transaction costs) are highlighted in red.

A commonality among these three strategies is the short length of the periods (2 to 10 days) that were used in arriving at the indicators for these three strategies. The use of shorter length moving averages generally identify price levels that are very close to the top and bottom of a trend, however, they also generate a few whipsaws (*i.e.* false signals in the strategy). Shorter length averages track smaller price trends; shorter moving averages react quicker to price changes, generate more signals and are quick for early entry. Theoretically, the MA crossover strategy aims to reduce the number of whipsaws, while minimizing the generation of delayed signals. However, these results show that the simple MA strategy outperformed all of the MA crossover strategies.

Table 1: Top 40 returns vs Strategy returns before transaction costs

Column		A	B
Strategy name		**Top 40 results**	**Strategy results**
Simple MA strategy	Starting capital value	100	100
	Ending capital value	208	301
	Return	108%	201%
RSI strategy	Starting capital value	100	100
	Ending capital value	204	216
	Return	104%	116%
MA crossover (5, 150)	Starting capital value	100	100
	Ending capital value	192	216
	Return	92%	116%
MA crossover (1, 50)	Starting capital value	100	100
	Ending capital value	192	109
	Return	92%	9%
MA crossover (1, 200)	Starting capital value	100	100
	Ending capital value	196	129
	Return	96%	29%
Trading range breakout 50 day			No signals
Trading range breakout 5 day	Starting capital value	100	100
	Ending capital value	208	197
	Return	108%	97%
Trading range breakout 10 day	Starting capital value	100	100
	Ending capital value	208	200
	Return	108%	100%
Filter rule 1%	Starting capital value	100	100
	Ending capital value	207	188
	Return	107%	88%
Filter rule 2%	Starting capital value	100	100
	Ending capital value	207	193
	Return	107%	93%
Filter rule 5%	Starting capital value	100	100
	Ending capital value	207	176
	Return	107%	76%

Kozyra and Lento (2011) conducted a similar study in the U.S. context, using the S&P 500 index as well as the Nasdaq, which served as proxies for the U.S stock market, making use of popular VIX-based technical rules to arrive at various trading strategies. One of the technical rules used by these researchers was the trading range breakout rule, which was tested using 50, 150, and 200 day ranges. It is noteworthy that in the present study no signal was generated for the entire period when 50 day ranges were used. It appears from the results that periods above a 10 day range are too long for trading breakouts in the South African market. Another contrasting finding is that of Kozyra and Lento (2011) is that the three most profitable trading strategies are the 2%, 1% and 5% filter rule, respectively, which in the present study perform poorly.

The graph below (Figure 6) shows the cumulative returns, before transaction costs, for all of the strategies over the entire sample period.

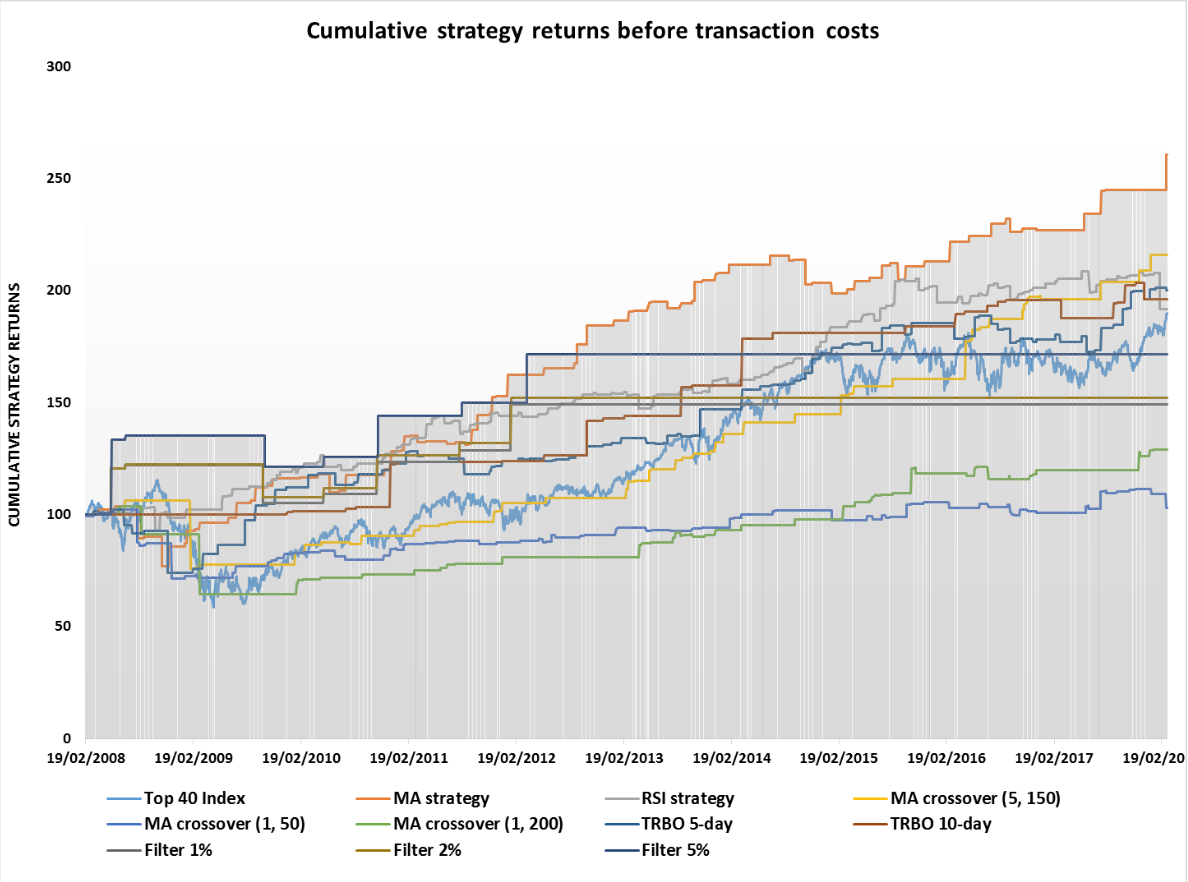

Figure 6: Cumulative strategy returns before transaction costs

Since the MA strategy, the RSI strategy and the MA crossover (5, 150) strategy were the three strategies to outperform the buy-and-hold strategy, further analysis was done on these strategies. The table below shows the percentage of accurate signals (see definition below) that were produced for each of the three strategies for the entire sample period.

Table 2: Analysis of the signals produced for the three top performing strategies

Strategy	Total number of signals	Number of accurate signals	% of accurate signals
MA strategy	48	21	44%
RSI strategy	127	36	28%
MA crossover (5, 150)	31	19	61%

For all of the trading strategies, the investor was either 100% invested in the Top 40 or 100% invested in the STeFI, therefore, the total number of signals produced is defined as a change in signal from a buy signal to a sell signal, i.e. the signal that prompts the investor to exit the Top 40. An accurate signal is defined as a signal where acting on that signal led to return outperformance relative to the buy-and-hold strategy over the period to the next (opposite) signal. The MA crossover (5, 150) strategy had the highest percentage of accurate signals produced, with 61% of the signals produced being accurate. This confirms the theoretical idea that the use of an MA crossover strategy (a shorter length MA combined with a longer length MA) reduces the number of false signals (Brock & LeBaron, 1992). As mentioned, the simple MA strategy outperformed the MA crossover strategies in terms of the total return gained over the entire period. Although the MA crossover strategy generated the highest number of accurate signals (i.e. the lowest number of false signals), the magnitude of the returns that were generated by the simple MA strategy were higher than the magnitude of the returns that were generated by the MA crossover strategy over the entire period, possibly because the simple MA strategy picks up on the smaller price movements and may generate a signal earlier than the MA crossover strategy.

A common finding among the three best performing strategies was that the outperformance of strategy returns (when compared to the buy-and-hold strategy) were clustered around three distinct time periods: November 2008 to February 2009, September 2011 to May 2012, and April 2015 to August 2015.

Figure 7 shows the strategy returns vs. the Top 40 returns from November 2008 to February 2009. This period showed extremely volatile returns, reaching negative returns multiple times. This period of volatile returns was during the time of the financial crisis which caused volatile returns in equity markets all over the world.

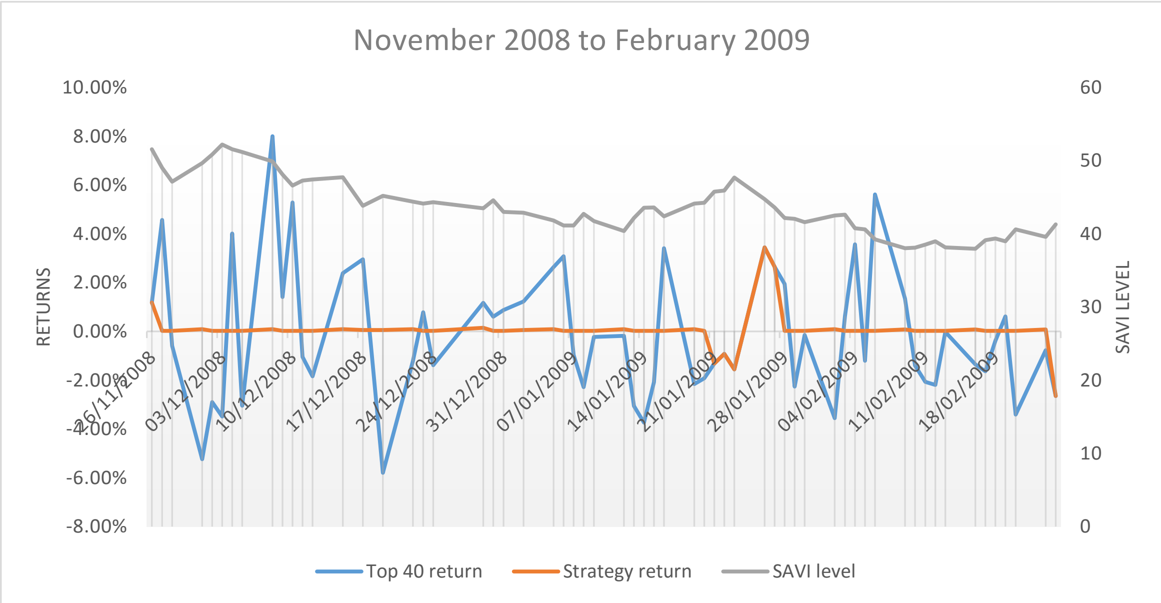

Figure 7: Strategy vs Top 40 returns over the period November 2008 to February 2009

Figure 8 shows the strategy returns vs the Top 40 returns from September 2011 to May 2012. Similarly, the volatility in returns was due to an extreme market event, in this case it was the Eurozone Debt Crisis which proved to be a contagious event that affected stock markets, including the JSE.

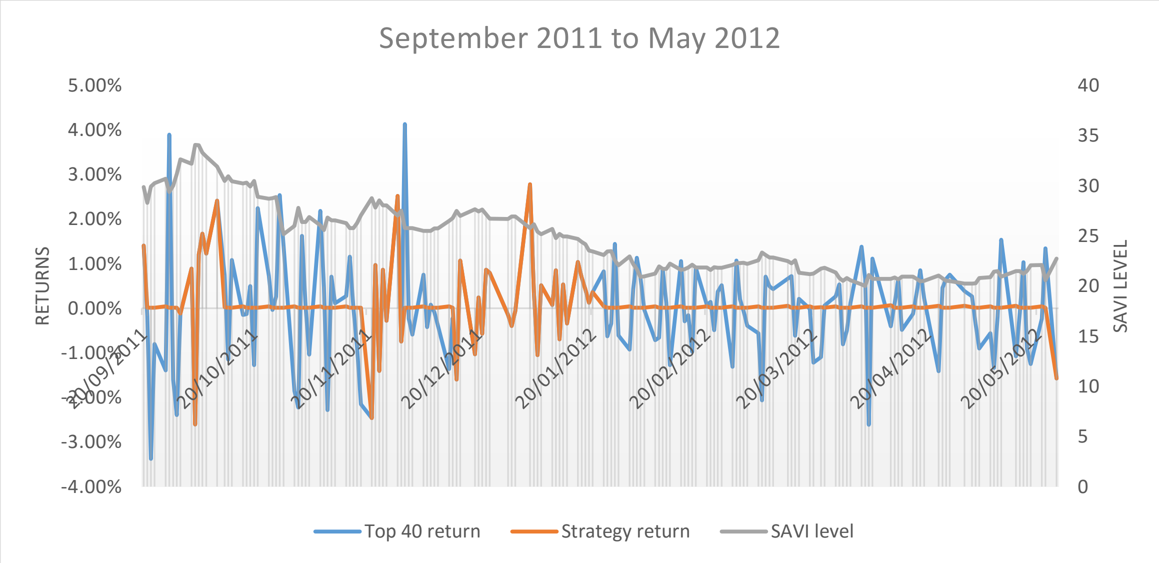

Figure 8: Strategy returns vs Top 40 return over the period September 2011 to May 2012

Lastly, the strategy returns vs. the Top 40 returns from April 2015 to August 2015 are presented in Figure 9. 2015 was a poor year for South Africa as a whole, the South African economy contracted (decline in real GDP) in the second quarter for only the second time in the 23 quarters since the end of the 2009 recession. In addition to South Africa's poor economic performance over the 2015 period, global events such as Greece's debt crisis and the Chinese equity market's "Black Monday" caused major volatility and periods of negative returns on the JSE.

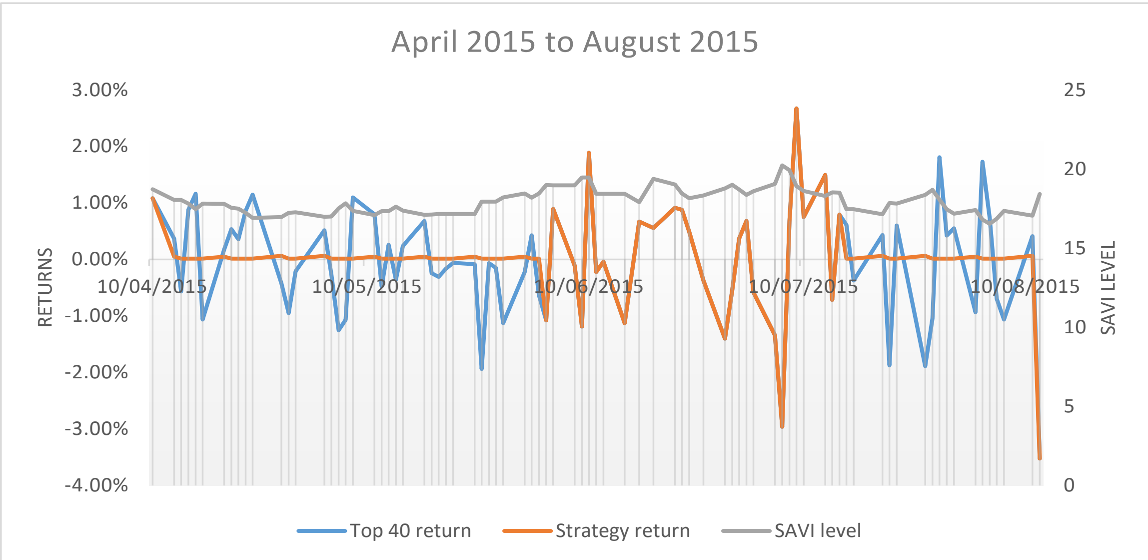

Figure 9: Strategy returns vs Top 40 return over the period April 2015 to August 2015

The table below shows the average returns and standard deviation of returns for the three best periods of outperformance of the simple MA trading strategy. In all three periods, the average trading strategy return was higher than the average buy-and-hold return over the period, and in two of the three periods the average return of the buy-and-hold strategy was negative. Additionally, the average standard deviation of returns (another proxy for volatility) was higher for the buy-and-hold returns as compared to the trading strategy returns. It is also noteworthy to point out the relatively high average SAVI level, which shows that the SAVI was an accurate indicator of the volatility that occurred during those periods.

It is worth noting that the periods in which the trading strategies performed the best occurred during extreme market events which caused the JSE to be mostly volatile, with numerous occurrences of negative returns of the Top 40. Kozyra and Lento (2011)'s findings in the US were similar, in that the VIX levels were much higher in the periods where the strategies outperformed as compared to when the strategies underperformed. It is therefore reasonable to assume that market timing through the use of trading strategies is profitable in extremely volatile periods, in this case the investor would have exited the poorly performing equity market and avoided the associated negative returns.

Table 3: Analysis of the MA strategy

MA strategy					
Period	Average strategy return	Average Top 40 return	Strategy: standard deviation of returns	Top 40: standard deviation of returns	Average SAVI level
November 2008 - February 2009	0.34%	-0.11%	1.68%	2.76%	43.87
September 2011 - May 2012	0.14%	0.04%	0.82%	1.16%	24.72
April 2015 - August 2015	0.07%	-0.04%	0.37%	1.05%	17.98

4.2.2 Results and analysis (with the effect of transaction costs)

Thus far the performance of the trading strategies have been discussed without taking into account the transactions costs that are incurred. Table 4 (from column C to F) shows the results of the trading strategies after a range of transaction costs have been applied to each trade.

All the trading strategies, other than the simple MA strategy, underperformed the buy-and-hold strategy when all ranges of transaction costs were applied, and in some cases the trading strategy returns were negative. The returns of the simple MA strategy still outperformed the returns of the buy-and-hold strategy when the two lower ranges of transaction costs were applied (column C and D). For transaction costs higher than 0.20% (sales) and 0.45% (purchases), the simple MA strategy underperformed the buy-and-hold strategy. The inclusion of transaction costs in assessing the net investment returns suggest that the use of market timing trading strategies are profitable when transaction costs are low; this means that these strategies may be more beneficial to institutional investors with a lower trading cost.

Table 4: Top 40 returns vs strategy returns after transaction costs

		Column	C	D	E	F
	Transaction costs {	**Sales:**	0.10%	0.20%	0.50%	0.75%
		Purchases:	0.35%	0.45%	0.75%	1.00%
Strategy name		**Top 40 results**	**Strategy results**			
Simple MA strategy	Starting capital value	100	100	100	100	100
	Ending capital value	208	243	221	166	131
	Return	108%	143%	121%	66%	31%
RSI strategy	Starting capital value	100	100	100	100	100
	Ending capital value	204	122	94	44	23
	Return	104%	22%	-6%	-56%	-77%
MA crossover (5, 150)	Starting capital value	100	100	100	100	100
	Ending capital value	192	187	176	145	124
	Return	92%	87%	76%	45%	24%
MA crossover (1, 50)	Starting capital value	100	100	100	100	100
	Ending capital value	192	73	61	35	22
	Return	92%	-27%	-39%	-65%	-78%
MA crossover (1, 200)	Starting capital value	100	100	100	100	100
	Ending capital value	196	105	96	73	58
	Return	96%	5%	-4%	-27%	-42%
Trading range breakout 50 day						No signals
Trading range breakout 5 day	Starting capital value	100	100	100	100	100
	Ending capital value	208	144	125	82	58
	Return	108%	44%	25%	-18%	-42%
Trading range breakout 10 day	Starting capital value	100	100	100	100	100
	Ending capital value	208	186	180	164	152
	Return	108%	86%	80%	64%	52%
Filter rule 1%	Starting capital value	100	100	100	100	100
	Ending capital value	207	183	182	176	172
	Return	107%	83%	82%	76%	72%
Filter rule 2%	Starting capital value	100	100	100	100	100
	Ending capital value	207	189	187	181	177
	Return	107%	89%	87%	81%	77%
Filter rule 5%	Starting capital value	100	100	100	100	100
	Ending capital value	207	173	172	167	164
	Return	107%	73%	72%	67%	64%

The Graph below (Figure 10) shows the cumulative returns, after transaction costs (of 0.20% and 0.45% for sales and purchases respectively), for all of the strategies over the entire sample period.

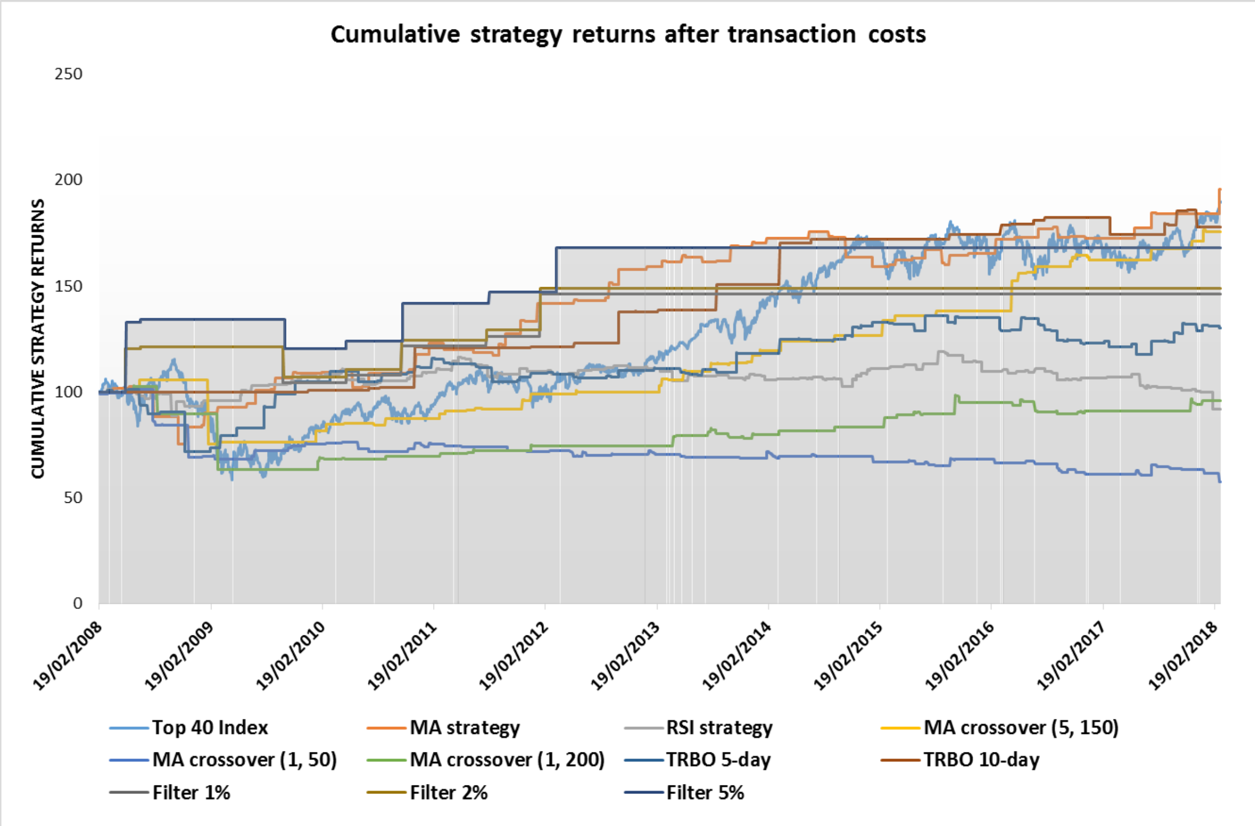

Figure 10: Cumulative strategy returns after transaction costs

4.2.3 Testing for the statistical significance of strategy returns

The returns of the ten strategies were tested for statistical significance in order to determine the significance of the differences between the returns of each strategy (before transaction costs), and the returns of the Top 40 Index (a proxy for the South African equities market), which is done via a t-test. The null hypothesis in this case is that the strategy returns are not statistically different from the returns of the Top 40 Index. The table below shows the results from the t-test; if the t-stat is greater than the t critical value, the null hypothesis would be rejected. The results, however, show that in the case of all ten strategies, the null hypothesis is not rejected (at a 95% confidence level), meaning that the strategy returns are not statistically significant.

Table 5: t-test for statistical significance of the strategy returns

		t-Test for significance		
Strategy	t stat	t critical (two-sided test)	p-value	Decision
MA strategy	-0.59	1.96	0.56	Accept null hypothesis
RSI strategy	0.20	1.96	0.84	Accept null hypothesis
MA crossover (5, 150)	0.03	1.96	0.98	Accept null hypothesis
MA crossover (1, 50)	1.49	1.96	0.14	Accept null hypothesis
MA crossover (1, 200)	1.35	1.96	0.18	Accept null hypothesis
TRBO rule 5-day	0.32	1.96	0.75	Accept null hypothesis
TRBO rule 10-day	0.27	1.96	0.79	Accept null hypothesis
Filter rule (1%)	-0.35	1.96	0.73	Accept null hypothesis
Filter rule (2%)	-0.41	1.96	0.68	Accept null hypothesis
Filter rule (5%)	-0.21	1.96	0.84	Accept null hypothesis

This chapter showed that by using the SAVI as a tool in the technical-based trading strategies it is possible to outperform the returns of a buy-and-hold strategy. However, transactions costs have a significant effect on the results, and the strategy returns (before transaction costs) are found not to be statistically different from the returns of the Top 40 Index. The following chapter (Chapter 5) will test the ability of using the SAVI in a market timing rule to take advantage of the documented size (small-capitalisation versus large-capitalisation) and style (value versus growth) anomalies on the JSE.

Chapter 5 Testing SAVI based style and size rotation strategies on the JSE

This chapter will start off by discussing the methodology applied in the analysis, and finally ending off with a discussion on the results and analysis found in this section.

5.1 Methodology

This chapter is broken down into two parts, namely firstly a discussion of the style rotation strategy, and secondly a discussion of the size rotation strategy. For each of these two strategies a long-short portfolio is formed, and in both rotation strategies there are two options for the formation of the long-short portfolio.

In the style rotation strategy, *when the SAVI is above its moving average*, the portfolio can either be short value (Value Index) and long growth (Growth Index) or long value, short growth. *When the SAVI is below its moving average*, the portfolio can either be long value and short growth or short value and long growth. Similarly, in the size rotation strategy, *when the SAVI is above its moving average*, the portfolio can either be short small-cap (Small Cap Index) and long large-cap (Top 40 Index) stocks or long short-cap, short large-cap stocks *When the SAVI is below its moving average*, the portfolio can either be long small-cap and short large-cap or short small cap and long large-cap.

This analysis therefore began by examining which long-short portfolio performs better for, respectively, the style and the size rotation strategy. The best long-short portfolio for the respective rotation strategies were then applied to the final market timing strategy (i.e. the inclusion of the long-short portfolio with the STeFI). For the purpose of this study, if the strategy was long value and short growth, for example, this would mean that the return of the growth index would be subtracted from the return of the value index. For the initial part of this analysis (i.e. before the STeFI is included to form the market timing strategy), the strategy involved either being invested in the long-short portfolio and earning the returns of that portfolio, or not being invested in anything at all, thereby earning zero returns. Once the best long-short portfolio for each of the two rotation strategies was determined, a market timing strategy was formed by switching between the respective long-short portfolio and the STeFI, depending on the level of the SAVI compared to its moving average.

A daily timing signal for all of the strategies was created by comparing the current day's SAVI level to its 75-day simple moving average. The 75 days length of the moving average was chosen because it made tracking of a medium to long term trend of the SAVI possible, and is consistent with the analysis of Copeland and Copeland (1999), whose research agrees with this length of time. A range of triggers was established for X% above or below the moving average (where X ranges from -80% to 80% in 10% increments). A timing signal for the current day was a signal to shift into a position the following day.

The long-short style portfolio*:* this is a portfolio that was short value (the Value Index) and long growth (the Growth Index) whenever the SAVI was X percent below its 75-day moving average and short growth long value whenever it was X percent above. This position of this strategy was either 100% invested in the long-short portfolio or 0% invested in the long-short portfolio. Copeland and Copeland (1999) test this relationship, as his hypothesis is that in highly volatile markets, value stocks outperform growth stocks, and conversely in low volatility markets growth stocks outperform value stocks.

In this study the reverse of this strategy was also tested (i.e. short value and long growth when the SAVI was X percent below, and long value and short growth when it was X percent above its 75-day moving average) in order to identify which would be the more profitable strategy. Similarly in this case, the position of this strategy was either 100% invested in the long-short portfolio or 0% invested in the long-short portfolio. This study tests whether the relationship hypothesized by Copeland and Copeland (1999) is true for the South African market by additionally testing the converse of this relationship. After testing which was the more profitable strategy, the more profitable strategy was applied going forward when implementing the market timing strategy (i.e. the strategy which includes the STeFI).

The long-short size portfolio: this is a portfolio that was long large-cap and short small-cap whenever the SAVI was X percent greater than its 75-day moving average and long small-cap and short large-cap when it was X percent below. Copeland and Copeland (1999) hypothesize that in highly volatile markets, large-cap stocks outperform small-cap stocks, and conversely in low volatility markets small-cap stocks outperform large-cap stocks. This position of this strategy was either 100% invested in the long-short portfolio or 0% invested in the long-short portfolio.

The reverse of this strategy was also tested (i.e. short large-cap and long small-cap when the SAVI was X percent above its 75-day moving average and long large-cap and short small-cap when the SAVI was X percent below it 75-day moving average) in order to identify which would be the more profitable strategy. Similarly in this case, the position of this strategy was either 100% invested in the long-short portfolio or 0% invested in the long-short portfolio. After testing which was the more profitable strategy, the more profitable strategy was applied going forward.

The long-short portfolio and the STeFI: in the strategies above, a position was either 100% invested in the long-short portfolio or 0% invested in the long-short portfolio. This part of the analysis includes the STeFI and is considered to be a market timing strategy. If the position was 0% invested in the long-short portfolio, then it was 100% invested in the STeFI.

5.2 Results and analysis

Table 6 shows the total number of daily timing signals, over the entire period, per trigger. 98.8% of the timing signals appeared around the trigger range [-20%:40%] and there were no signals generated above the 60% trigger. Although there were some signals that occurred in the negative trigger range, 55.2% of the signals clustered around the positive side of the triggers, which indicated that the triggers had a positively skewed distribution. The results of the trigger are therefore only presented for the triggers ranging [-20%:60%].

Table 6: Number of daily timing signals per trigger

	80%	70%	60%	50%	40%	30%	20%	10%	10%	20%	30%	40%	50%	60%	70%	80%
Total Number of Daily Timing signals	2	2	2	2	2	2	49	605	529	207	56	22	4	2	0	0

5.2.1 The style trading strategy

The long-short portfolio: the results from this analysis showed that it was more profitable to use the strategy where a portfolio that was long value and short growth was switched into whenever the SAVI was X percent below its 75-day moving average, and long growth short value when it was X percent above. This was the strategy that was employed going forward when implementing the market timing strategy (including the STeFI) as it produced positive returns for most of the holding periods and was therefore deemed to be more profitable. This portfolio construction is in contrast to the portfolio that was constructed by Copeland and Copeland (1999), who conducted their study in the U.S context. Copeland and Copeland (1999)'s idea is that investors would want to invest in value stocks during periods of uncertainty, since value stocks provide less risk, conversely, during periods when the market is stable investors would look for higher yields and therefore invest in growth stocks. According to the results of this study, investors in the South African market should react differently; i.e. they should invest in growth stocks in times of market uncertainty and should invest in value stocks when markets are stable. This indicates a possible difference in the behaviours and characteristics of emerging markets as compared to developed markets.

Table 7 shows a summary of the total returns, based on the long-short portfolio strategy, for certain holding periods. The holding period in which returns are calculated ranges from 1-day to 10-days; this is the length of time that the position was held for after a timing signal occurred (either a position that was 100% invested in the long-short portfolio or 0% invested in the long short portfolio). The number of days in which the position is actively-held refers to the number of days in which the position was 100% invested in the long-short portfolio and is therefore exposed to risk (i.e. it does not include the days in which the position was 0% invested in the long-short portfolio).

Table 7 shows that the positive returns were mostly generated from a positive percentage change from the moving average of the SAVI as compared to a negative deviation from the moving average. The -10% trigger only resulted in positive returns for the 1-day holding period but for longer holding periods had negative returns. The positive returns achieved by the long-short portfolio provides some evidence that a style anomaly exists in the South African market; the style anomaly in the South African market has been confirmed by other studies, such as that of Van Rensburg and Robertson (2003).

Table 7: Summary of total trigger returns based on style

	-20%	-10%	10%	20%	30%	40%	50%	60%
	1 day holding period							
Total return over the period	-3.96%	3.66%	17.39%	22.27%	11.39%	14.50%	3.44%	1.27%
Basis point cumulative return	-396.49	365.67	1738.71	2227.37	1138.58	1450.02	344.49	126.98
Number of days position held	47.00	603.00	529.00	207.00	56.00	22.00	4.00	2.00
Total Bp return per day for holding period	-8.44	0.61	3.29	10.76	20.33	65.91	86.12	63.49
	2 day holding period							
Total return over the period	0.08%	-3.04%	22.16%	21.36%	12.05%	17.60%	4.44%	2.71%
Basis point cumulative return	7.99	-303.57	2215.79	2136.39	1204.60	1760.44	443.78	271.13
Number of days position held	57.00	669.00	578.00	246.00	64.00	28.00	5.00	3.00
Total Bp return per day for holding period	0.14	-0.45	3.83	8.68	18.82	62.87	88.76	90.38
	3 day holding period							
Total return over the period	1.34%	-7.70%	24.05%	22.68%	11.12%	14.15%	3.96%	3.44%
Basis point cumulative return	133.68	-770.47	2405.30	2268.08	1111.59	1414.81	396.16	344.49
Number of days position held	67.00	718.00	621.00	276.00	71.00	33.00	6.00	4.00
Total Bp return per day for holding period	2.00	-1.07	3.87	8.22	15.66	42.87	66.03	86.12
	9 day holding period							
Total return over the period	7.72%	-15.00%	27.44%	16.87%	16.92%	8.99%	3.77%	3.29%
Basis point cumulative return	772.48	-1499.74	2743.69	1687.25	1691.85	898.77	377.08	328.70
Number of days position held	107.00	920.00	809.00	396.00	112.00	58.00	12.00	10.00
Total Bp return per day for holding period	7.22	-1.63	3.39	4.26	15.11	15.50	31.42	32.87
	10 day holding period							
Total return over the period	9.85%	-23.18%	29.58%	15.13%	18.82%	5.30%	1.63%	5.25%
Basis point cumulative return	984.63	-2317.53	2957.97	1513.12	1882.04	530.02	162.88	525.29
Number of days position held	113.00	945.00	835.00	412.00	118.00	62.00	13.00	11.00
Total Bp return per day for holding period	8.71	-2.45	3.54	3.67	15.95	8.55	12.53	47.75

Secondly, it was found that the length of the holding period had an impact on the magnitude of the returns whereby in most cases, except for the -20% trigger, the average total basis point (bp) return per day decreased as the holding period increased (see Figure 11). This relationship indicates that the style anomaly found is short-term in nature, as better returns are produced when the holding period is shorter. The magnitude of the trigger also had a trend relating to the returns, as the trigger increased past 10% on the positive side, the average total bp return per day increased. This indicates that the long-short portfolio performs better in more volatile markets and when the SAVI is more stretched above its moving average. The highest average total daily return of 90.38bp occurred when using the 60% trigger over the 2-day holding period; this provides further evidence of the two trends (holding period length and trigger magnitude) mentioned above.

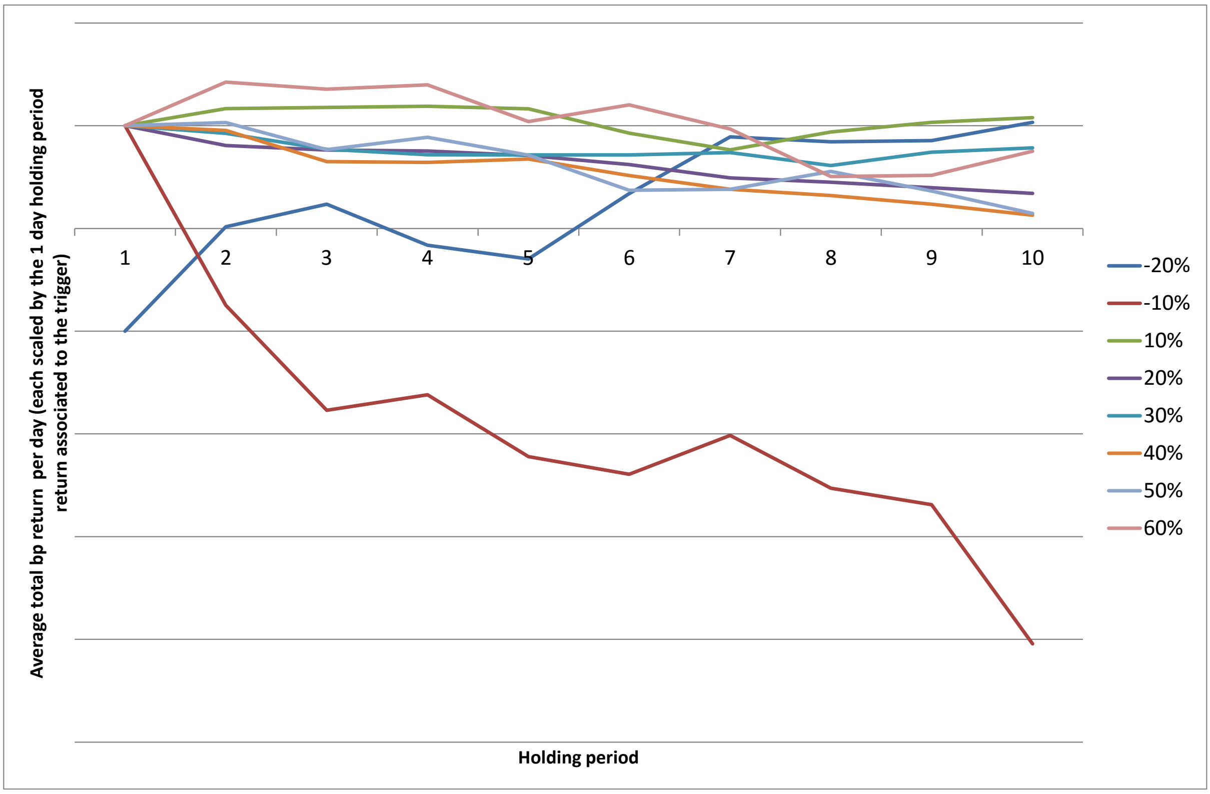

Figure 11: Average total bp return per day vs holding period

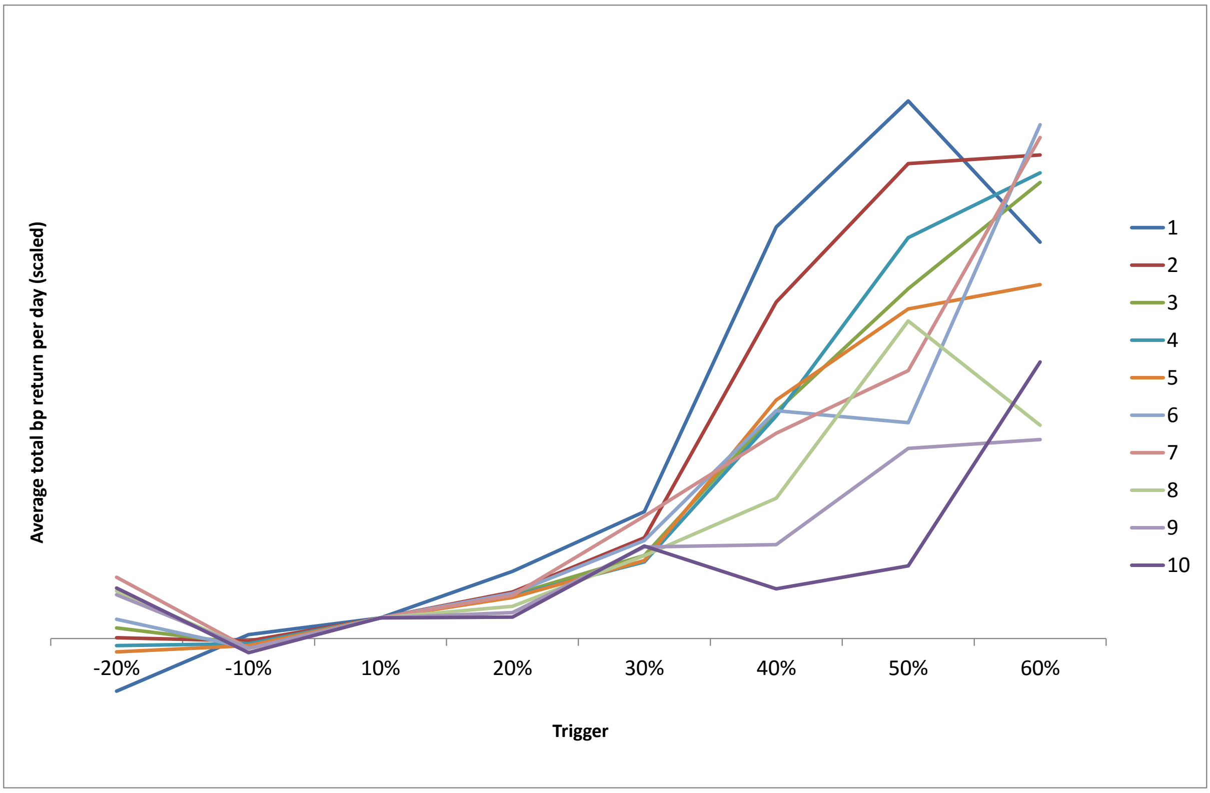

Figure 12: Average total bp return per day vs trigger size

The long-short portfolio and the STeFI: this part of the study will discuss the results relating to the strategy that involved switching fully between the long-short portfolio and the STeFI, depending on the relevant timing signal. The average daily return of the pure STeFI position for the whole period was 2.42bp. The table below shows the returns of the strategy, and specifically that 17 out of 80 of the strategy returns were lower than the 2.42bp return of the pure STeFI position (these are indicated in red). In the previous section, the highest returns from the pure long-short portfolio were achieved when the 50% and 60% triggers were used. In this section, which includes STeFI returns, the result from the triggers differ in that the highest returns were achieved when the 10%, 20%, 30%, and 40% triggers were used. This result is, however, expected due to the calculation of the average total return per day for the given holding period. In the previous section this was calculated by dividing the sum of all the daily returns by the number of days that the long-short position was actively held and therefore the return would be higher for the outlying triggers (with fewer timing signals). In this section, however, the cumulative returns of the long-short portfolio and the STeFI are divided by the total period of the study for all triggers and therefore there is no more bias toward the fewer trades in the outlying triggers.

Table 8: Total returns of strategy based on style rotation

	-20%	-10%	10%	20%	30%	40%	50%	60%
1 day holding period								
Total Bp return per day for holding period	2.22	1.98	2.55	3.04	2.77	2.92	2.54	2.46
2 day holding period								
Total Bp return per day for holding period	2.36	1.68	2.69	2.97	2.78	3.03	2.58	2.51
3 day holding period								
Total Bp return per day for holding period	2.39	1.46	2.72	2.99	2.74	2.90	2.56	2.54
4 day holding period								
Total Bp return per day for holding period	2.30	1.43	2.75	3.03	2.74	2.96	2.61	2.58
5 day holding period								
Total Bp return per day for holding period	2.25	1.28	2.74	3.02	2.77	3.05	2.59	2.56
6 day holding period								
Total Bp return per day for holding period	2.42	1.20	2.55	2.93	2.80	2.93	2.51	2.61
7 day holding period								
Total Bp return per day for holding period	2.58	1.23	2.41	2.78	2.85	2.81	2.53	2.59
8 day holding period								
Total Bp return per day for holding period	2.57	1.08	2.58	2.73	2.78	2.76	2.60	2.51
9 day holding period								
Total Bp return per day for holding period	2.59	1.01	2.68	2.66	2.91	2.67	2.54	2.53
10 day holding period								
Total Bp return per day for holding period	2.65	0.68	2.74	2.58	2.98	2.52	2.46	2.60

The highest returns on average, across all trigger ranges, were achieved when using the 2-day holding period. These returns therefore motivate the case for statistical testing to test for the significance of the differences between the returns of the strategy (for the trigger range of 10% to 40%, when using a 2-day holding period) and the returns of the Top 40 Index (a proxy for the South African equities market), which is done via a t-test. The null hypothesis in this case is that the strategy returns are not statistically different from the returns of the Top 40 Index. The table below shows the results from the t-test; if the t-stat is greater than the t critical value, the null hypothesis would be rejected. The results, however, show that in the case of all four trigger ranges, the null hypothesis is not rejected, meaning that the strategy returns are not statistically significantly different from those of the Top 40.

Table 9: t-test for significance of the style strategy returns

t-Test for significance Style strategy for a 2-day holding period				
	t stat	t critical (two-sided test)	p-value	Decision
10% trigger	0.34	1.96	0.74	Accept null hypothesis
20% trigger	0.24	1.96	0.81	Accept null hypothesis
30% trigger	0.31	1.96	0.75	Accept null hypothesis
40% trigger	0.22	1.96	0.83	Accept null hypothesis

The results thus far have not taken into account the effect of transaction costs on the net returns of the strategy; transaction costs will now be addressed in this section and is shown in Table 10. The range of transaction costs applied to each trade in this study are 0.10%, 0.20%, 0.50%, and 0.75%, to account for the lower range that applies to institutional investors (0.10%) and the higher range that applies to retail investors (0.75%) in the South African market. Due to the modelling complexity with these strategies, the same range of transaction costs were applied to both sales and purchases. The average net bp return per day for the whole sample period of the pure STeFI position was 2.41, 2.40, 2.38, and 2.36bp for the associated transaction cost range respectively (all strategy returns that are lower than the pure STeFI position are shown in red in the table below). In this case, the highest average net bp return for the entire sample period, across the entire range of transaction costs, occurred when using the 40% trigger for the 5-day holding period (see Appendix 2). The highest net average returns across all holding periods, across the entire range of transaction costs, occurred when using the 20%, 30%, and 40% triggers. 43.44% of the 320 net returns calculated across all holding periods, triggers, and transaction costs, were on average only 0.28bp (per day) above the returns of the pure STeFI position. In reality, transaction costs are likely to be higher than what was used in this part of the study due to the inclusion of other costs (such as Securities Transfer Tax on purchases); this indicates that this strategy may not be profitable in practice.

Table 10: Summary of net returns from strategy based on style rotation

	-20%	-10%	10%	20%	30%	40%	50%	60%
	1 day holding period							
Net Basis point return per day for holding period (10 bp transaction cost per trade)	2.11	1.12	1.88	2.53	2.65	2.84	2.52	2.44
Net Basis point return per day for holding period (20 bp transaction cost per trade)	1.99	0.27	1.21	2.02	2.54	2.76	2.50	2.42
Net Basis point return per day for holding period (50 bp transaction cost per trade)	1.66	-2.29	-0.82	0.49	2.20	2.51	2.43	2.35
Net Basis point return per day for holding period (75 bp transaction cost per trade)	1.38	-4.43	-2.50	-0.78	1.92	2.31	2.37	2.29
	2 day holding period							
Net Basis point return per day for holding period (10 bp transaction cost per trade)	2.20	0.94	2.04	2.52	2.68	2.96	2.55	2.49
Net Basis point return per day for holding period (20 bp transaction cost per trade)	2.04	0.20	1.39	2.07	2.57	2.88	2.53	2.47
Net Basis point return per day for holding period (50 bp transaction cost per trade)	1.57	-2.03	-0.57	0.72	2.26	2.66	2.46	2.40
Net Basis point return per day for holding period (75 bp transaction cost per trade)	1.18	-3.88	-2.19	-0.40	2.00	2.47	2.41	2.35
	3 day holding period							
Net Basis point return per day for holding period (10 bp transaction cost per trade)	2.26	0.81	2.15	2.63	2.63	2.82	2.53	2.52
Net Basis point return per day for holding period (20 bp transaction cost per trade)	2.14	0.15	1.58	2.27	2.53	2.75	2.51	2.50
Net Basis point return per day for holding period (50 bp transaction cost per trade)	1.76	-1.80	-0.12	1.19	2.21	2.52	2.44	2.43
Net Basis point return per day for holding period (75 bp transaction cost per trade)	1.44	-3.43	-1.55	0.29	1.95	2.34	2.39	2.37
	9 day holding period							
Net Basis point return per day for holding period (10 bp transaction cost per trade)	2.49	0.60	2.26	2.42	2.82	2.61	2.52	2.50
Net Basis point return per day for holding period (20 bp transaction cost per trade)	2.39	0.19	1.84	2.18	2.73	2.55	2.49	2.48
Net Basis point return per day for holding period (50 bp transaction cost per trade)	2.10	-1.05	0.58	1.46	2.46	2.37	2.43	2.41
Net Basis point return per day for holding period (75 bp transaction cost per trade)	1.86	-2.08	-0.47	0.86	2.24	2.22	2.37	2.36
	10 day holding period							
Net Basis point return per day for holding period (10 bp transaction cost per trade)	2.56	0.29	2.32	2.34	2.89	2.46	2.43	2.57
Net Basis point return per day for holding period (20 bp transaction cost per trade)	2.46	-0.09	1.90	2.10	2.80	2.40	2.41	2.55
Net Basis point return per day for holding period (50 bp transaction cost per trade)	2.17	-1.23	0.64	1.38	2.53	2.22	2.35	2.48
Net Basis point return per day for holding period (75 bp transaction cost per trade)	1.92	-2.19	-0.41	0.78	2.30	2.08	2.29	2.43

5.2.2 The size trading strategy

The long-short portfolio: the results from this analysis showed that it was more profitable to use the strategy where a portfolio that was long small-cap and short large-cap was switched into whenever the SAVI was X percent below its 75-day moving average, and long large-cap (Top 40 Index) short small-cap (Small Cap Index) when it was X percent above. This was the strategy that was employed going forward as it produced positive returns for most of the holding periods and was therefore deemed to be more profitable. This relationship between volatility and the performance of small-cap/large-cap stocks is consistent with the findings of Copeland and Copeland (1999).

Table 11 shows a summary of the total returns, based on the long-short portfolio strategy, for certain holding periods. All of the average total bp returns per day were positive with the exception of four cases: the -20% trigger for the 1, 5, 6 and 10-day holding periods.

Table 11: Summary of total trigger returns based on size rotation

	-20%	-10%	10%	20%	30%	40%	50%	60%
	1 day holding period							
Total Cumulative Return over the period	-2.51%	25.73%	72.65%	58.96%	27.53%	24.07%	9.09%	1.89%
Basis point cumulative return	-251.17	2572.68	7265.34	5896.02	2753.33	2407.41	909.02	189.16
Number of days position held	47.00	603.00	529.00	207.00	56.00	22.00	4.00	2.00
Total Bp return per day for holding period	-5.34	4.27	13.73	28.48	49.17	109.43	227.25	94.58
	2 day holding period							
Total Cumulative Return over the period	0.80%	32.35%	73.74%	53.05%	26.59%	27.16%	9.67%	6.54%
Basis point cumulative return	79.57	3235.41	7373.94	5304.93	2658.74	2715.98	966.67	654.32
Total Bp return per day for holding period	1.40	4.84	12.74	21.56	41.54	97.00	193.33	218.11
Number of days position held	57.00	669.00	579.00	246.00	64.00	28.00	5.00	3.00
	3 day holding period							
Total Cumulative Return over the period	3.51%	27.45%	63.08%	51.31%	22.90%	20.31%	9.95%	9.09%
Basis point cumulative return	350.95	2744.90	6308.01	5130.79	2290.17	2030.68	994.53	909.02
Total Bp return per day for holding period	5.24	3.82	10.13	18.59	32.26	61.54	165.75	227.25
Number of days position held	67.00	718.00	623.00	276.00	71.00	33.00	6.00	4.00
	9 day holding period							
Total Cumulative Return over the period	4.57%	16.81%	45.68%	36.18%	34.18%	14.44%	4.18%	2.98%
Basis point cumulative return	457.14	1681.33	4568.40	3618.18	3418.39	1443.75	417.85	298.25
Total Bp return per day for holding period	4.27	1.83	5.63	9.14	30.52	24.89	34.82	29.82
Number of days position held	107.00	921.00	811.00	396.00	112.00	58.00	12.00	10.00
	10 day holding period							
Total Cumulative Return over the period	-1.89%	14.74%	43.82%	32.76%	34.94%	8.92%	1.96%	8.36%
Basis point cumulative return	-188.80	1474.14	4382.10	3276.37	3493.67	891.76	196.11	836.03
Total Bp return per day for holding period	-1.67	1.56	5.24	7.95	29.61	14.38	15.09	76.00
Number of days position held	113.00	947.00	837.00	412.00	118.00	62.00	13.00	11.00

Similar to the findings of the style rotation analysis (Section 5.2.1), the results from this section show that the average total bp return per day generally decreased as the holding period increased (see Figure 13). This relationship indicates that the size anomaly found is also short-term in nature as better returns are generally produced when the holding period is shorter. It must be noted that for both the style and size trading strategies, the longer the holding period, the larger the deviation from the trading strategy; i.e. when the investor gets closer to the end of the holding period, the returns generated are more due to the performance of the market as opposed to the performance of the market timing trading strategy. Conversely, when a shorter holding period is used and the investor has just entered into the position caused by the timing signal, the returns earlier on in the holding period (closer to the signal) appear greater; it can therefore be inferred that the predictive value of a trigger is more effective for a short time period.

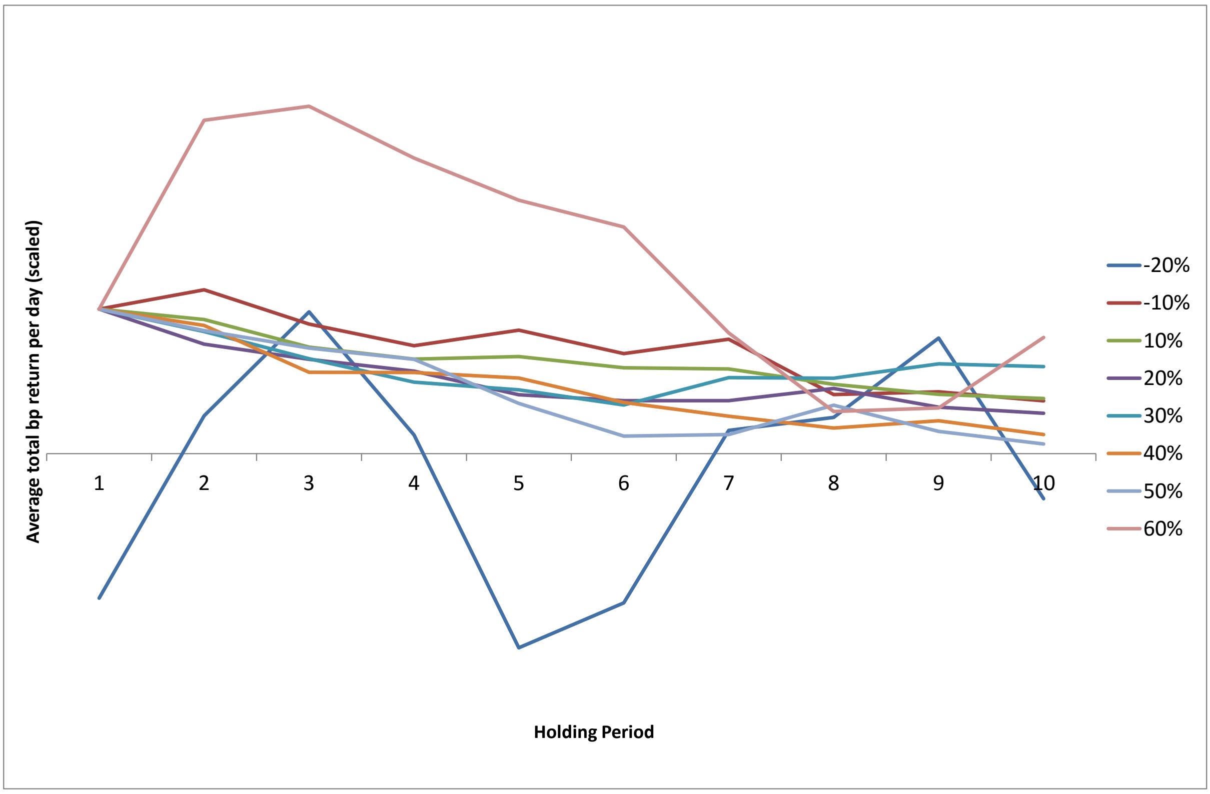

Figure 13: Average total bp return per day vs holding period

For any given holding period used, the highest average total bp return per day came from either the 50% or 60% trigger (this result may be overstated due to the fact that fewer trades occur when higher triggers are used). However it does indicate that this strategy performs better in volatile markets, i.e. the greater the SAVI is above its moving average (see figure 14).

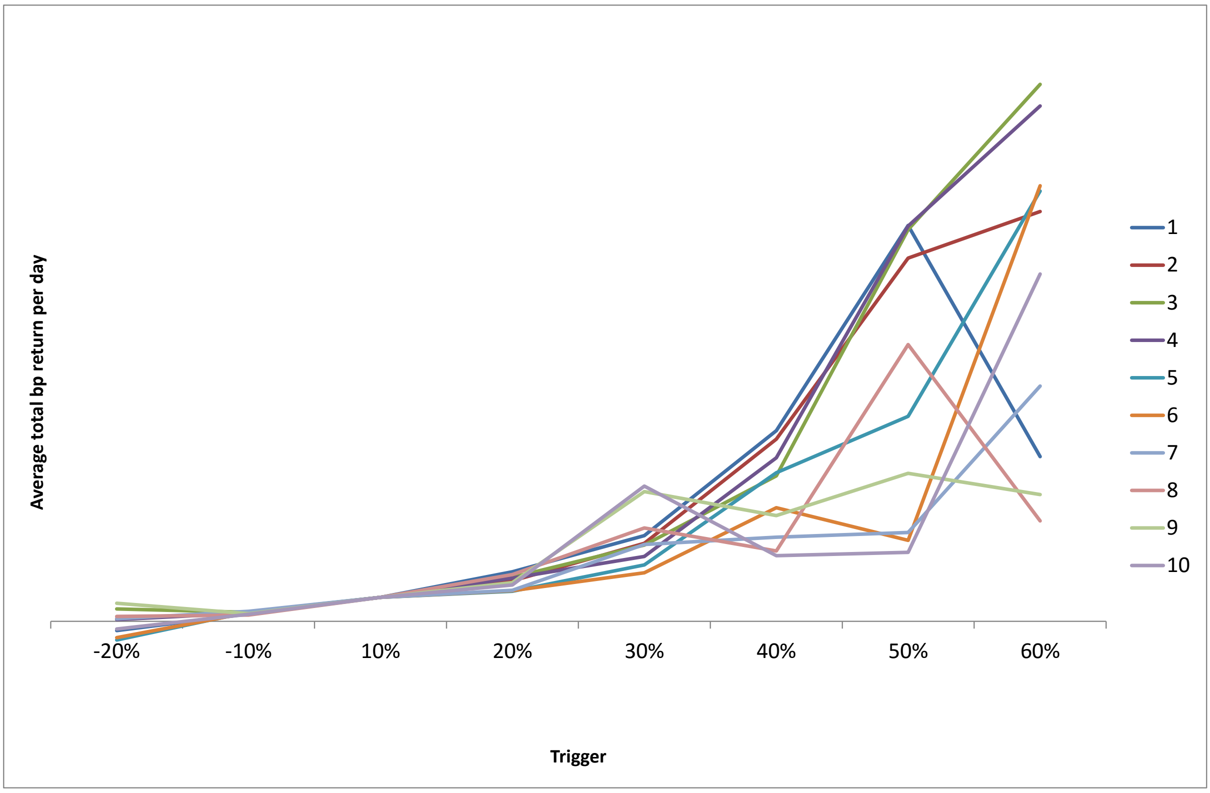

Figure 14: Average total bp return per day vs trigger

A noteworthy finding in this section is that the average total returns per day from this size rotation strategy outperform the average total returns per day from the style rotation strategy (Section 5.2.1) in 86.3% of the cases. This indicates that the size anomaly is stronger and more pronounced than the style anomaly in the South African market. This result differs from the findings of Van Rensburg and Robertson (2003), who find the opposite effect of size *vs*. style. However, it must be noted that they use price-earnings ratios as a proxy for value. It must also be noted that the findings of this study relating to size *vs,* style may be overstated due to the specific indices used as proxies for the portfolios (see Section 5.1); the construction of style indices are viewed to be more subjective than the construction of a market capitalisation index since a market capitalisation index (especially the JSE Top 40) is a broader representation of the market.

The long-short portfolio and the STeFI: this part of the study will discuss the results relating to the strategy of fully switching the investment between the long-short portfolio and the STeFI (*i.e.* being 100% in either the one or the other). The average daily of the pure STeFI position for the whole period was 3.81bp. Table 12 shows the returns of the strategy, and specifically that 11 out of 80 (14%) of the strategy returns are lower than the 3.81bp return of the pure STeFI position (these are indicated in red). It is worth noting that for a 1 to 7-day holding period, the highest returns come from the 10% trigger, this is in contrast to the results found with the pure long-short portfolio without the inclusion of the STeFI where it was found that the highest returns were achieved when using the highest triggers (50% and 60%). As mentioned previously, this is partly due to the fact that the cumulative returns of the long-short portfolio and the STeFI are divided by the total period of the study (as opposed to the number of days that the position was actively held) for all triggers. The maximum return of 8.43bp was achieved when using the 10% trigger with a 1-day holding period.

Table 12: Total returns of strategy based on size rotation

	-20%	-10%	10%	20%	30%	40%	50%	60%
	1 day holding period							
Total Bp return per day for holding period	3.56	4.89	8.43	7.89	5.76	5.57	4.50	3.97
	2 day holding period							
Total Bp return per day for holding period	3.79	5.29	8.39	7.39	5.68	5.79	4.54	4.31
	3 day holding period							
Total Bp return per day for holding period	3.98	4.86	7.54	7.22	5.39	5.27	4.56	4.50
	4 day holding period							
Total Bp return per day for holding period	3.74	4.56	7.20	6.99	5.09	5.48	4.59	4.54
	5 day holding period							
Total Bp return per day for holding period	3.25	4.87	7.49	6.11	5.04	5.53	4.28	4.56
	6 day holding period							
Total Bp return per day for holding period	3.31	4.48	7.09	5.97	4.79	5.06	3.99	4.59
	7 day holding period							
Total Bp return per day for holding period	3.73	4.78	7.16	6.08	5.55	4.77	4.03	4.28
	8 day holding period							
Total Bp return per day for holding period	3.76	3.73	6.44	6.87	5.66	4.49	4.43	3.99
	9 day holding period							
Total Bp return per day for holding period	3.99	3.78	5.97	5.91	6.17	4.78	4.11	4.03
	10 day holding period							
Total Bp return per day for holding period	3.50	3.59	5.80	5.64	6.21	4.36	3.95	4.43

Similar to the style strategy, the highest returns on average for the size strategy across all trigger ranges, were achieved when using the 2-day holding period. These returns therefore motivate the case for statistical testing to test for the significance of the differences between the returns of the strategy (for the trigger range of 10% to 40%, when using a 2-day holding period) and the returns of the Top 40 Index (a proxy for the South African equities market). The null hypothesis in this case is that the strategy returns are not statistically different from the returns of the Top 40 Index. The table below shows the results from the t-test; the results show that in the case of all four trigger ranges, the null hypothesis is not rejected meaning that the strategy returns are not statistically significant.

Table 13: t-test for significance of the style strategy returns

t-Test for significance Size strategy for a 2-day holding period				
	t stat	t critical (two-sided test)	p-value	Decision
10% trigger	-0.91	1.96	0.37	Accept null hypothesis
20% trigger	-0.79	1.96	0.43	Accept null hypothesis
30% trigger	-0.51	1.96	0.61	Accept null hypothesis
40% trigger	-0.54	1.96	0.59	Accept null hypothesis

The results thus far have not taken into account the effect of transaction costs on the net returns of the strategy; transaction costs will now be addressed in this section and is shown in the table below. The same transaction costs used in the style trading strategy have been applied in this section, the range of transaction costs applied to each trade are 0.10%, 0.20%, 0.50%, and 0.75%. The net bp return per day for the whole sample period of the pure STeFI position was 3.82, 3.82, 3.79, and 3.77bp for the associated transaction cost range respectively (all strategy returns that are lower than the pure STeFI position are shown in red in table 14). The maximum average net bp return for the entire sample period (7.74, 7.08, 5.12, and 3.48bp for the associated transaction costs) are achieved when using the 10% trigger with a 2-day holding period. Furthermore, in 7 of the 10 cases, the highest return generated over all the holding periods occurs when using the 10% trigger. This is a noteworthy finding when compared to the style strategy (in Section 5.2.1) where the highest net average returns across all holding periods, across the entire range of transaction costs, occurred when using the 20%, 30%, and 40% triggers. This shows that higher levels of the SAVI are required for growth to outperform value than what is required for large-cap to outperform small-cap.

75.6% of the 320 net returns calculated across all holding periods, triggers, and transaction costs, were on average 1.03bp (per day) above the returns of the pure STeFI position (this outperformance of the STeFI is approximately 4 times higher than what was achieved when using the style strategy).

Table 14: Summary of net returns based on size rotation

	-20%	-10%	10%	20%	30%	40%	50%	60%
	1 day holding period							
Net Basis point return per day for holding period (10 bp transaction costs)	3.45	4.04	7.76	7.38	5.65	5.49	4.48	3.94
Net Basis point return per day for holding period (20 bp transaction costs)	3.34	3.19	7.09	6.88	5.54	5.41	4.45	3.92
Net Basis point return per day for holding period (50 bp transaction costs)	3.00	0.64	5.08	5.36	5.21	5.16	4.39	3.86
Net Basis point return per day for holding period (75 bp transaction costs)	2.73	-1.48	3.41	4.09	4.93	4.96	4.33	3.80
	2 day holding period							
Net Basis point return per day for holding period (10 bp transaction costs)	3.64	4.55	7.74	6.94	5.58	5.72	4.52	4.29
Net Basis point return per day for holding period (20 bp transaction costs)	3.64	4.55	7.74	6.94	5.58	5.72	4.52	4.29
Net Basis point return per day for holding period (50 bp transaction costs)	3.48	3.82	7.08	6.50	5.47	5.64	4.49	4.27
Net Basis point return per day for holding period (75 bp transaction costs)	3.01	1.60	5.12	5.16	5.16	5.42	4.43	4.20
	3 day holding period							
Net Basis point return per day for holding period (10 bp transaction costs)	3.85	4.21	6.99	6.86	5.29	5.20	4.53	4.48
Net Basis point return per day for holding period (20 bp transaction costs)	3.72	3.56	6.44	6.50	5.19	5.12	4.51	4.45
Net Basis point return per day for holding period (50 bp transaction costs)	3.34	1.62	4.78	5.43	4.87	4.90	4.45	4.39
Net Basis point return per day for holding period (75 bp transaction costs)	3.03	0.00	3.41	4.54	4.61	4.71	4.39	4.33
	9 day holding period							
Net Basis point return per day for holding period (10 bp transaction costs)	3.89	3.39	5.59	5.68	6.08	4.72	4.09	4.01
Net Basis point return per day for holding period (20 bp transaction costs)	3.80	2.99	5.20	5.44	5.99	4.66	4.07	3.98
Net Basis point return per day for holding period (50 bp transaction costs)	3.50	1.81	4.04	4.72	5.72	4.49	4.00	3.92
Net Basis point return per day for holding period (75 bp transaction costs)	3.26	0.82	3.07	4.13	5.50	4.34	3.95	3.86
	10 day holding period							
Net Basis point return per day for holding period (10 bp transaction costs)	3.40	3.23	5.41	5.40	6.12	4.30	3.92	4.40
Net Basis point return per day for holding period (20 bp transaction costs)	3.30	2.86	5.02	5.16	6.04	4.25	3.90	4.38
Net Basis point return per day for holding period (50 bp transaction costs)	3.01	1.77	3.86	4.45	5.77	4.07	3.83	4.32
Net Basis point return per day for holding period (75 bp transaction costs)	2.77	0.86	2.90	3.85	5.54	3.92	3.78	4.26

Chapter 6 Conclusion

In the first part of this study (Chapter 4), the SAVI was used as a tool in various technical trading rules which served as market timing strategies. It was found that three of the market timing trading strategies outperformed the buy-and-hold strategy, with the best performing strategy being the simple MA strategy. The simple MA strategy applied the use of a 5-day moving average which indicated the possibility of shorter length averages (and hence the use of shorter periods) being more profitable since they react quicker to price changes, generate more signals and are quick for early entry. A key finding in this section was that the outperformance of strategy returns were clustered around the three most volatile periods that the JSE experienced. Furthermore, in periods when the JSE Top 40 returns performed poorly and were most volatile, the SAVI was at relatively high levels which shows that on average the SAVI was an accurate indicator of the volatility that occurred in the market during those periods as well as an accurate indicator of market movements. Although the trading strategies are more successful under the specific conditions mentioned above, the results from the three outperforming strategies show that it is possible to use the SAVI as a market timing tool to determine when to optimally enter and exit the JSE.

In the second part of the study (Chapter 5), the SAVI was used in a market timing strategy which generated signals to shift between growth stocks and value stocks (the style strategy), and to shift between small-cap and large-cap stocks (the size strategy). The style strategy showed that, in contrast to the theoretical hypothesis, growth stocks outperform value stocks in volatile markets, in the South African context, for the period under investigation. The size strategy produced expected results where it was found that large-cap stocks outperform small-cap stocks in volatile markets. It was found that the returns of the style strategy were not significant enough to deem it a profitable market timing strategy. However, the returns of the size strategy were significant enough to make it a profitable strategy. It can be concluded that the SAVI can be used as a signal to shift between a size portfolio strategy (large-cap versus small-cap), in order to generate positive excess returns.

There were three trends that were found to be common in both the first part of this study as well as the second part. Firstly, the length of the holding period has an impact on the profitability of a market timing strategy. In the first part of the study this was proved by the profitability of the shorter length moving averages and hence shorter holding periods; similarly the second part of the study was generally more profitable when using shorter holding periods. This shows that market timing is a short term strategy where signals have to be quickly acted on. Secondly, the market timing strategy is more profitable the more volatile the market is; this was shown in the first part of the study for the three periods categorized by extreme market events and high SAVI levels. This was also shown in the second part of the study whereby in most cases, the more profitable returns were generated when using the higher positive triggers (i.e. the more stretched the SAVI was above its moving average). Additionally, in the second part of the study, most of the negative triggers (i.e. when the SAVI was below its moving average) produced returns that underperformed the risk-free asset, meaning that in periods of low volatility, the market timing strategy underperforms. Thirdly, transaction costs have a significant impact on the profitability of net strategy returns. The inclusion of transaction costs in assessing the net investment returns suggest that the use of market timing strategies are profitable when transaction costs are low; this means that these strategies may be more beneficial to institutional investors with a lower trading cost.

The purpose of this study was to assess the profitability of market timing using the SAVI in creating a timing signal. The large outperformance of the simple MA strategy (even after transaction costs were accounted for) as well as the profitable returns of the size strategy suggests that it is both possible and profitable to time the market using the SAVI.

Chapter 7 Limitations to the study and recommendations

Due to the practicality of modelling these strategies, assumptions have been made which cause limitations to the study. In this study, a range of 10, 20, 50, and 75bp have been used as the transaction costs (as well as the Securities Transfer Tax of 25bp that was included in section 4.3); while this is the most accurate assumption we could practically apply, it does not account for other costs such as management costs and brokerage fees. An additional limitation relates to Section 5, where indices are used as proxies for portfolios. The growth, value, and small-cap indices are not tradable and it is therefore not possible to practically replicate this study exactly. Furthermore, since the above three indices are not tradable, transaction costs are understated because in reality multiple shares would have to be traded for each index in order to replicate the returns of these indices.

Considering the above limitations, there are some recommendations that could be used to make this study more practical. Actual portfolios of individual tradable stocks could be formed. Moreover, the use of an investable exchange traded fund (ETF) that tracks an index such as the SATRIX 40 could be used and would incur lower transaction costs. Additionally, at some point in the future when the South African futures market becomes more developed and liquid, the use of futures in implementing these strategies would be more profitable by reducing transaction costs.

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Appendix 1: Total returns based on style

	-20%	-10%	10%	20%	30%	40%	50%	60%
				1 day holding period				
Total return over the period	-3.96%	3.66%	17.39%	22.27%	11.39%	14.50%	3.44%	1.27%
Basis point cumulative return	-396.49	365.67	1738.71	2227.37	1138.58	1450.02	344.49	126.98
Number of days position held	47.00	603.00	529.00	207.00	56.00	22.00	4.00	2.00
Total Bp return per day for holding period	-8.44	0.61	3.29	10.76	20.33	65.91	86.12	63.49
				2 day holding period				
Total return over the period	0.08%	-3.04%	22.16%	21.36%	12.05%	17.60%	4.44%	2.71%
Basis point cumulative return	7.99	-303.57	2215.79	2136.39	1204.60	1760.44	443.78	271.13
Number of days position held	57.00	669.00	578.00	246.00	64.00	28.00	5.00	3.00
Total Bp return per day for holding period	0.14	-0.45	3.83	8.68	18.82	62.87	88.76	90.38
				3 day holding period				
Total return over the period	1.34%	-7.70%	24.05%	22.68%	11.12%	14.15%	3.96%	3.44%
Basis point cumulative return	133.68	-770.47	2405.30	2268.08	1111.59	1414.81	396.16	344.49
Number of days position held	67.00	718.00	621.00	276.00	71.00	33.00	6.00	4.00
Total Bp return per day for holding period	2.00	-1.07	3.87	8.22	15.66	42.87	66.03	86.12
				4 day holding period				
Total return over the period	-1.03%	-7.47%	25.73%	24.33%	11.37%	16.11%	5.35%	4.44%
Basis point cumulative return	-103.33	-746.86	2573.26	2432.78	1136.78	1611.38	534.88	443.78
Number of days position held	75.00	761.00	658.00	300.00	78.00	38.00	7.00	5.00
Total Bp return per day for holding period	-1.38	-0.98	3.91	8.11	14.57	42.40	76.41	88.76
				5 day holding period				
Total return over the period	-2.06%	-10.73%	26.45%	24.58%	12.37%	18.69%	4.92%	3.96%
Basis point cumulative return	-205.76	-1073.13	2645.40	2457.81	1236.74	1868.77	492.00	396.16
Number of days position held	82.00	797.00	691.00	322.00	85.00	42.00	8.00	6.00
Total Bp return per day for holding period	-2.51	-1.35	3.83	7.63	14.55	44.49	61.50	66.03
				6 day holding period				
Total return over the period	2.54%	-12.05%	22.03%	22.96%	13.40%	15.59%	2.89%	5.35%
Basis point cumulative return	254.03	-1204.54	2202.90	2296.39	1339.95	1558.77	288.80	534.88
Number of days position held	89.00	830.00	722.00	343.00	92.00	46.00	9.00	7.00
Total Bp return per day for holding period	2.85	-1.45	3.05	6.70	14.56	33.89	32.09	76.41
				7 day holding period				
Total return over the period	7.14%	-10.52%	18.93%	19.20%	14.86%	12.59%	3.29%	4.92%
Basis point cumulative return	713.93	-1052.12	1893.27	1919.91	1485.71	1259.07	328.70	492.00
Number of days position held	95.00	861.00	752.00	362.00	99.00	50.00	10.00	8.00
Total Bp return per day for holding period	7.52	-1.22	2.52	5.30	15.01	25.18	32.87	61.50
				8 day holding period				
Total return over the period	7.19%	-13.67%	24.10%	18.32%	13.21%	11.39%	5.25%	2.89%
Basis point cumulative return	719.35	-1366.50	2409.98	1832.02	1321.10	1138.76	525.29	288.80
Number of days position held	101.00	891.00	781.00	379.00	106.00	54.00	11.00	9.00
Total Bp return per day for holding period	7.12	-1.53	3.09	4.83	12.46	21.09	47.75	32.09
				9 day holding period				
Total return over the period	7.72%	-15.00%	27.44%	16.87%	16.92%	8.99%	3.77%	3.29%

Basis point cumulative return	772.48	-1499.74	2743.69	1687.25	1691.85	898.77	377.08	328.70
Number of days position held	107.00	920.00	809.00	396.00	112.00	58.00	12.00	10.00
Total Bp return per day for holding period	7.22	-1.63	3.39	4.26	15.11	15.50	31.42	32.87
	10 day holding period							
Total return over the period	9.85%	-23.18%	29.58%	15.13%	18.82%	5.30%	1.63%	5.25%
Basis point cumulative return	984.63	-2317.53	2957.97	1513.12	1882.04	530.02	162.88	525.29
Number of days position held	113.00	945.00	835.00	412.00	118.00	62.00	13.00	11.00
Total Bp return per day for holding period	8.71	-2.45	3.54	3.67	15.95	8.55	12.53	47.75

Appendix 2: Net returns based on style

	-20%	-10%	10%	20%	30%	40%	50%	60%
	1 day holding period							
Net Basis point return per day for holding period (10 bp transaction cost per trade)	2.11	1.12	1.88	2.53	2.65	2.84	2.52	2.44
Net Basis point return per day for holding period (20 bp transaction cost per trade)	1.99	0.27	1.21	2.02	2.54	2.76	2.50	2.42
Net Basis point return per day for holding period (50 bp transaction cost per trade)	1.66	-2.29	-0.82	0.49	2.20	2.51	2.43	2.35
Net Basis point return per day for holding period (75 bp transaction cost per trade)	1.38	-4.43	-2.50	-0.78	1.92	2.31	2.37	2.29
	2 day holding period							
Net Basis point return per day for holding period (10 bp transaction cost per trade)	2.20	0.94	2.04	2.52	2.68	2.96	2.55	2.49
Net Basis point return per day for holding period (20 bp transaction cost per trade)	2.04	0.20	1.39	2.07	2.57	2.88	2.53	2.47
Net Basis point return per day for holding period (50 bp transaction cost per trade)	1.57	-2.03	-0.57	0.72	2.26	2.66	2.46	2.40
Net Basis point return per day for holding period (75 bp transaction cost per trade)	1.18	-3.88	-2.19	-0.40	2.00	2.47	2.41	2.35
	3 day holding period							
Net Basis point return per day for holding period (10 bp transaction cost per trade)	2.26	0.81	2.15	2.63	2.63	2.82	2.53	2.52
Net Basis point return per day for holding period (20 bp transaction cost per trade)	2.14	0.15	1.58	2.27	2.53	2.75	2.51	2.50
Net Basis point return per day for holding period (50 bp transaction cost per trade)	1.76	-1.80	-0.12	1.19	2.21	2.52	2.44	2.43
Net Basis point return per day for holding period (75 bp transaction cost per trade)	1.44	-3.43	-1.55	0.29	1.95	2.34	2.39	2.37
	4 day holding period							
Net Basis point return per day for holding period (10 bp transaction cost per trade)	2.18	0.87	2.24	2.70	2.63	2.90	2.58	2.55
Net Basis point return per day for holding period (20 bp transaction cost per trade)	2.07	0.31	1.72	2.37	2.53	2.84	2.56	2.53
Net Basis point return per day for holding period (50 bp transaction cost per trade)	1.73	-1.37	0.17	1.38	2.21	2.66	2.49	2.46
Net Basis point return per day for holding period (75 bp transaction cost per trade)	1.45	-2.78	-1.12	0.56	1.95	2.51	2.44	2.41
	5 day holding period							
Net Basis point return per day for holding period (10 bp transaction cost per trade)	2.14	0.77	2.25	2.70	2.66	2.99	2.57	2.53
Net Basis point return per day for holding period (20 bp transaction cost per trade)	2.02	0.27	1.77	2.39	2.56	2.93	2.54	2.51
Net Basis point return per day for holding period (50 bp transaction cost per trade)	1.69	-1.23	0.31	1.45	2.25	2.75	2.48	2.44
Net Basis point return per day for holding period (75 bp transaction cost per trade)	1.41	-2.49	-0.91	0.66	1.98	2.60	2.42	2.39
	6 day holding period							
Net Basis point return per day for holding period (10 bp transaction cost per trade)	2.32	0.72	2.08	2.65	2.70	2.87	2.49	2.58
Net Basis point return per day for holding period (20 bp transaction cost per trade)	2.22	0.24	1.61	2.37	2.59	2.81	2.47	2.56
Net Basis point return per day for holding period (50 bp transaction cost per trade)	1.93	-1.20	0.19	1.51	2.28	2.63	2.40	2.49
Net Basis point return per day for holding period (75 bp transaction cost per trade)	1.69	-2.40	-0.99	0.80	2.02	2.48	2.34	2.44
	7 day holding period							
Net Basis point return per day for holding period (10 bp transaction cost per trade)	2.48	0.76	1.95	2.52	2.74	2.75	2.50	2.57
Net Basis point return per day for holding period (20 bp transaction cost per trade)	2.38	0.29	1.50	2.27	2.64	2.69	2.48	2.54
Net Basis point return per day for holding period (50 bp transaction cost per trade)	2.09	-1.13	0.13	1.50	2.33	2.51	2.41	2.48
Net Basis point return per day for holding period (75 bp transaction cost per trade)	1.85	-2.31	-1.02	0.87	2.06	2.36	2.36	2.42
	8 day holding period							
Net Basis point return per day for holding period (10 bp transaction cost per trade)	2.47	0.63	2.13	2.47	2.69	2.70	2.57	2.49
Net Basis point return per day for holding period (20 bp transaction cost per trade)	2.38	0.17	1.68	2.22	2.60	2.64	2.55	2.47
Net Basis point return per day for holding period (50 bp transaction cost per trade)	2.08	-1.20	0.33	1.45	2.33	2.47	2.48	2.40
Net Basis point return per day for holding period (75 bp transaction cost per trade)	1.84	-2.34	-0.79	0.82	2.10	2.32	2.43	2.34
	9 day holding period							
Net Basis point return per day for holding period (10 bp transaction cost per trade)	2.49	0.60	2.26	2.42	2.82	2.61	2.52	2.50
Net Basis point return per day for holding period (20 bp transaction cost per trade)	2.39	0.19	1.84	2.18	2.73	2.55	2.49	2.48

Net Basis point return per day for holding period (50 bp transaction cost per trade)	2.10	-1.05	0.58	1.46	2.46	2.37	2.43	2.41
Net Basis point return per day for holding period (75 bp transaction cost per trade)	1.86	-2.08	-0.47	0.86	2.24	2.22	2.37	2.36
	10 day holding period							
Net Basis point return per day for holding period (10 bp transaction cost per trade)	2.56	0.29	2.32	2.34	2.89	2.46	2.43	2.57
Net Basis point return per day for holding period (20 bp transaction cost per trade)	2.46	-0.09	1.90	2.10	2.80	2.40	2.41	2.55
Net Basis point return per day for holding period (50 bp transaction cost per trade)	2.17	-1.23	0.64	1.38	2.53	2.22	2.35	2.48
Net Basis point return per day for holding period (75 bp transaction cost per trade)	1.92	-2.19	-0.41	0.78	2.30	2.08	2.29	2.43

Appendix 3: Total returns based on size

	-20%	-10%	10%	20%	30%	40%	50%	60%
	1 day holding period							
Total Cumulative Return over the period	-2.51%	25.73%	72.65%	58.96%	27.53%	24.07%	9.09%	1.89%
Basis point cumulative return	-251.17	2572.68	7265.34	5896.02	2753.33	2407.41	909.02	189.16
Number of days position held	47.00	603.00	529.00	207.00	56.00	22.00	4.00	2.00
Total Bp return per day for holding period	-5.34	4.27	13.73	28.48	49.17	109.43	227.25	94.58
	2 day holding period							
Total Cumulative Return over the period	0.80%	32.35%	73.74%	53.05%	26.59%	27.16%	9.67%	6.54%
Basis point cumulative return	79.57	3235.41	7373.94	5304.93	2658.74	2715.98	966.67	654.32
Number of days position held	57.00	669.00	579.00	246.00	64.00	28.00	5.00	3.00
Total Bp return per day for holding period	1.40	4.84	12.74	21.56	41.54	97.00	193.33	218.11
	3 day holding period							
Total Cumulative Return over the period	3.51%	27.45%	63.08%	51.31%	22.90%	20.31%	9.95%	9.09%
Basis point cumulative return	350.95	2744.90	6308.01	5130.79	2290.17	2030.68	994.53	909.02
Number of days position held	67.00	718.00	623.00	276.00	71.00	33.00	6.00	4.00
Total Bp return per day for holding period	5.24	3.82	10.13	18.59	32.26	61.54	165.75	227.25
	4 day holding period							
Total Cumulative Return over the period	0.52%	24.24%	59.23%	48.73%	18.95%	23.31%	10.38%	9.67%
Basis point cumulative return	51.73	2424.20	5923.49	4872.83	1894.90	2331.22	1037.79	966.67
Number of days position held	75.00	761.00	660.00	300.00	78.00	38.00	7.00	5.00
Total Bp return per day for holding period	0.69	3.19	8.97	16.24	24.29	61.35	148.26	193.33
	5 day holding period							
Total Cumulative Return over the period	-5.89%	29.08%	63.87%	37.30%	18.46%	24.05%	6.32%	9.95%
Basis point cumulative return	-588.65	2907.65	6386.62	3730.06	1845.86	2404.63	631.66	994.53
Number of days position held	82.00	798.00	693.00	322.00	85.00	42.00	8.00	6.00
Total Bp return per day for holding period	-7.18	3.64	9.22	11.58	21.72	57.25	78.96	165.75
	6 day holding period							
Total Cumulative Return over the period	-4.92%	24.53%	58.97%	35.83%	15.20%	17.80%	2.48%	10.38%
Basis point cumulative return	-491.58	2453.03	5896.87	3583.05	1520.49	1779.95	248.36	1037.79
Number of days position held	89.00	831.00	724.00	343.00	92.00	46.00	9.00	7.00
Total Bp return per day for holding period	-5.52	2.95	8.14	10.45	16.53	38.69	27.60	148.26
	7 day holding period							
Total Cumulative Return over the period	0.82%	29.11%	60.57%	37.70%	25.55%	14.11%	2.98%	6.32%
Basis point cumulative return	81.63	2911.13	6056.56	3770.27	2555.17	1410.99	298.25	631.66

Number of days position held	95.00	862.00	754.00	362.00	99.00	50.00	10.00	8.00
Total Bp return per day for holding period	0.86	3.38	8.03	10.42	25.81	28.22	29.82	78.96
	8 day holding period							
Total Cumulative Return over the period	1.35%	15.55%	51.47%	48.70%	27.16%	10.45%	8.36%	2.48%
Basis point cumulative return	135.13	1555.37	5146.70	4869.52	2716.21	1044.73	836.03	248.36
Number of days position held	101.00	892.00	783.00	379.00	106.00	54.00	11.00	9.00
Total Bp return per day for holding period	1.34	1.74	6.57	12.85	25.62	19.35	76.00	27.60
	9 day holding period							
Total Cumulative Return over the period	4.57%	16.81%	45.68%	36.18%	34.18%	14.44%	4.18%	2.98%
Basis point cumulative return	457.14	1681.33	4568.40	3618.18	3418.39	1443.75	417.85	298.25
Number of days position held	107.00	921.00	811.00	396.00	112.00	58.00	12.00	10.00
Total Bp return per day for holding period	4.27	1.83	5.63	9.14	30.52	24.89	34.82	29.82
	10 day holding period							
Total Cumulative Return over the period	-1.89%	14.74%	43.82%	32.76%	34.94%	8.92%	1.96%	8.36%
Basis point cumulative return	-188.80	1474.14	4382.10	3276.37	3493.67	891.76	196.11	836.03
Number of days position held	113.00	947.00	837.00	412.00	118.00	62.00	13.00	11.00
Total Bp return per day for holding period	-1.67	1.56	5.24	7.95	29.61	14.38	15.09	76.00

Appendix 4: Net returns based on size

	-20%	-10%	10%	20%	30%	40%	50%	60%
	1 day holding period							
Net Basis point return per day for holding period (10 bp transaction costs)	3.45	4.04	7.76	7.38	5.65	5.49	4.48	3.94
Net Basis point return per day for holding period (20 bp transaction costs)	3.34	3.19	7.09	6.88	5.54	5.41	4.45	3.92
Net Basis point return per day for holding period (50 bp transaction costs)	3.00	0.64	5.08	5.36	5.21	5.16	4.39	3.86
Net Basis point return per day for holding period (75 bp transaction costs)	2.73	-1.48	3.41	4.09	4.93	4.96	4.33	3.799
	2 day holding period							
Net Basis point return per day for holding period (10 bp transaction costs)	3.64	4.55	7.74	6.94	5.58	5.72	4.52	4.29
Net Basis point return per day for holding period (20 bp transaction costs)	3.48	3.82	7.08	6.50	5.47	5.64	4.49	4.27
Net Basis point return per day for holding period (50 bp transaction costs)	3.01	1.60	5.12	5.16	5.16	5.42	4.43	4.20
Net Basis point return per day for holding period (75 bp transaction costs)	2.62	-0.24	3.48	4.04	4.90	5.23	4.37	4.14
	3 day holding period							
Net Basis point return per day for holding period (10 bp transaction costs)	3.85	4.21	6.99	6.86	5.29	5.20	4.53	4.48
Net Basis point return per day for holding period (20 bp transaction costs)	3.72	3.56	6.44	6.50	5.19	5.12	4.51	4.45
Net Basis point return per day for holding period (50 bp transaction costs)	3.34	1.62	4.78	5.43	4.87	4.90	4.45	4.39
Net Basis point return per day for holding period (75 bp transaction costs)	3.03	0.00	3.41	4.54	4.61	4.71	4.39	4.33
	4 day holding period							
Net Basis point return per day for holding period (10 bp transaction costs)	3.63	4.00	6.71	6.66	4.99	5.42	4.56	4.52
Net Basis point return per day for holding period (20 bp transaction costs)	3.52	3.44	6.21	6.34	4.88	5.36	4.54	4.49
Net Basis point return per day for holding period (50 bp transaction costs)	3.18	1.77	4.74	5.35	4.57	5.19	4.47	4.43
Net Basis point return per day for holding period (75 bp transaction costs)	2.90	0.37	3.51	4.53	4.31	5.04	4.42	4.37
	5 day holding period							
Net Basis point return per day for holding period (10 bp transaction costs)	3.14	4.37	7.03	5.79	4.94	5.47	4.26	4.53
Net Basis point return per day for holding period (20 bp transaction costs)	3.03	3.87	6.57	5.48	4.83	5.41	4.24	4.51
Net Basis point return per day for holding period (50 bp transaction costs)	2.69	2.38	5.19	4.54	4.52	5.23	4.17	4.45
Net Basis point return per day for holding period (75 bp transaction costs)	2.42	1.13	4.03	3.76	4.26	5.08	4.11	4.39
	6 day holding period							
Net Basis point return per day for holding period (10 bp transaction costs)	3.22	4.02	6.64	5.68	4.68	5.00	3.97	4.56
Net Basis point return per day for holding period (20 bp transaction costs)	3.12	3.55	6.19	5.40	4.58	4.94	3.95	4.54
Net Basis point return per day for holding period (50 bp transaction costs)	2.83	2.14	4.85	4.55	4.27	4.76	3.88	4.47
Net Basis point return per day for holding period (75 bp transaction costs)	2.59	0.97	3.74	3.84	4.01	4.61	3.827	4.42
	7 day holding period							

Net Basis point return per day for holding period (10 bp transaction costs)	3.63	4.33	6.73	5.82	5.44	4.72	4.01	4.26
Net Basis point return per day for holding period (20 bp transaction costs)	3.54	3.87	6.30	5.57	5.34	4.66	3.98	4.24
Net Basis point return per day for holding period (50 bp transaction costs)	3.25	2.51	5.00	4.81	5.03	4.48	3.92	4.17
Net Basis point return per day for holding period (75 bp transaction costs)	3.00	1.38	3.92	4.18	4.77	4.33	3.86	4.11
	8 day holding period							
Net Basis point return per day for holding period (10 bp transaction costs)	3.66	3.29	6.03	6.62	5.57	4.43	4.40	3.97
Net Basis point return per day for holding period (20 bp transaction costs)	3.57	2.85	5.61	6.36	5.48	4.38	4.38	3.95
Net Basis point return per day for holding period (50 bp transaction costs)	3.28	1.54	4.36	5.60	5.21	4.20	4.32	3.88
Net Basis point return per day for holding period (75 bp transaction costs)	3.03	0.44	3.32	4.97	4.99	4.05	4.26	3.827
	9 day holding period							
Net Basis point return per day for holding period (10 bp transaction costs)	3.89	3.39	5.59	5.68	6.08	4.72	4.09	4.01
Net Basis point return per day for holding period (20 bp transaction costs)	3.80	2.99	5.20	5.44	5.99	4.66	4.07	3.98
Net Basis point return per day for holding period (50 bp transaction costs)	3.50	1.81	4.04	4.72	5.72	4.49	4.00	3.92
Net Basis point return per day for holding period (75 bp transaction costs)	3.26	0.82	3.07	4.13	5.50	4.34	3.95	3.86
	10 day holding period							
Net Basis point return per day for holding period (10 bp transaction costs)	3.40	3.23	5.41	5.40	6.12	4.30	3.92	4.40
Net Basis point return per day for holding period (20 bp transaction costs)	3.30	2.86	5.02	5.16	6.04	4.25	3.90	4.38
Net Basis point return per day for holding period (50 bp transaction costs)	3.01	1.77	3.86	4.45	5.77	4.07	3.83	4.32
Net Basis point return per day for holding period (75 bp transaction costs)	2.77	0.86	2.90	3.85	5.54	3.92	3.78	4.26