COPYRIGHT AND CITATION CONSIDERATIONS FOR THIS THESIS/ DISSERTATION

How to cite this thesis

- Attribution — You must give appropriate credit, provide a link to the license, and indicate if changes were made. You may do so in any reasonable manner, but not in any way that suggests the licensor endorses you or your use.

- NonCommercial — You may not use the material for commercial purposes.

- ShareAlike — If you remix, transform, or build upon the material, you must distribute your contributions under the same license as the original.
The performance of a momentum investment strategy during bull and bear periods on the FTSE/JSE Africa Top 40 Index

By

MATTHEW ROBIN DEVONPORT

A dissertation submitted as partial fulfilment for the MASTERS DEGREE IN FINANCIAL MANAGEMENT

in the Faculty of Economic and Financial Sciences

at the University of Johannesburg

Supervisor: Mr.N.Oberholzer

2012
Abstract

This paper studies the effects of bull and bear market states on the profitability of a momentum investment strategy. That is, a strategy that buys past winners and sells past losers is simulated over the period 3 July 2002 to 8 August 2012 and its profitability is reviewed in light of bull and bear sub-periods.

Such an investment strategy has been shown to yield abnormal returns in several markets around the world, including the South African stock market. By doing so, these studies challenge the efficient market hypothesis, a central and widely accepted hypothesis within traditional portfolio theory.

There are many theories that have been used to explain why abnormal profits are achievable using a momentum investment strategy. By determining the effects of bull and bear market states on the profitability of a momentum investment strategy, this paper provides some insight into which theories, if any, are most relevant to the South African stock market context.

It is found that on average, a momentum portfolio yields abnormal returns over the full sample period, with the chief driver of these returns being the winner component of the portfolio. When broken into bull and bear sub-periods, it was found that a momentum investment strategy only yields abnormal returns during a bull period, whilst these abnormal returns became negative during a bear period.

These results are consistent with one efficient market hypothesis explanation and two behavioural models presented in past studies. The results indicate that the market may be efficient and that changes in macroeconomic risk are the cause of momentum profits.

However, insofar as the macroeconomic risk explanation is inaccurate, these results support the behavioural models of Daniel, Hirshleifer, and Subrahmanyam (1998); and Hong and Stein (1999). Both these models predict that momentum returns will be strongest during bull periods.

Key words

Momentum investment strategy, technical investment strategy, efficient market hypothesis, market anomaly, South African stock market, bull market state, bear market state.
Declaration of original work

I, Matthew Robin Devonport, declare that this minor dissertation is my own unaided work. Any assistance that I have received has been duly acknowledged in the dissertation. It is submitted in partial fulfilment of the requirements for the degree of Master of Commerce at the University of Johannesburg. It has not been submitted before for any degree or examination at this or any other University.

___________________     _20/04/2013_

Signature       Date
Acknowledgements

I have many people to thank for helping me to get to this point in my academic career, the most important of which I would like to thank here. A big thank you to the following persons:

- My supervisor, Mr Niël Oberholzer for his guidance throughout this project;
- My mother and late father for their undying love and support; and
- My loving fiancé for reading through this paper and supporting me while I worked on it.
# Table of contents

1.1. Introduction ........................................................................................................... 1  
1.2. Factors identified in the literature leading to the research...................................... 4  
1.3. Problem statement ................................................................................................. 5  
1.3.1. Research question ............................................................................................... 5  
1.3.2. Research objectives ............................................................................................. 5  
1.4. Contributions of the study...................................................................................... 6  
1.5. Scope of the study ................................................................................................ 7  
1.6. Research methodology ......................................................................................... 7  
1.7. Collecting and analysing the data.......................................................................... 8  
1.8. Limitations of the study ......................................................................................... 9  
1.8.1. Use of daily closing price data ............................................................................... 9  
1.8.2. Transaction costs not taken into account ............................................................ 10  
1.8.3. Inter-temporal variation in risk ............................................................................. 10  
1.8.4. Lack of FTSE/JSE Africa Top 40 Index constituent data ..................................... 10  
1.8.5. Generalisability ................................................................................................... 10  
1.8.6. Use of parametric statistics ................................................................................. 11  
1.8.7. Model misspecifications ...................................................................................... 11  
1.9. Chapter outline .................................................................................................... 11  
2.1. Introduction ......................................................................................................... 13  
2.2. Neoclassical finance ........................................................................................... 13  
2.3. Market efficiency and the efficient market hypothesis defined ............................. 14  
2.4. The assumptions of the efficient market hypothesis ............................................ 15  
2.4.1. Assumption 1: individuals are rational ................................................................. 17  
2.4.2. Assumption 2: access to homogeneous information............................................ 17  
2.4.3. Assumption 3: large number of independent valuations ...................................... 18  
2.4.4. Assumption 4: rapid reaction to new information ................................................. 18  
2.4.5. Assumption 5: information arrives in a random fashion ....................................... 19  
2.5. Evidence of market efficiency .............................................................................. 19  
2.5.1. Implications of the efficient market hypothesis .................................................... 20  
2.6. Market anomalies ................................................................................................ 21  
2.6.1. Investors' preference for cash dividends .............................................................. 22  
2.6.2. Seasonality effects in stock returns ..................................................................... 24  
2.6.3. The small firm effect .......................................................................................... 27  
2.6.4. The price earnings ratio anomaly ....................................................................... 28  
2.7. Momentum and contrarian investment strategies................................................. 29
2.7.1. The contrarian investment strategy ................................................................. 30
2.7.2. The momentum investment strategy ............................................................. 31
2.8. Summary ............................................................................................................ 32
3.1. Introduction ......................................................................................................... 34
3.2. Behavioural explanations for momentum strategy success ............................... 35
3.2.1. Under-reaction ............................................................................................... 36
3.2.2. Overreaction .................................................................................................. 38
3.2.3. Behavioural biases and models that explain under- and overreaction .......... 39
3.2.3.1. The representativeness heuristic ................................................................. 39
3.2.3.2. Behavioural models: representativeness heuristic and the presence of momentum traders ................................................................. 40
3.2.3.3. The conservatism bias ................................................................................ 41
3.2.3.4. Behavioural models: representativeness heuristic and conservatism bias .... 42
3.2.3.5. Overconfidence bias ................................................................................... 43
3.2.3.6. Behavioural models: overconfidence bias ...................................................... 44
3.2.3.7. Self-attribution bias ...................................................................................... 44
3.2.3.8. Behavioural models: overconfidence and self-attribution bias ...................... 45
3.2.3.9. The availability heuristic and salience bias .................................................... 47
3.2.3.10. Behavioural models: availability heuristic and salience bias ....................... 47
3.2.3.11. The adjustment and anchoring biases .......................................................... 47
3.2.3.12. Behavioural models: adjustment and anchoring biases ............................... 48
3.2.3.13. Behavioural models: market composition ..................................................... 49
3.2.3.14. Behavioural models: market composition and information diffusion effects .... 49
3.2.3.15. Behavioural models: market composition and the disposition effect .......... 51
3.3. EMH explanations for momentum strategy profits ............................................ 52
3.3.1. Misspecification of asset pricing models ......................................................... 52
3.3.2. Time-varying systematic risk .......................................................................... 53
3.3.3. Bid-ask bounce effects .................................................................................... 55
3.3.4. Transaction costs ............................................................................................ 56
3.3.5. Data mining bias ............................................................................................. 57
3.4. Bull and bear market states: implications for the momentum investment strategy 58
3.4.1. Research into varying market states and their contribution to under- and overreaction evidence ........................................................................ 58
3.4.1.1. Data mining bias ......................................................................................... 59
3.4.1.2. Macroeconomic risk .................................................................................... 59
3.4.2. Insights into investor psychology and bull and bear market states ................. 60
3.4.2.1. Evidence for larger profits during bull periods .............................................. 60
List of tables

Table 1: Benchmark returns over the sample period ........................................................... 93
Table 2: Number of bull and bear periods ................................................................. 95
Table 3: Momentum profitability over the sample period .............................................. 96
Table 4: Average momentum portfolio alpha ......................................................... 97
Table 5: Difference in market states during formation (full sample period) ............... 100
Table 6: Difference in market states during formation (robust sample period) .......... 100
Table 7: Difference in alpha terms for bull and bear formation period portfolios (full sample period) ................................................................. 101
Table 8: Difference in alpha terms for bull and bear formation period portfolios (robust sample period) ................................................................. 102
Table 9: Difference in market states during holding (full sample period) .................... 103
Table 10: Difference in market states during holding (robust sample period) .......... 104
Table 11: Difference in alpha terms for bull and bear holding period portfolios (full sample period) ................................................................. 105
Table 12: Difference in alpha terms for bull and bear holding period portfolios (robust sample period) ................................................................. 105
List of figures

Figure 1: Change in the benchmark index level over the sample period.............................. 94
Figure 2: 6-Month benchmark return................................................................................... 94
Figure 3: Winner-minus-loser portfolio alphas ................................................................. 98
Chapter 1

1.1. Introduction

Over the history of financial markets, researchers have presented various theories trying to explain and predict market behaviour. The efficient market hypothesis (EMH) is one such theory and most empirical studies in financial markets are based on its concepts. The EMH states that at the very least, which is known as the weak-form EMH, all past and present information about a security that is available to the public has been accounted for when pricing it. Information is assumed to be circulated and processed rapidly throughout the market and rational-competitive investors act on information without delay. As a result, it is implied that it should not be possible to profit from any past information, which includes the investment's past price path.

The EMH makes several assumptions about how market participants behave and make use of information, and how information flows throughout the market. It asserts that if a large amount of competitive, rational, profit-maximising investors are each valuing securities independently from one another, then the market will behave in an efficient manner. An efficient market in this context is one in which rational investors take advantage of irrational deviations from an equilibrium price that reflects the investment’s true value. Arbitrage is the action of taking equal but opposite positions in two or more markets to make a riskless profit. These actions by rational investors will therefore bring the market back to equilibrium. Additionally, price changes will be independent from past and current public information about a security and as a result, investors should follow a passive buy-and-hold diversification strategy as their valuation efforts, fundamental or otherwise, will be useless in identifying abnormal profit opportunities.

Strong evidence for the EMH was presented in earlier studies such as Fama (1965a) and Jensen (1978), ensuring its wide acceptance. However, many efficient market anomalies contradictory to one or more of the assumptions of the EMH, have been observed in various developed (US, UK, and Europe) and developing markets (China, Taiwan, Korea, and South Africa) around the world. As a result, the EMH has become one of the more widely debated concepts in finance.

These anomalies include but are not limited to: investors’ preference for cash dividends rather than capital gains (Long, 1978; Miller & Scholes, 1982; Miller, 1986); seasonality in stock returns (Branch, 1977); irrationally high equity risk premiums (Mehra & Prescott, 1985); the higher than expected risk-adjusted returns earned by smaller firms, given Capital
Asset Pricing Model (CAPM) estimates (Banz, 1981); the price-earnings (P/E) ratio anomaly (Basu, 1977); and the related market under- and overreaction effects, which can be seen through the profits earned on momentum and contrarian investment strategies discussed throughout this study (De Bondt & Thaler, 1985; Jegadeesh & Titman, 1993).

Miller (1986:451) discussed these market anomalies as they relate to traditional financial theory and stated that they reveal the "soft spots in the current body of theory." Researchers have sought to explain these anomalies through the use of either traditional financial theory or the more recent behavioural finance theories. Tvede (1999) stated that securities market fluctuations are not only a result of fundamental demand and supply news events, which are the only aspects taken into account by traditional finance, but also the mass reactions by investors towards these events.

Therefore, although fundamental demand and supply dynamics are important, securities pricing is also, to a large extent, governed by the behaviour of millions of individual investors, which in turn are governed by emotions. As such, security prices are said to include a psychological aspect that should not be dismissed when making investment decisions.

There are literally thousands of studies examining EMH anomalies and their possible causes, yet there is still no broadly accepted theory that explains all these "soft spots" in a parsimonious way. Because many of these studies either refute the presence of these anomalies through the use of traditional finance arguments, such as Conrad and Kaul (1998), Berk, Green, and Naik (1999), and Lesmond, Schill, and Zhou (2004), or make use of some psychological bias when explaining them, such as Daniel, Hirshleifer, and Subrahmanyan (1998), Hong, Lim, and Stein (2000), and Grinblatt and Han (2002), conformity in beliefs has become difficult to attain.

However, momentum and contrarian investors believe that it is still possible to profit from past information. Specifically, these investors believe that a stock’s past price path, its trading volumes, and/or its market capitalisation should still be taken into account when determining whether to buy or sell a security. In fact, these are the only variables taken into account when these investors make trading decisions.

In the context of this study, momentum investors will purchase a stock when its price has been rising over his/her formation period, the period over which the investor watches a stock before buying, selling, or holding it, and sell a stock that has been falling over the same period. A contrarian investor on the other hand will do the opposite. He/she will sell a stock that has been rising in price and buy a stock that has been falling in price over his/her formation period. However, trading strategies that are based on past information, such as
these, imply that the market is inefficient and therefore the EMH is inadequate in explaining its behaviour.

Like many EMH anomalies, the presence of momentum and contrarian price behaviour can be explained through the use of behavioural and social psychological concepts. Researchers including De Bondt and Thaler (1985), Jegadeesh (1990), Jegadeesh and Titman (1993), and Mazouz and Li (2007), often attribute the residual momentum and/or contrarian profits to under- and/or overreaction effects within the market. Under-reaction and overreaction effects being investors' inappropriate reaction to news, which results in an under or overvalued asset.

On the one hand, the overreaction hypothesis, which has its roots in applied psychology, was first thought to explain the observed price reversion behaviour presented by De Bondt and Thaler (1985). This hypothesis states that investors buy a stock at a higher price or sell a stock at a lower price than what their new information warrants. De Bondt and Thaler (1985:795) hypothesised that if an overreaction effect is indeed present, then extreme movements in stock prices will be followed by subsequent price movements in the opposite direction. Secondly, the authors further (1985:795) stated that the more extreme the initial price movement, the greater the subsequent adjustment will be. The second point is also known as the magnitude effect.

De Bondt and Thaler (1985) also noted that if the above hypotheses are proven to be true, then they imply a violation of the weak-form EMH due to the ability of investors to predict future stock price movements based on the stock’s past information that is freely available to the public. So by constructing a contrarian or momentum portfolio based on past return data, De Bondt and Thaler (1985) and Jegadeesh and Titman (1993) were able to show evidence of weak-form market inefficiency. Additionally, these papers highlight the importance of incorporating behavioural biases, which are a form of human behaviour that sways investors from acting in a rational manner, when explaining and predicting market behaviour.

Since the work of De Bondt and Thaler (1985), researchers in addition to repeating the De Bondt and Thaler (1985) study in other markets have posited many alternative explanations for the market anomaly. Traditional EMH explanations for the presence or perceived presence of momentum and contrarian profits are that researchers’ valuation models have been misspecified (Conrad & Kaul, 1998), errors have occurred and biases introduced due to market microstructure effects (Conrad, Gultekin, & Kaul, 1997), and/or the investment’s risk has changed over time, whether it be systematic or non-systematic risk. If one conforms to these thoughts then standard financial theory still holds, at least to the extent that certain microstructure effects cannot entirely be explained by the EMH.
Irrespective of misspecification issues and even after controlling for risk and market microstructure effects, Bowman and Iverson (1998) still found evidence of short-run price reversals and intermediate momentum in stock returns. Conrad et al. (1997) in contrast found all short-term abnormal contrarian profits are eliminated when bid-ask spread bias is taken into account, while Chan (1988) proposed that these apparent under- and overreaction effects are present as a result of the time-varying nature of risk.

The behavioural explanation, on the other hand, posited that the assumptions of the EMH models are inappropriate and possibly too simplistic to explain the behaviour of the market. The main thought underpinning the behavioural pillar of finance is that instead of the market comprising rational investors who analyse and value securities independently of one another and who adjust prices rapidly to the arrival of new information, the market consists of investors who are subject to various social biases (Shiller, 1995) and behavioural heuristics (Schiereck, De Bondt, & Weber, 1999), which are working with, or a cause of a slower rate of information diffusion into security prices, thereby reducing the speed and suitability of market price adjustments (Balsara, Zheng, Vidozzi, & Vidozzi, 2006).

As a result, a market that was previously presumed to follow a no arbitrage, fundamental approach to security valuation, is now being assumed to have a behavioural and social psychological element. Thus a financial world where the human element plays a significant role in price behaviour is being recognised by practitioners and academics alike.

1.2. Factors identified in the literature leading to the research

The topic of this research paper stems from the findings of De Bondt and Thaler (1985; 1987) and Jegadeesh and Titman (1993) who were first to formally present their observations and findings that the selection of stocks, based on past return data, yields returns that exceed those explained by the efficient market models of Sharpe (1964) and Lintner (1965).

In addition, the thought that social and behavioural biases may play a role in creating a type of return pattern, may indicate that the profits from these strategies may be impacted by the prevailing bull or bear market state. As stated by Schuknecht, von Hagen, and Wolswijk (2010), the presence of market inefficiencies and irrational behaviour is often revealed through a crisis.

Three main observations have been identified within the literature: Firstly, there is evidence of market under- and overreaction in various countries, including South Africa (SA). Secondly, when under- and overreaction evidence is found, researchers generally attribute it
to behavioural heuristics, social biases, a slow rate of information diffusion throughout the market, model misspecification problems, changes in risk over time or a combination thereof. Thirdly, model misspecifications aside, behavioural, social, and informational biases may be affected by past price paths.

1.3. Problem statement

A natural development in this area of research is to look at different sub-periods, as proposed by Cubbin, Eidne, Firer, and Gilbert (2006), not only to see whether this market anomaly is consistently present, but also to see if different market states have an impact on under- or overreaction, as measured through momentum investment strategy profits. The issue has not been explored in SA to date and Cubbin et al. (2006) suggested that it be explored in the SA market context and also stressed the importance of such an analysis over time.

1.3.1. Research question

The central research question addressed in this study is: "Are momentum strategy profits or losses affected by the state of the SA market, namely when in a bull or a bear phase?" This main research question will be supported by three sub-questions:

1. Does a momentum strategy produce positive returns when implemented on the FTSE/JSE Africa Top 40 Index?
2. To what extent are the returns in one above affected during bear periods?
3. To what extent are the returns in one above affected during bull periods?

1.3.2. Research objectives

Given the research questions as stated above, the research objectives are to determine whether:

1. A momentum investment strategy provides profits when implemented on the FTSE/JSE Africa Top 40 Index (Top 40 Index);
2. The profits in objective one are positive after controlling for possible bias; and
3. The profits in objective two are superior in a bull or bear market state.

In order to meet these objectives, several hypotheses have been formulated.

If under- or overreaction is present in the market, it is expected that there will be momentum or reversals in stock prices and therefore stock returns. As a result, a zero cost momentum
portfolio will provide an indication of under- and/or overreaction, depending on the view one takes of its causes. The first null hypothesis to be tested is then:

1. \( H_0: \) The abnormal return on the average momentum portfolio is equal to zero. By testing this hypothesis, one is able to determine if there was a momentum or contrarian effect within that time period.

In order to see whether momentum profits are influenced by the state of the market, the returns on momentum portfolios that are formed and held over different market states should be compared. Thus, the second and third null hypotheses to be tested are:

2. \( H_0: \) The abnormal return on the average momentum portfolio with a bull formation period is equal to the abnormal return on the average momentum portfolio with a bear formation period; and
3. \( H_0: \) The abnormal return on the average momentum portfolio with a bull holding period is equal to the abnormal return on the average momentum portfolio with a bear holding period.

The formation period is the period where the returns of stocks are observed in order to pick the best and worst performing stocks. The holding period on the other hand is the period in which a position is taken and held in order to derive a return on the portfolio.

1.4. Contributions of the study

By answering the research question and meeting the research objectives posed above, this study will contribute to the available literature in several respects. Firstly, this study represents a first in SA where sub-periods, relating to different market states, are analysed using a momentum investment strategy.

Secondly, this study retests the results of past studies (Griffin, Ji, & Martin, 2003; Fraser & Page, 2000) that provide empirical evidence for the ability of a momentum investment strategy to yield abnormal returns.

Thirdly, this study should indicate whether the apparent abnormal returns earned on a momentum strategy are a result of changes in macroeconomic risk as hypothesised by Griffin et al. (2003). Additionally, some indication of the validity of the EMH in the SA stock market will also be conveyed.

Lastly, this study will provide some insight into the workings of the SA stock market by providing assenting or conflicting evidence for the various explanations hypothesised in the
literature for the under- and overreaction anomaly, as seen through the success of a momentum investment strategy. This will be done by determining how a momentum strategy’s profits may vary over distinct periods of market stress, as determined by bull and bear market phases. As a result, this study adds to the current body of evidence related to the under- and overreaction phenomenon on the JSE.

1.5. Scope of the study

As stated in the previous section, this research is focused on the SA equity market, specifically the Johannesburg Stock Exchange (JSE) in order to gain further understanding of the behaviour of the SA stock market.

However, the entire SA equity market is not analysed in the study in order to reduce any bias that may enter the study due to small and illiquid stocks (in terms of trade volumes). As a result, the portfolios that are tested during the bull and bear sub-periods are based solely on the top stocks on the JSE as measured by market capitalisation.

That is, the top five stocks, based on their past returns, within the Top 40 Index are allocated to the winner portfolio, while the bottom five stocks within the Top 40 Index are allocated to the loser portfolio in order to create a zero cost momentum portfolio. In addition to the analysis of these portfolios being conducted over each of the bull and bear periods found, they will also be analysed over the entire sample period in order to support or refute the results of past studies in this area. A bull period is defined as being a period over which the general market has increased, while a bear period is defined as being a period over which the general market has decreased. In this case the general market is seen as the Top 40 Index.

Due to the methodology that will be employed in this study and the fact that the JSE indices ceased to exist in their old format and were replaced with the new FTSE/JSE Africa Index Series on 21 June 2002, the period chosen for the analysis was 3 July 2002 to 8 February 2011. The period allowed for enough weekly data points to conduct a regression analysis in addition to providing at least one bull market phase and one bear market phase so that the two different market phases or states could be compared.

1.6. Research methodology

In order to meet the research objectives, this study utilises a quantitative research paradigm whereby a momentum investment strategy is simulated using secondary data. The momentum investment strategy simulated here is one in which the top five performing stocks
in the Top 40 Index are purchased and the bottom five performing stocks on the Top 40 Index are sold short.

Once these portfolios have been formed and simulated over the sample period, they are categorised into four overlapping categories:

1. Portfolios with a bull formation period;
2. Portfolios with a bear formation period;
3. Portfolios with a bull holding period; and
4. Portfolios with a bear holding period.

Categories one(1) and two(2) are compared and categories three(3) and four(4) are compared to determine whether they yield significantly different results.

1.7. Collecting and analysing the data

To conduct the simulation methodology presented above, two secondary data sets were required:

1. Stock returns for all Top 40 Index constituents; and
2. Equally Weighted Top 40 Index returns.

The daily stock return data was attained from McGregor BFA, while the Top 40 Index constituents were attained from SATRIX. Each of these institutions holds price data as a business service to market professionals and for the institution’s own research agendas. The sources are deemed to provide reliable stock market data due to the fact that they are used by economists, portfolio managers, investment analysts, journalists and other investment professionals.

Once collected, the data was analysed in six steps by using a regression analysis to find the average abnormal return, as determined by the CAPM, on the momentum portfolios and several t-tests on the average returns and the differences in returns, both abnormal and absolute, on the momentum portfolios over the bull and bear sample periods.

1. Rank sampled stocks based on their past twelve-month daily geometrically linked returns;
2. Create momentum portfolios by selecting the top five performing stocks to buy and selecting the bottom five performing stocks to sell;
3. Determine momentum portfolio performance by calculating the average absolute return and comparing it to the benchmark portfolio's average return of the Top 40
Index using a *t-test* and an abnormal portfolio return over their six-month holding periods;

4. Allocate portfolios into bull and bear phases based on the benchmark return over the formation and holding periods;

5. Determine the effects of market states by utilising *t-statistics* on the average returns and average alphas over bull and bear market phases; and

6. Conduct the analysis over a more robust sample period where the Top 40 Index constituents are known.

Once the data has been analysed, it is interpreted in light of the literature that is reviewed in Chapter 2 and Chapter 3 of this paper.

1.8. Limitations of the study

There are several limitations that stem from either missing data or as a result of the methodology used. Each one of these limitations is highlighted when they become relevant to the discussion; however they are briefly discussed here. The limitations of this study result from:

1. The use of daily closing stock price data;
2. Transaction costs not being taken into account;
3. Inter-temporal variation in risk;
4. Lack of Top 40 Index constituent data;
5. Lack of generalisability;
6. The use of parametric statistics; and
7. Possible model misspecification.

1.8.1. Use of daily closing price data

This study used daily closing price data to calculate daily stock price returns. However, it has been found that daily data may increase the possible bias resulting from bid-ask bounce, infrequent trading, and non-synchronous trading (Chowdhury & Michello, n.d.).

These effects are expected to be relatively muted as returns are geometrically linked over a relatively long period of twelve or six months. Moreover, selecting large, frequently traded stocks further reduces the potential for these effects to bias the results, although the limitation should still be noted when reviewing the results of this study.
1.8.2. Transaction costs not taken into account

Transaction costs are not taken into account when determining the profitability of the momentum portfolio. Therefore this study will only provide an indication of market efficiency or inefficiency. It may be necessary to reduce the portfolio returns by some percentage in order to take these costs into account. However, Rey and Schmid (2007) noted that such a methodology is crude and is more of an approximation.

1.8.3. Inter-temporal variation in risk

Another limitation of the methodology employed in this study is that it does not take into account Chordia and Shivakumar’s (2002) argument that certain macroeconomic instruments that measure market conditions can explain a significant part of abnormal momentum profits. As such this macroeconomic risk cannot be ruled out as a source of momentum profits.

1.8.4. Lack of FTSE/JSE Africa Top 40 Index constituent data

The benchmark used in this study was only an approximation of the equally weighted Top 40 Index as changes in the individual index constituents could only be determined at discrete points in time (March, June, September and December) from March 2004 to December 2011.

Although the Top 40 Index is only reviewed quarterly and therefore changes to the index only happen quarterly, there are some exceptions and therefore any changes that may have happened between quarters would have been missed. As a result, the results found here and the results of a practical momentum investment strategy employed in the same manner may be different.

1.8.5. Generalisability

It is not possible to generalise past the SA context where either the behavioural or EMH theory explanation is assumed to be the cause of momentum profits or lack thereof. The reason being, the composition of the market in terms of the types of investors and the way in which they react to information in SA may be different from other parts of the world. As such, one can only relate these findings to what has been found in other markets.
The SA stock market comprises a relatively small number of stocks that are frequently traded when compared to more developed markets such as those in the US and the UK. As a result, this study only utilises the largest stocks on the JSE as a sampling frame.

However, the use of the small sampling frame limited the scope of this study and therefore has another implication in terms of generalisability. Specifically, each industry or market sector is not represented appropriately, if at all, in the Top 40 Index stocks over the entire sample period and in each sub-period. Thus the results may reflect a specific industry momentum rather than a stock-specific momentum. One cannot necessarily expect these results to remain where a wider sample of stocks is used.

1.8.6. Use of parametric statistics

This study employs parametric statistics and therefore the population parameters tested were assumed to be normally distributed. This is a serious limitation to this study as stock returns are generally not normally distributed.

If stock prices and indices do indeed follow a random walk pattern, as stated by the EMH, any regression of a non-stationary data series on another non-stationary data series would result in a spurious regression model with low explanatory power.

However, one should note that the vast majority of research studying momentum strategy profits utilised parametric statistics, including Jegadeesh and Titman (2001). Additionally, the statistics used are relatively robust to violations to the normality assumption where more than 30 observations are available. This study has far more than 30 observations for all variables being analysed. As a result the analysis performed is also relatively robust to the possibility that the data is not normally distributed.

1.8.7. Model misspecifications

Unfortunately, there is still no known model that can be presented as perfectly representing an efficient market. Hence, one cannot unconditionally conclude that there are abnormal profits from a momentum investment strategy, thereby leading to a significant limitation to this and previous studies.

1.9. Chapter outline

Now that a brief overview of this study has been provided, the five remaining chapters will discuss the theoretical basis for the study, the methodology employed, the results and the
conclusion of the study. Chapter 2 discusses the literature that leads to the objectives of this study. Specifically, it presents the EMH, evidence for and against this hypothesis and some of the explanations provided for the various EMH anomalies. Chapter 3 then focuses on the momentum investment strategy and the many explanations provided in the literature for the apparent success of the strategy.

Chapter 4 presents the research methodology utilised in this study. Specifically, it presents the research question and objectives, the target population and sampling strategy, the data collection and analysis methods, in addition to a description of the statistical tests used. Lastly, Chapter 4 presents the assumptions and limitations of the research methodology employed.

Chapter 5 presents the results of the analysis conducted, and Chapter 6 finally concludes this study by summarising its salient points. This is done by summarising the results of the study, the conclusions drawn and the contributions made by this study. Chapter 6 also discusses the limitations of this study and provides some points for future research that may advance this area of knowledge.
Chapter 2

Literature review

2.1. Introduction

This chapter presents and discusses the literature that leads to, and to some extent, addresses the objectives of this study. Specifically, the literature surrounding the EMH, and EMH anomalies, evidence of successful momentum investment strategies and the possible explanations for the inefficient market behaviour are discussed from both traditional and behavioural finance perspectives.

The remainder of this chapter is divided into eight sections. Section 2.2 briefly introduces neoclassical finance. The EMH is discussed in Section 2.3 followed by its assumptions, and the implications thereof in section 2.4. Section 2.5 presents some of the evidence for the EMH together with the implications. Evidence against the EMH is presented in section 2.7 with the use of several well-known anomalies that violate EMH assumptions. Section 2.8 then summarises the salient points of this chapter before Chapter 3 delves deeper into the technical trading strategy used to meet the research objectives of this study.

2.2. Neoclassical finance

Many studies have been conducted to determine the most profitable trading strategy and in doing so, the EMH and its assumptions are generally called into question. This is because it forms the theoretical basis upon which true risk-adjusted profits are determined.

Neoclassical finance and modern portfolio theory rest on the assumptions of the EMH. When one reads the investment literature, it may become apparent that neoclassical finance is synonymous with the term efficient market hypothesis and that a distinction is quite difficult to make. Maginn, Tuttle, McLeavey, and Pinto (2007) stated that this line of theory dates back to the work of Nobel laureate Harry Markowitz (1952) while researchers such as Sharpe (1967) extended Markowitz’s work by further establishing the field of modern portfolio theory (MPT).

The literature (Markowitz, 1952; Sharpe 1967) presents the theoretical basis that many investors use when setting up an optimal portfolio. However, the concept of market efficiency can actually be traced back to the work of Bachelier (1990) where he stated that òpast, present and even discounted future events are reflected in market price, but often show no apparent relation to price changes.ò
This section presents the most applicable literature around the EMH. It will provide some understanding of an efficient market, the EMH and its assumptions, and why the market is generally deemed by researchers as being efficient. This section will present the basis upon which the conflict between the topic of this study and that of traditional finance will be understood. Specifically, the study focuses on deriving abnormal profits using a momentum investment strategy during bull and bear market states, while traditional finance maintains that one cannot attain abnormal profits from information on past price paths.

2.3. Market efficiency and the efficient market hypothesis defined

Before the theory behind the EMH is presented, it should first be noted that the arguments and studies presented here are one-sided in support of the EMH. There are many studies and theories that contradict or contextualise profits in a different way to the EMH; however these thoughts are presented later when they become relevant to the research question at hand.

Efficiency has primarily been used to describe markets that are effective in terms of the rate at which information is distributed to all market participants. Jensen (1978:98) stated that a market is efficient with respect to information set \( \Theta \) if it is impossible to make economic profits by trading on the basis of information set \( \Theta \). Where \( \Theta \) denotes a piece of information attained at a point in time and the term economic profits refers to returns earned after accounting for risk and any transaction costs.

Equally, efficiency may also be used when referring to operational efficiency, whereby resources are deployed to the most efficient areas, which are also assumed to be the most profitable within the market in order to attain the most benefit (Dimson & Mussavian, 2000). It should therefore be stated that this section is only concerned with the former definition of efficiency.

In this context, an efficient market is one in which all information is incorporated into market prices. The EMH assumes that prices incorporate all available information in order for an asset or security to provide an acceptable level of return for a given level of risk, both of which should be indicated through publicly available information (Jensen, 1978).

There are however three different characterisations or levels of efficiency theories, each one concerned with the type or level of information that has been incorporated into a stock's market price and each level incorporating the previous level's type of information:
1. Weak form efficiency hypothesis: affirms that all historical return data is reflected in a stock’s price. What this means is that stock prices follow a random walk as price movements will not be dependent on any past price movements and as a result one cannot earn abnormal profits using a stock’s past price data;

2. Semi-strong form efficiency hypothesis: according to Jensen (1978) the semi-strong form of market efficiency is the generally accepted form and states that in addition to the weak form efficiency hypothesis, all public information (such as a company’s annual reports) is also fully incorporated into market prices and therefore one cannot earn above-average risk-adjusted returns using any historic or publicly available information. The semi-strong form of market efficiency implies that fundamental analysis, where public information is used to determine the intrinsic value of securities, should not be able to yield above-average risk adjusted returns; and

3. Strong form efficiency hypothesis: states that one cannot profit from any past information, whether it be public or private (i.e. inside information), as it has also been fully accounted for when determining market prices (Aga & Kocaman, 2008).

As such the EMH is counter-intuitive as the more information one has about a stock the more efficient the market is likely to be and therefore the less profitable that information will become as others would have acted upon it when setting its price. In summary, the EMH implies that investors cannot consistently outperform the market as price changes are random and unpredictable.

2.4. The assumptions of the efficient market hypothesis

According to Lo (2007), the EMH was independently developed in the 1960s by Paul A. Samuelson and Eugene F. Fama. Samuelson (1965) provided proof that if the expectations of all market participants are correctly anticipated, then price changes should become completely random and follow what is known as a random walk pattern or martingales in mathematical terms. Thus, if expectations are fully incorporated into market prices then successive price changes are completely independent of any previous or future price changes and as a result one cannot use them to predict the future (Samuelson, 1965).

Consequently one of the main assumptions upon which the EMH rests is that all information is considered when a price is formed and as a result price changes are completely unpredictable. Although Samuelson (1965:48) provided the theoretical basis for why the market might follow a random walk pattern, one should note that it still does not prove that actual competitive markets work wellé that would require a different investigationö
To define an efficient market, Fama (1965b) set out the requirements for market efficiency. Fama (1965b) stated that a large number of rational profit maximising investors, who compete with one another and therefore to a large extent value securities independently of one another, need to be present.

Fama (1965b) also stated that the presence of competition within the market should lead to stock prices that adjust rapidly to new information and fully incorporate all available information, whether it is information about what has happened and/or information about what the market expects to happen. In addition, in order to maximise profits through forecasts of individual securities’ market values, investors should not only make use of all information but the information should also be freely available.

As such, the following assumptions can be said to explain the random walk behaviour of an efficient market and therefore can be said to characterise the EMH:

1. Individuals are rational and make decisions based on all the information available to them and as a result, they take both risk and reward into account and do so without delay (Cubbin et al., 2006). Rationality from an EMH perspective means that investors will choose an investment that has a low risk with the same return or an investment with the same risk but a higher return. Additionally, a rational investor makes use of unbiased subjective probabilities when making an investment decision and understands these probabilities (Rubinstein, 2001);

2. The market is informationally efficient. That is, all investors have access to the same information. The assumption also implies that there are no costs associated with attaining information or any other kind of market friction such as tax;

3. There is a large number of investors each valuing securities independently of one another; and

4. Equilibrium prices instantly reflect all available information as market participants react rapidly to the arrival of new information.

Jagric, Podobnik, and Kolanovic (2005) provided an additional assumption that needs to be met in order for the market to be efficient:

5. New and relevant information arrives in a random fashion.

These assumptions mean that a stock’s current market price is the best reflection of its intrinsic value, given the information available at that point in time (Chowdhury & Michello, n.d.).
Although some of these assumptions do not seem applicable in the real world many advocates and even challengers of the EMH have argued that they need not be in order for the market to behave in an efficient manner. These researchers generally propose that there may be neutralising factors or actions within the market that correct for any dependence in prices that are caused by relaxing these assumptions (Daniel, Hirshleifer, and Subrahmanyam, 2001).

2.4.1. Assumption 1: individuals are rational

The rationality assumption, although one of the main pillars of support for the way in which an efficient market is presumed to react, has been argued to be inaccurate in practice. Yet its implications may still be applicable (Hirshleifer, 2001; Scharfstein & Stein, 1990). For example, Daniel et al. (2001) showed that there only needs to be a few rational and unbiased investors in the market in order for it to behave rationally as those rational investors will arbitrage any mispricing away.

Hirshleifer (2001) maintains a similar point and stated that irrational investors will be pushed out of the market as they lose more and more of their wealth due to irrational decisions. Hirshleifer, Subrahmanyam, and Titman (2006) took a slightly different view. They showed that even if market participants are irrational, the irrationality has a feedback effect whereby trades affect prices and prices affect the underlying cash flows of the firm. Although it causes an inflated or deflated stock price, they show that it can still cause prices to follow the random walk pattern associated with an efficient and rational market.

2.4.2. Assumption 2: access to homogeneous information

The access to homogeneous information assumption can be relaxed in two interrelated ways:

1. One can assume that market participants do not have access to the same information, known as asymmetric information; or
2. One can assume that there are market frictions such as transaction costs, taxes and costs for acquiring information, which would be more representative of reality.

If there are transaction costs then, according to Timmermann and Granger (2004), past and future price changes may become dependent upon one another as investors are unable to profitably take advantage of arbitrage opportunities. As a result, one may find that not all information has been incorporated into market prices as it may not be profitable to utilise that information once transaction costs have been taken into account.
2.4.3. Assumption 3: large number of independent valuations

If one was to relax the assumption that there are a large number of independent investors and instead assume that investors' valuations and/or actions affect the perceptions of others, then what is known as a herding effect may ensue. That is, investors may follow the actions or valuation assumptions of others.

By doing so one may expect the creation of market prices that do not necessarily reflect the true intrinsic value of a stock and price changes should be positively correlated. However, as Fama (1965a) stated, if there are many savvy investors in the market, they may recognise the departure from rationality or the departure from fundamentals and trade in the opposite direction to the market.

The reaction by the so-called savvy investor may or may not cause others in the market to do the same, however if there are enough of them, the price continuation from herding will be reversed before it has a chance to gain any real traction in the market.

2.4.4. Assumption 4: rapid reaction to new information

If all other assumptions hold, the rapid reaction to new information assumption can be relaxed with little effect on the main implications of the EMH. If market participants do not rapidly react to new information then market prices can be seen to either have some kind of momentum effect or there would be a small window of opportunity to take advantage of the new information to derive abnormal profits. Such a window of opportunity would depend on how long it takes for the market to react to the said information.

On the one hand, if there is a momentum effect, then price changes will be positively serially correlated and therefore one should be able to make abnormal profits off the back of past information. However, in keeping with the rest of the EMH assumptions, serial correlation is information in itself and therefore the rest of the market will also be using that information at some point when pricing securities.

As a result, the serial correlation will no longer be present as the market catches onto the fact that price changes have historically been dependent on past price changes (Fama, 1965b). In such a situation, one can argue that the only assumption that needs to hold is that there are large amounts of rational profit maximising investors who compete in the market and therefore look for these profitable opportunities.
On the other hand, if there is no momentum effect, then the random walk behaviour of the market may still hold, however all it would mean is that there would be some lag time between the arrival of information and changes in prices.

2.4.5. Assumption 5: information arrives in a random fashion

If information does not arrive in a random fashion, it implies that there is some kind of pattern in information, which may result in a pattern in price changes. However, if the assumption that - there is a large amount of rational, profit maximising investors competing in the market - holds then the mere fact that a pattern of information can be found, would render such a pattern useless to investors as it would have already been priced into the market (Fama, 1965b).

2.5. Evidence of market efficiency

Before some of the evidence in favour of the EMH is presented here, it is first necessary to note that all the tests for the EMH that have been used in the literature thus far are tests with joint hypotheses:

1. The asset pricing model used is specified correctly; and
2. The market is efficient.

Consequently one first needs to assume that the efficient market model being used correctly models an efficient market before the market can be said to be (in)efficient (Jensen 1978). Thus it is difficult to offer support or reject that the market is (in)efficient.

Researchers (Kendall, 1953; Fama, 1963; Basu, 1977; and Lo, 2007) have tested the EMH in many ways, the first of which was to determine if security prices are serially correlated. In fact, a lot of the literature that first showed evidence of random walk behaviour in the stock market was written before the phrase ‘market efficiency’ was ever coined.

As Fama (1970) noted, the empirical evidence for the theory actually preceded the theory itself. Some examples of these are Kendall (1953), Roberts (1959), and Osborne (1959). Kendall (1953) studied the UK stock and commodity markets and found very small, practically insignificant serial correlation while Roberts (1959) demonstrated that a series of randomly generated numbers was comparable to that of US stock prices. Osborne (1959) on the other hand likens the movement of stock prices to that of molecules.

Fama (1963; 1965a) also provided strong empirical evidence for the EMH when he, like Kendall (1953), found that price changes are slightly positively correlated in the US but not
The performance of a momentum strategy during bull and bear periods on the JSE/FTSE Top 40 index
M.R. Devonport

sufficiently so to gain any benefit from the correlation. Fama (1965a:57) went on to say that he knows of no study in which statistical tools have produced evidence of important dependence in series of successive price changes. However, Fama subsequently (1991) found evidence of significant serial correlation using lagged return data.

Subsequently, there have been many studies in other markets around the world such as in Argentina, Brazil, Chile, Mexico (Urrutia, 1995), Hong Kong (Cheung & Coutts, 2001), Istanbul (Aga & Kocaman, 2008), and the UK (Hudson, Dempsey, & Keasey, 1996). But as stated in the introduction to this section, the studies cited here are only a small fraction of all the empirical evidence that has been presented and if there is a market for it, the EMH has more than likely been tested in that market.

An alternative method that has been utilised to test weak-form market efficiency is to use other market variables and stock characteristics, such as size, market capitalisation (Banz, 1981), or a P/E ratio (Basu, 1977), and after accounting for risk and any other bias that may enter the study, determine whether these variables can be used to accurately forecast future performance and as a result, provide abnormal profits.

Much of the earlier work focussed on tests of weak-form market efficiency, which is obviously a natural starting point as each level incorporates the last. The next step was to test the semi-strong form of market efficiency. It was done with the use of event studies, whereby the speed at which market prices adjusted to the arrival of new information was examined (Lo, 2007). Ball and Brown (1968) were one of the first studies of this nature; they considered the stock market’s reaction to earnings announcements with the use of the CAPM and found that stock prices seemed to incorporate the information even before the announcement took place.

2.5.1. Implications of the efficient market hypothesis

If the EMH is indeed true, or at least partially true, then there are several implications for researchers and investors alike. Firstly it undermines the basis for security analysis from a technical perspective as there is nothing to be gained from past information and therefore these charting techniques (Fama, 1965a).

From a fundamental analyst’s perspective the principles behind the EMH make it difficult for a fundamental type of analysis to add value when selecting securities unless:

1. It is able to glean further information that has not yet been fully incorporated into the market price; or
2. It can provide new insights into the stock’s actual or future intrinsic value (Fama, 1965a).

From a general investment perspective, the EMH implies that the best prediction of tomorrow’s stock price is the stock price today (Al-Loughani & Chappel, 1997). As a result, an investor will always be paying the correct amount for any given stock at any given time and receive a return that will correctly compensate the investor for the risk incurred, given what is known at that point in time.

Therefore the EMH implies that little benefit can be gained from an active management strategy; in fact there is a large body of literature where the returns from passive and active portfolio management strategies are compared. Although the results are mixed, many researchers find that active strategies are less profitable than passive buy-and-hold strategies and they generally attribute these results to transaction costs and management fees (Jensen, 1968; Malkiel, 1995).

2.6. Market anomalies

In the previous section the theory behind and the evidence for the EMH was presented. In this section the reasoning for researchers to question its validity in practice is discussed through the use of a few market anomalies. This is done in order to provide a more holistic view of the EMH and the theoretical and empirical basis for this study.

Brav and Heaton (2002) stated that a financial anomaly is a pattern of price behaviour that violates the assumptions or predictions of efficient market theory. That is, such behaviour deviates from what is expected if market participants process information rationally, make optimal decisions based on that information, and have access to all information available to the public.

Although there are many financial anomalies, only the most common of these EMH criticisms is discussed, namely: investors’ preference for cash dividends rather than capital gains, the seasonality effect as it relates to the under- and overreaction evidence, the higher risk-adjusted returns earned by smaller firms, the P/E ratio anomaly, and the EMH tests using certain trading rules, specifically the presence of momentum and contrarian investment strategy profits. These financial anomalies were chosen as they highlight some of the same concepts, both behavioural and fundamental, that are used to explain the success of a momentum investment strategy.
Hong and Stein (1999) noted that in order for a new theory to be of any significance to the world of finance, it needs to:

1. Be able to make certain assumptions on participant behaviour that is either intuitively possible or consistent with what is observed empirically;
2. Explain the existing evidence in a relatively simple and unified manner; and
3. From the samples, make predictions that can be validated.

The theories and models made by neoclassical financial theorists such as Miller and Modigliani (1961), Markowitz (1952), Sharpe (1967), Lintner (1965), and Black and Scholes (1973), did just that and thus appealed to academics and practitioners alike.

However, the evidence for and against efficient capital markets is mixed (Reilly & Brown, 2006). While Fama (1963, 1965a, 1965b, 1970) provided strong evidence for the EMH, he was subsequently criticised for using a small data set of 1200 to 1700 data points, when Poterba and Summers (1986) showed that as many as 6000 data points are required to provide a 50% chance of rejecting a false null hypothesis. Additionally, various efficient market anomalies, which violate the main assumptions of the EMH, have been observed and documented in various markets around the world.

Jensen (1978) believes that the emergence of the conflicting evidence is due to superior data and econometric techniques that were previously unavailable. Although individually these anomalies do not provide grounds for the complete rejection of the EMH, they have sparked the interest of researchers and investors alike as they may provide further untold truths about the market (Ball, 1978).

2.6.1. Investors' preference for cash dividends

In the well-known study by Miller and Modigliani (1961), it was shown that in a perfect world:

1. There are no taxes;
2. There are no transaction costs;
3. Investors have complete information, which is otherwise known as symmetric information where all market participants have exactly the same information;
4. There are complete contracting possibilities where there is no agency problem between managers and shareholders; and
5. There are complete markets.

The search to create a dividend payout policy that will maximise shareholder wealth is null and void. The basic principle of their argument was that a firm's value is based on its
investment decisions only and that dividends are the residual earnings on a firm’s investments (Miller and Modigliani, 1961).

From an investor’s perspective a firm’s payout policy should be irrelevant as it has no bearing on the value of that firm. Additionally, a shareholder can artificially create any desired stream of cash flows through the purchase or sale of equity. As such, rational investors should not have any preference to receive dividends over capital gains and therefore investors should not be willing to pay a premium for any particular dividend policy.

Empirical evidence suggests that this is not the case. It has become apparent that investors tend to prefer dividends to capital gains (Dong, Robinson, & Veld, 2005). As a result, many companies have been found to raise capital through share issues shortly before or after dividend payouts (Easterbrook, 1984), which seems pointless and therefore irrational.

Miller and Modigliani (1961) hypothesised that there may be a clientele effect that can be said to be rational where it derives from differences in the way income types are taxed. Subsequently, there have been many studies (Dhaliwal, Erickson, & Trezevant, 1999; Grinstein & Michaely, 2005; Graham & Kumar, 2006) that have advanced Miller and Modigliani’s (1961) train of thought and have found empirical evidence that a clientele effect exists, at least within institutional investor circles.

Another explanation for the anomalous behaviour is the signalling theory posited by Battacharya (1978). It is argued that asymmetric information exists in the market for the simple reason that managers will know more about the company and its prospects than external investors. As a result, the declaration of any payout policy change provides some indication of how managers feel about the company’s prospects.

The asymmetric information effect is studied extensively by Noe and Rebello (1996) where they found that investors read too much into announcements such as the restriction of dividends, equity financing decisions, and the purchase or sale of shares by managers.

According to Dong et al. (2005), much of the more recent literature surrounding the dividend puzzle is focussed on individual investor behaviour and how it may relate to their needs. Miller and Modigliani (1961) allude to it when they posited that the clientele effect may result from differences in investors’ stages of life.

Thaler and Shefrin (1981) also posited that an investor’s stage of life may influence their preference for dividends; however they take it a step further when saying that it is also due to considerations of self-control. Investors prefer to meet their consumption needs from
dividends and other income producing assets, while utilising capital gains producing assets for aspects such as retirement.

Shefrin and Statman (1984) took a similar view to the behavioural bias explanation of Thaler and Shefrin (1981). Shefrin and Statman (1984) further stated that it may be a result of a behavioural bias known as 'mental accounting'. Under that explanation, investors separate income producing investments from capital producing investments and may not treat each category the same. Shefrin and Statman (1984) posited that the clientele effect might also occur as a result of age differences and that investors who are in the accumulation stage prefer non-dividend paying stocks, while retired individuals prefer high yielding stocks.

Accordingly, the rationality assumption of the EMH is challenged given the evidence presented above. Theories such as the uncertainty resolution theory (Gordon, 1961), the signalling theory (Battacharya, 1978), and the behavioural finance theory (Shefrin & Statman, 1984) focus on investors' uncertainty of the future, information asymmetries, and self-control; and have received a lot of support. However, there is still no solid consensus among researchers as to why investors would prefer dividends over capital gains.

2.6.2. Seasonality effects in stock returns

The term 'seasonality effects' as its name suggests, refers to the situation where stock returns or movements can, to some extent, be correctly forecasted based on time. As stated by Bowman and Iverson (1998), the most notable of these seasonality effects is the January effect. The January effect anomaly may affect the results of this study and therefore warrants some discussion here.

The January effect has been studied in various countries around the world. Gultekin and Gultekin (1983) investigated the monthly stock returns in seventeen countries from January 1959 to December 1979 and found the January effect in each of the countries studied, thirteen of which had significantly larger returns in January. Hawawini and Keim (1993) also analysed monthly returns across eighteen developed countries over various periods, ranging from 1955 to 1982, and found returns in January were always larger than the returns in other months.

The evidence for the January effect is not only confined to developed markets however. Nassir and Mohammad (1987) found evidence in Malaysia over the period 1970 to 1986, Ho (1990) found similar evidence in Hong Kong, Korea, Malaysia, Philippines, Singapore and Taiwan over the period 1975 to 1987, while Muller and Ward (2006) found evidence of the January effect on the Johannesburg Stock Exchange (JSE). On the other hand, Fountas and
Segredakis (1999) found very little evidence of a January effect in the eighteen emerging stock markets they studied.

Some of the first researchers to document seasonality effects in stock returns were Rozeff and Kinney (1976). They found a seasonal pattern in the returns of an equally weighted index of all stocks on the New York Stock Exchange (NYSE) over the period 1904 to 1974. Here the average monthly return on an equally weighted index of NYSE stocks in January was about 3.5 percent, while in other months the same index only averaged half a percent (0.5%).

What is interesting to note is that no seasonal pattern was found on the Dow Jones Industrial Average (an index comprised of blue-chip stocks in the US) (Lakonishok & Smidt, 1988). As Thaler (1987) suggests, it indicates that seasonality in stock returns may be confined to smaller, less liquid stocks. Hawawini and Keim (1993) found similar evidence for seasonality as the broader, equally-weighted indices, which are weighted more heavily in smaller stocks in each of the eighteen countries they studied, had a significantly larger January effect than their value-weighted counterparts.

Branch (1977) found that an investment strategy of selling past losers at the end of the year and buying past losers at the beginning of the year provided abnormal profits and therefore could take advantage of this inefficient market behaviour. Branch (1977) and authors such as Dyl (1977) posited that investors tend to sell stocks that have made a loss over the past year in order to realise tax benefits at the end of the year. Once the new year starts these investors would then purchase the same or some other stock that looks attractive.

The practice of realising tax benefits at the end of the year is known as tax loss selling and it puts downward pressure on poor performing stocks at the end of the year and upward pressure on these poor performing stocks at the beginning of the year. As a result, one may find some momentum in loser stocks in December and return reversals on poor performing stocks in January.

The seasonal pattern, although rational for the tax-loss sellers, should not occur from an EMH perspective as arbitragers should buy these stocks at the end of the year and sell them at the beginning of the year in order to realise gains from under-valued stocks. At the same time these other investors would also anticipate excess returns in January due to increased purchasing activity.

Although Roll (1983:20) calls the tax-loss selling argument “patently absurd” he, together with other authors such as Reinganum (1983), also found evidence that confirms the tax-
loss selling theory as stocks that had negative returns in the previous year, had higher returns in January. In Reinganum (1982), similar results were found in the US, particularly within smaller stocks, thereby providing further evidence of this anomaly being confined to small, less liquid stocks or at least more prevalent stock returns.

Brown, Keim, Kleidon, and Marsh (1983) asserted that smaller stocks are more affected by tax-loss selling phenomena as they generally have larger price swings and as a result, are more likely to incur larger declines in price.

While tax-loss selling has been presented as the rational explanation for the anomaly, Kato and Schallheim (1985) found the anomaly to be present in Japan, where no capital gains tax or loss offsetting exists. In the same way, Berges, McConnell and Schlarbaum (1984) found the January effect on the Toronto Stock Exchange prior to capital gains tax being imposed.

As a result, Zarowin (1990) hypothesised that another anomaly may be at work—the overreaction phenomenon (presented in section 3.2.2) and that it may cause the seasonal pattern. Therefore tax-loss selling, although a rational, yet debated explanation for the anomaly, cannot be the only explanation.

Another explanation for the January effect that has been proposed in the literature is what is known as 'window dressing'. Under the 'window dressing' rationale, investment managers sell stocks that have underperformed in order to hide their suboptimal investments, however, the argument can only be characterised as being weak in the face of arbitrage (Bildersee & Kahn, 1987). Another peripheral explanation of the January effect, provided by Rozeff and Kinney (1976), is that firms generally provide new information to the market in January due to their fiscal year end and the subsequent publication of their results.

A stronger argument provided for the January effect and indeed many other market anomalies such as the related size anomaly is that risk is seasonal and that residual risk for smaller firms increases in January (Tinic & West, 1984; Corhay, Hawawini, & Michel, 1987).

The implication of these findings is that, like the rest of the anomalies presented here, it undermines the EMH. Specifically, the presence of seasonality may lead one to reject the informational efficiency aspect of the EMH (Fountas & Segredakis, 1999), thereby providing some grounds for technical analysts to use of charting techniques. Additionally it indicates that there is far more opportunity for fundamental analysts to attain information that is yet to be incorporated into stock prices.
2.6.3. The small firm effect

The small firm effect refers to the anomaly whereby small firms earn higher average rates of return than larger firms, even after accounting for differences in risk. This relationship was first extensively studied by Banz (1981). He found that the size characteristic of a stock within his sample provided considerably more explanatory power than the systematic risk variable $\beta$ within the CAPM and that there was a negative association between size and returns. As such, it was found that the smaller a stock, the higher its returns and the higher its abnormal returns, given CAPM return estimates.

Abnormal returns can be defined as those returns in excess of what the CAPM would estimate. Abnormal returns can be calculated by regressing the return on the market portfolio on the return on the asset or portfolio being assessed.

Since Banz’s study (1981), the size effect has been tested and documented in various markets around the world including Spain, the UK, France, Japan, Canada, and New Zealand, and most of these tests point to a significant size effect. Reinganum (1981; 1982) made use of the size effect to test the EMH as measured through the CAPM and the arbitrage pricing theory (APT). Both studies found a significant size effect that cannot be explained by these efficient market models.

Roll (1981) suggested that the size effect can be explained by the bias that is introduced due to infrequent trading. He went on to explain that the risk measures obtained from daily data may understate the actual risk present within small infrequently traded firms. Roll (1981) even goes so far as to suggest that the abnormal returns resulting from other anomalies, such as the P/E ratio anomaly, may also be explained by that bias as these two anomalies have been found to be highly correlated (Reinganum, 1981a).

As noted by Reinganum (1982), the problem with Roll’s (1981) study was that he did not have market capitalisations of individual stocks and as a result he had to indirectly test his hypothesis using value-weighted and equally-weighted indices rather than individual stocks. Reinganum (1982:35) directly tested Roll’s (1981) hypothesis in the US and concluded that the small firm effect is still a significant economic and empirical anomaly. Thus although Roll’s (1981) basic thought was correct, that daily data from infrequently traded firms may understate their risk, daily data only very marginally biases the risk estimates of small infrequently traded stocks and therefore cannot completely explain the anomaly.

Although researchers have yet to explain the small firm effect they do not conclude that the market is inefficient but rather that the efficient market models of our time, specifically the
APT and CAPM, have yet to incorporate a factor that will, to some extent, proxy the anomalies such as the size effect (Berk, 1995). Indeed authors such as Lo and MacKinlay (1990) have incorporated size in their market models and therefore implicitly utilise it as a proxy for risk as some argue that it is a risk type that has yet to be explained or grounded in theory.

2.6.4. The price earnings ratio anomaly

The P/E ratio anomaly refers to the finding, first documented by Nicholson (1960), where stocks with low P/E ratios consistently provided returns in excess of the average stock in the same period. Similarly, Basu (1977) found that differences in cross-sectional stock returns could be explained better by differences in P/E ratios than differences in betas, which represent the systematic risk of a stock, and that the anomaly is still present after accounting for differences in risk. In fact, Basu (1977) put forth the notion that P/E ratios could oppose the CAPM as he found a significant negative relationship between P/E ratios and the returns predicted by the CAPM within his sample of NYSE stocks over the period from 1957 to 1975.

Graham (2006) contended that the anomaly is a result of the overreaction effect whereby investors overreact to information, which results in undervalued stocks that are least favourable and overvaluing the more favourable stocks. Smidt (1968) argued the very same point and stated that P/E ratios are able to indicate the mispricing where earnings remain constant or increase slightly while stock prices rise or fall by an inordinate amount.

However, according to Goodman and Peavy (1983), some critics of the anomaly, like the critics of the seasonality effect, often attribute the stock price behaviour to the well-known size effect, discussed in section 2.6.3, and the infrequent trading that comes with smaller company stocks. Reinganum (1981) found that small firm stocks generate returns that also consistently outperform the returns expected by the CAPM. Additionally, the size characteristic and P/E ratios of these firms were found to be significantly positively correlated. Thus it seems many of the anomalies discussed here are interrelated.

The empirical evidence suggests that either the CAPM is simply misspecified as a result of some undefined risk variable that size, P/E ratios, and dividend yields may be a proxy for, or the market is not efficient in the traditional sense. Hawawini and Keim (1993) noted that what is lacking within the literature surrounding the empirical evidence is a workable theory that explains why these anomalies are present.
2.7. Momentum and contrarian investment strategies

Now that the EMH and the evidence for and against the line of theory have been presented, the main investment strategy that is studied here can be discussed. As stated previously, one of the methods generally used to testing the weak-form EMH and its models is a simulation technique where a pattern or trend is gleaned from past data alone and the past data is used to predict future price changes, otherwise known as technical analysis. If one is able to derive abnormal profits from a technical type of trading strategy, then evidence against the weak-form EMH is created and vice versa.

The EMH implies that a trading strategy based on historic data will not consistently yield returns above a simple buy-and-hold strategy because all past data should already be priced into the market. Additionally, information is presumed to come into the market in a random fashion and as a result stock returns should follow a random walk pattern. Therefore, by comparing the risk-return results of a simple buy-and-hold strategy and some technical trading rule, researchers are able to support or reject the weak-form EMH (Reilly & Brown, 2006).

There are various technical trading strategies, however arguably the most widely known are the contrarian and momentum strategies. On the one hand, a contrarian investment strategy asserts that the best performing stocks today will be the worst performing stocks in the future and the worst performing stocks today will be the best performing stocks in the future. While on the other hand, a momentum investment strategy affirms that poor performing stocks will continue to perform badly while successful stocks will continue to provide positive returns in the future.

As a result, a contrarian investor will purchase the worst performing stocks and sell the best performing stocks in the hope that their future relative performance will be contradictory to their past relative performance, while a momentum investor will do the opposite.

Section 2.7.1 and 2.7.2 presents these two trading strategies, which attempt to take advantage of weak-form market inefficiency. Although there are many variants of momentum and contrarian investment strategies, in the context of this and most of the previous research, they are strategies which condition the investment decision on past return data alone.

What is interesting to note is that many of the same theories that explain price momentum have also been used to explain price reversion behaviour (contrarian profits). Therefore the
contrarian strategy warrants some explanation here and will be followed by a discussion on the momentum investment strategy.

2.7.1. The contrarian investment strategy

De Bondt and Thaler (1985; 1987) were the first to document evidence of price reversals in the US and as a result, most of the literature on contrarian and momentum strategy profits can be attributed to their seminal work. They found that a long-term (three to five years) contrarian investment strategy, conditioned on past return data alone, could beat the market in the US. That is, such an investment strategy was able to provide excess returns, even after accounting for risk. Subsequently, their findings have been tested in many other markets over various time periods around the world, the results of which have been mixed.

Authors such as Schiereck et al. (1999) and Baytas and Cakici, (1999) found evidence of successful long-term (approximately three years) contrarian strategies in Germany and in Canada, the UK, Japan, Germany, France, and Italy respectively, while Cubbin et al. (2006) found similar evidence in SA. However, Conrad and Kaul (1993), and Baytas and Cakici (1999) did not find these contrarian profits in the US while Dissanaikke (2002) also reported conflicting evidence in the UK.

While De Bondt and Thaler (1985) and many others (cited above) found the contrarian strategy to be profitable over long time horizons (three to five years), Jegadeesh (1990) and Lehmann (1990) found that it could also be profitable over periods of one and six months respectively. Further, Bowman and Iverson (1998) found the strategy could even work over a period of two days to two weeks. That was despite the fact that Park (1995) found a short-term contrarian strategy would not have provided enough returns to account for the transaction costs involved.

Much of the literature, such as De Bondt and Thaler (1985) as well as Jegadeesh (1990), has associated return reversal behaviour to applied psychologists' overreaction hypothesis. The overreaction hypothesis, discussed further in section 3.2.2, asserts that investors generally overreact to new information and as a result, stock prices increase or decrease by too much when good or bad information enters the market. As time passes, so stocks return to their fundamentals as investors either attain more information that provides more clarity about a stock's intrinsic value or as investors calculate a more accurate intrinsic value. Therefore, as more information comes into the market, so stock returns may exhibit price adjustments in the opposite direction to the initial information (Shefrin & Statman, 1985; Lehmann, 1990).
Although the overreaction hypothesis holds a central place within the literature, other explanations have been proposed. These explanations refute the presence of abnormal contrarian profits altogether (Chan, 1988; Conrad & Kaul, 1993), make use of behavioural biases other than the overreaction hypothesis (Barberis, Shleifer, & Vishny, 1998; Daniel et al., 1998), or assume something about the composition of the market and the way in which information circulates throughout the market when explaining the return reversion behaviour (Hong & Stein, 1999). Alternatively they maintain that market behaviour is a result of some other anomaly such as the small firm and seasonality effects and is therefore not a separate issue (Zarowin, 1990).

2.7.2. The momentum investment strategy

A seemingly contradictory investment strategy to the contrarian strategy is what is known as a momentum strategy. The momentum strategy, like the contrarian strategy, is based on the thought that past returns are an indicator of future returns. It assumes however that stocks that provided good returns in the past will continue to do so in the future. If that is the case then stock returns should exhibit positive serial correlation as opposed to the contrarian strategy where stock returns exhibit negative serial correlation.

The first to formally present evidence of a successful momentum investment strategy was Jegadeesh and Titman (1993). Jegadeesh and Titman (1993) found that a momentum strategy using a formation and holding period of between three and twelve months provided positive and statistically significant returns in the US. Additionally, these returns could not be explained by the traditional CAPM.

The prevalence of literature surrounding the momentum investment strategy resembles that of the contrarian investment strategy as many momentum investment strategy studies have been conducted in various markets around the world. However, in contrast to the contrarian evidence, the evidence for successful momentum strategies is overwhelmingly one-sided with very few studies refuting its success (Rey & Schmid, 2007).

The authors finding evidence supporting Jegadeesh and Titman’s (1993) conclusions include: Schiereck et al. (1999) in Germany; Fraser and Page (2000) in SA; Kang, Liu and Ni (2002) in China; Gunasekarage and Kot (2007) in New Zealand; and Rey and Schmid (2007) in Switzerland. Few others (Lesmond et al., 2004) have found an absence of abnormal profits resulting from such a strategy after accounting for risk and transaction costs. Where these momentum profits are observed it seems the optimal time horizon over
which such a strategy may be profitable is between three and twelve months for both the formation and holding periods (Rey & Schmid, 2007).

While there is little controversy as to the presence of stock price continuation behaviour, there is far less understanding as to its cause and therefore the way in which these results are interpreted. Many researchers including Jegadeesh and Titman (1993), Schiereck et al. (1999), and Fraser and Page (2000), have attributed momentum to under-reaction and/or delayed overreaction phenomena; however the question of whether under-reaction and/or delayed overreaction is a result of irrational behaviour by market participants or illusionary in nature is still uncertain (Scowcraft & Sefton, 2005).

Some authors concluded that momentum profits are a natural consequence of the EMH and can largely be explained by the risk of the individual portfolio (Conrad & Kaul, 1998), market microstructure effects (Park, 1995), or subsumed by the well-known size effect (Zarowin, 1990). Others concluded that it is a result of a slow rate of information diffusion in the market (Hong & Stein, 1999), behavioural heuristics (Daniel et al., 1998), or social biases (Bikhchandani, Hirshleifer, & Welch, 1992).

While the momentum strategy profits by using one set of rules, the contrarian strategy profits by using an exact opposite set of rules. Although the literature suggests that a difference in time horizons separates the two, what is quite interesting, given the evidence of momentum strategies beating the market over a 52-week time horizon, is that Howe (1986) found the contrarian strategy to be profitable over the very same time horizon. Nevertheless, the question still remains: Is the market efficient and if not, what causes market inefficiency as seen through the success of a momentum investment strategy?

2.8. Summary

The key assumptions of the EMH and the implications for stock price behaviour that are most relevant to this study are that individuals are rational and make decisions based on all information available to them. Additionally, it is presumed that investors swiftly react to new information. Consequently, prices in the market must at the very least incorporate all past information and should be representative of their current intrinsic values.

Price changes should therefore follow a random walk pattern as information is presumed to come into the market in a random fashion, thereby implying that stock returns should be totally unpredictable (Cubbin et al., 2006). Thus, in keeping with what is known as the weak-form EMH, investors who condition their portfolios on past price data alone cannot consistently derive above average returns (Fama, 1970).
From the EMH, various efficient asset pricing models have been derived. These models generally assert that one should be able to trace patterns in asset returns, over any horizon, back to certain weightings on fundamentally meaningful risk factors (Hong & Stein, 1999). However, as Hong and Stein (1999) stated, there is little evidence of that being the case due to the evidence of financial anomalies such as those presented above.

These anomalies contradict many of the assumptions of the EMH, specifically with regards to the rationality assumption, and therefore call the validity of the EMH into question. As such they highlight many of the issues or inadequacies within the current state of knowledge (Jensen, 1978).

As such, the question of whether markets are efficient is one of the most controversial issues in finance. Nevertheless the EMH still holds weight in all financial circles and cannot be disregarded based on that evidence alone. As Schwert (2002) stated, EMH anomalies may well disappear as the market either becomes more efficient with regards to costs, or as investors increasingly try to take advantage of known inefficient market behaviour. However, to the extent that it is not true, tests for market efficiency through the use of trading strategies such as the momentum or contrarian investment strategies are still relevant.

The finding that contrarian and momentum investment strategies may be abnormally profitable was first presented by DeBondt and Thaler (1985) and Jegadeesh and Titman (1993) respectively. Subsequently, additional evidence for both trading strategies' success has been documented in many other markets around the world.

Some researchers, which present evidence for these technical trading strategies, support the notion that behavioural biases stimulate the abnormal profitability, while others maintain that the profits are a natural consequence of the EMH and are explained by the relative riskiness of portfolio constituents. There are however many explanations that have been discussed in the literature. These explanations will therefore be discussed in more detail in the next chapter.
Chapter 3
Explanations for momentum strategy profits

3.1. Introduction

The investment strategy, which will be tested in this study, together with the reason why its success challenges the EMH, has been discussed in the preceding sections. However, the explanations for these profits - although briefly introduced - have not yet been fully discussed.

Where abnormal returns from momentum or contrarian strategies are found, two sets of explanations have been proposed within the literature. The first set of explanations corresponds with the EMH and proposes that abnormal profits exhibited by the momentum strategies are illusionary and are a result of risk (specifically the time-varying nature of risk proposed by Chan, 1988), size effects (Chan, 1988; Ball & Kothari, 1989), market microstructure effects (Park, 1995; Conrad et al., 1997), transaction costs (Grundy & Martin, 2001), model specification issues, and data mining bias.

The other set of explanations advocates weak-form market inefficiency (Park, 1995) and can be broken down into:

1. Behavioural bias explanations: that cause market under-reaction (Jegadeesh & Titman, 1993) and overreaction (DeBondt & Thaler, 1985);
2. Alternative anomalies: that make it seem like there is stock price momentum such as seasonality effects (Zarowin, 1990); and
3. Information diffusion effects: that assumes a difference in the way information flows throughout the market, causing information asymmetries (Balsara et al., 2006).

The explanations that conform to the EMH and those that do not will be discussed in more detail here. Before the behavioural set of explanations are discussed however, it is first necessary to present certain documented psychological biases that have been mentioned within the momentum strategy literature to support the various behavioural explanations.

Once these have been presented, the behavioural models used to explain the momentum anomaly will be presented. It is followed by the more traditional views of why the anomaly is said to be illusionary. Consequently, this section is divided into two main sub-sections:

1. Behavioural explanations: this sub-section includes a discussion around the various behavioural and social biases that are documented in the literature, followed by the behavioural models whereby the former are used to explain under- and overreaction in stock returns; and
2. EMH explanations: this sub-section will present the explanations that conform to the traditional view of efficient markets and therefore reject the notion that behavioural, social or asymmetric information affects stock prices.

3.2. Behavioural explanations for momentum strategy success

On the one hand there is traditional financial theory, which assumes that market participants are rational. The implications of the rationality assumption are twofold. Firstly, market participants update their beliefs correctly after the arrival of new information. It is assumed that market participants update their beliefs according to Bayes’ Law, where a subjective belief is updated rationally in order to account for new information (Stigler, 1983). As a result, investors should not be influenced by behavioural or social biases.

Secondly, if a stock’s price is the sum of all discounted expected future cash flows then market participants will make use of all available information when arriving at estimates of these cash flows and a discount rate that is acceptable given the level of risk inherent in the stock (Barberis & Thaler, 2002). Accordingly, stock prices should reflect their true intrinsic value, as determined by fundamentals and the information available at the time, and no investment strategy should derive profits that exceed what is required to compensate for risk.

On the other hand, behavioural finance theory assumes that asset prices tend to deviate from their true intrinsic values due to the irrational behaviour of market participants. The line of theory examines the effects of relaxing the traditional rationality assumption by incorporating one or more behavioural or social dynamics (Prothmann, 2009). As a result, if one takes a behavioural finance perspective, it is possible to derive abnormal profits from an investment strategy that takes advantage of these behavioural or social dynamics, which cause biases in investor rationality and therefore inefficient market prices.

The introduction of behavioural and social psychology into the classic view of finance has had important implications for financial theorists’ views and ways of explaining anomalies that previously were quite difficult to explain using pure neoclassical financial theory alone. However, a behavioural theory or model that explains the broad range of the anomalous evidence, presented in section 2.6, has yet to win acceptance within the literature.

Also, economists generally criticise behavioural finance as having too many possible explanations for any given economic situation or observation (Daniel et al., 1998). Despite that fact, the behavioural explanations that will be presented in the following sections seem
to hold the most promise in explaining the apparent success of momentum investment strategies.

In general, where abnormal profits from momentum and/or contrarian investment strategies are observed, and the relevant variables such as risk, market microstructure, and seasonality effects have been controlled for, market under- or overreaction are posed as the causes of such profits. However, whether the under- or overreaction is due to psychological and/or social biases or a natural consequence of the EMH has yet to be determined. This section presents the literature that utilises behavioural theories, social theories, and differences in the information diffusion process as explanations for momentum strategy profits.

3.2.1. Under-reaction

Momentum investors otherwise known as positive feedback traders or technical analysts, in the context of this paper and in much of the literature, condition their equity portfolios on past stock return data. That is, stocks that performed well over some previous period, known as the formation period, are purchased and stocks that performed poorly over the same period are sold (Goetzmann & Massa, 2000). As Assogbavi and Leonard (2008) stated, an investor who follows the strategy believes that there is momentum in stock prices that push them in their current direction.

There is a significant amount of evidence of price momentum behaviour in the stock market; however researchers are still unsure as to what causes momentum as it does not easily fit into traditional financial theory (Hong, Lim, & Stein, 2000). One explanation and arguably one of the two central explanations for stock price momentum is that the market under-reacts to new information, which is only later fully incorporated into a stock's price (Jegadeesh & Titman, 2001).

Under-reaction is defined by Barberis et al. (1998) as follows: when investors get good or bad news about a stock they initially increase or decrease the stock price by less than what they should. As a result, new information about a stock is initially not appropriately incorporated into its price. However, the inappropriate price adjustment is corrected in subsequent periods with a higher or lower return.

If under-reaction is indeed present, then the explanation has severe consequences for the assumptions of the EMH and therefore many of the traditional financial theories. Specifically, it implies those investors or some subset thereof, do not react rationally to new information and only later appropriately adjust their price estimates (Barberis et al., 1998).
When studying the under-reaction phenomena, Schiereck, De Bondt, and Weber (1999) make three related observations: momentum strategies seem profitable (Jegadeesh & Titman, 1993), the size of momentum profits are associated with the slow adjustment of prices to surprises in fundamentals, and the slow rate with which analysts adjust their forecasts. As they stated, these observations all point to Jegadeesh and Titman’s (1993) conclusion that the market exhibits an under-reaction effect to the presence of new information.

Chan, Jegadeesh, and Lakonishok (1996) concluded that it is especially true when such information is about a company’s earnings. Consequently, the under-reaction hypothesis has been attributed as the main source of momentum profits within the literature (McInish, Ding, Pyun, & Wongchoti, 2008).

Like the over-reaction effect, which is explained in the next section, authors have tried to explain the under-reaction effect through the use of both behavioural financial theory and the interactions between market participants (social psychology), or the information diffusion process. Hong et al. (2000) divided the behavioural theories of under-reaction into these two groups.

The first is that investors are prone to what is known as a conservatism bias and as a result, they do not update their beliefs enough to sufficiently account for the arrival of new information that may be contradictory to, or too different from their previous beliefs. Thus securities, after the arrival of new information, are initially under- or overvalued. As more information comes into the market, confirming the previous information, securities move closer and closer to their real values (Barberis et al., 1998).

The second behavioural finance category is based on the composition of market participants and the way in which information diffuses into the market. Although Hong et al. (2000) only speak of Hong and Stein’s (1999) behavioural model, there are a few other behavioural models presented by other authors, such as Bikhchandani et al. (1992), which may also fall into that category.

The main thought underpinning the market composition and information diffusion group is that there is less emphasis placed on the individual behavioural heuristics, which may bias price estimates, and more emphasis on the social interactions between market participants, and the way in which information arrives into the market.

So in general, the under-reaction effect is explained by behavioural biases and the way in which information flows throughout the market and as a result of its presence, one can
achieve abnormal returns by following a momentum strategy. The next question however is how the opposite strategy (contrarian) can also seem profitable?

### 3.2.2. Overreaction

Now that the under-reaction hypothesis has been explained, a seemingly contradictory, yet possibly complementary hypothesis will be presented. That is, the overreaction hypothesis used by De Bondt and Thaler (1985) in explaining the abnormal profits they found using a contrarian investment strategy on the US stock market.

The overreaction hypothesis can be defined in a similar manner to that of the under-reaction hypothesis: overreaction is where stock price adjustments, as a result of new good or bad information, are too large and therefore stocks are initially under- or overvalued. However, in subsequent periods there is a price reversal in the opposite direction in order to correct the initial over-adjustment.

The overreaction hypothesis, like the under-reaction hypothesis, has its roots in applied psychology. According to Mun, Vasconcellos, and Kish (2000), the overreaction hypothesis states that individuals generally over-react to both good and bad news. Kahneman and Tversky (1974) found that people generally evaluate losses and gains differently and are more sensitive to losses than gains. They moved on to describe a behavioural bias known as the representativeness heuristic whereby individuals tend to draw far-reaching conclusions based on too little statistical data or too little empirical evidence. What De Bondt and Thaler (1985) did was to incorporate this idea when explaining the contrarian strategy profits they found in the US, as traditional financial theory has trouble in providing such an explanation.

Like the under-reaction hypothesis, the presence of the overreaction effect indicates weak-form market inefficiency as stock returns are predictable based on past return patterns and prices do not fully reflect all information that should be present in their past movements (Mazouz & Li, 2007). The main thought behind the under-reaction hypothesis is that stock prices exhibit large movements away from what fundamentals would infer due to persistent investor pessimism or optimism (De Bondt & Thaler, 1985).

By establishing such a theory, one can explain the presence of long-term contrarian profits. From a short-term perspective however, the overreaction hypothesis states that investors are biased to more recent information and as a result, overreact to dramatic and unexpected information (Bowman & Iverson, 1998). The question still remains, what causes investors
and therefore the market to over-react to information in some instances and under-react to informa-

3.2.3. Behavioural biases and models that explain under- and overreaction

In terms of the overreaction effect, De Bondt and Thaler (1985) stated that it may be a result of investors overweighing recent information and underweighting prior information. Such behaviour is also known as extrapolation bias and may be caused by Kahneman and Tversky’s (1974) representativeness heuristic. The representativeness heuristic is concerned with the way in which individuals assess information under uncertainty and it forms part of the many behavioural biases that economists use to explain several market anomalies (Prast, 2004).

While the representativeness heuristic is generally labelled as the main culprit for the overreaction effect, a conservatism bias is attributed to the under-reaction effect. However, these behavioural biases can be argued to be one and the same. In fact, Kahneman and Tversky (1974) attribute the conservatism bias as being a result of the representativeness heuristic. However, for the purposes of this paper, these concepts will be explained separately.

In addition to the representativeness heuristic, there are other behavioural biases, which may also contribute to the under- and/or overreaction effects. Specifically, Prast (2004) refers to six types of heuristics and biases that are used by individuals to process information, and which are used to explain many market anomalies.

Prast (2004) refers to: cognitive dissonance, conservatism, overconfidence, self-attribution bias, the availability heuristic, and the representativeness heuristic. However, there are two other biases that have been put forward within the literature to explain under- and/or overreaction evidence and include the adjustment and anchoring bias and salience bias. Each of these biases is briefly explained below.

3.2.3.1. The representativeness heuristic

The representativeness heuristic is explained by Kahneman and Tversky (1974) through the use of various examples and is described as the practice of making a decision, under uncertainty, whereby the expected outcome most closely represents the signal or the information obtained. Prast (2004:12) defines it as the practice of looking for a pattern in a series of random events. Thus the main thought here, like the biases presented below, is
that individuals tend to deviate from certain rational or Bayesian decision-making criteria and therefore ignore the laws of probability (Barberis et al., 1998).

Specifically, six factors are ignored or given less significance than should be the case when the representativeness heuristic is present within an individual. Kahneman and Tversky (1974) refer to these deviations or factors as the individual’s: insensitivity to prior probability of outcomes, insensitivity to sample size, misconceptions of chance, insensitivity to predictability, illusion of validity, and misconceptions of regression.

In a study by Griffin and Tversky (1992), conservatism and representativeness biases are reconciled in a framework that explains how people might update their beliefs. They stated that individuals update their beliefs or estimates based on two information attributes: strength and weight: strength referring to how that information strikes the individual’s attention, and weight referring to the credibility of the information.

According to Griffin and Tversky (1992) individuals tend to put too little emphasis on the weight and too much emphasis on the strength of information. It results in conservatism where information has a high amount of credibility and a low amount of strength while representativeness occurs where information has a high amount of strength but a low amount of weight. As such, representativeness can be seen as the tendency to pay too much attention to insignificant information when it is striking to the individual.

One may assume this kind of behaviour is only present in more ignorant individuals, who are unaware of basic probability concepts. However, Kahneman and Tversky (1974) show that the representative heuristic is also found in experienced psychologists, while De Bondt and Thaler (1990) found evidence of its presence in experienced market professionals such as security analysts. Thus one cannot confine the behavioural heuristic to the more ignorant investors.

### 3.2.3.2. Behavioural models: representativeness heuristic and the presence of momentum traders

A central model that has been used to explain the existence of overreaction and therefore momentum profits is that of De Long, Shleifer, Summers, and Waldmann (1990). Like Hong and Stein (1999), discussed in section 3.2.3.14, De Long et al. (1990) showed that the very presence of momentum traders or positive feedback traders may cause overreaction in the market. In their study, De Long et al. (1990) defined positive feedback traders, which are comparable to momentum traders that do not short sell stocks, as those investors who purchase securities that have recently increased.
In their model, De Long et al. (1990) made the assumption that positive feedback traders are present in the market and that investors are subject to the representativeness heuristic. De Long et al. (1990) based these assumptions on:

1. An experiment by Andreassen and Kraus (1988) and empirical evidence by Case and Shiller (1988), and Frankel and Froot (1988), showing the presence of investors who trade on trends inferred from past data; and
2. Literature, such as Kahneman & Tversky (1974), presenting evidence of the representativeness bias and its possible effects on human behaviour in the presence of uncertainty.

Under the representativeness bias, investors are presumed to extrapolate past returns too far into the future.

DeLong et al. (1990) hypothesised that when prices increase as a result of new positive information then positive feedback traders push these prices even further in subsequent periods. Because the price moves beyond what fundamentals infer, rational investors bring the prices back to their true intrinsic values in later periods. As a result, stock prices will exhibit delayed overreaction behaviour and subsequent reversals. Therefore, according to their model, a momentum strategy should be profitable over some period and a contrarian strategy should be profitable over a subsequent period.

3.2.3.3. The conservatism bias

The psychological concept of conservatism implies that people tend to only gradually adjust their forecasts or beliefs to the arrival of new information (Edwards, 1968). In an experiment by Edwards (1986) subjects' reactions were measured against how a rational Bayesian was presumed to react when new evidence was provided. He found that although the subjects updated their beliefs in the correct direction, the weightings used were insufficient and therefore inconsistent with an idealised rational Bayesian. Edwards (1968) noted that it can take between three and five pieces of similar evidence in order for a person to update his/her beliefs where a Bayesian would only require one.

From an investment perspective, Barberis et al. (1998) stated that the need for more evidence may be due to the belief that the information contained within more recent observations may be temporary. As a result, investors disregard a portion, if not all of that information, until a more temporary shift in fundamentals can be inferred.
Griffin and Tversky (1992) stated that individuals update their beliefs or estimates based on two information attributes – strength and weight; strength referring to how that information strikes the individual's attention, and weight referring to the credibility of that information.

According to Griffin and Tversky (1992) individuals tend to put too little emphasis on the weight of information and too much emphasis on the strength of information. So conservatism occurs where information has a high amount of credibility and a low amount of strength and conversely representativeness occurs when the information has a low amount of credibility and a high amount of strength.

Conservatism bias is comparable to the definition of under-reaction stated previously: when investors get good news about a stock they initially increase the stock price by less than what they should and vice versa. So if the bias is prevalent within market participants then it is obvious how it can cause an under-reaction effect and therefore momentum behaviour in stock prices as investors gradually revise their calculations of true intrinsic values in order to fully and correctly incorporate this new information.

It is implied that investors are not fully rational in the EMH sense of the word. Conservatism biases the processing of information in a way that is inconsistent with Bayesian learning, where one observation should be enough to revise one's forecasts (Prast, 2004).

3.2.3.4. Behavioural models: representativeness heuristic and conservatism bias

Barberis et al. (1998) have set up a model that is consistent with the under- and overreaction evidence. They utilised the representativeness heuristic and conservatism bias and indicated that if investors attain information that is highly credible and therefore should be given a large weighting when updating forecasts, but which is not sufficiently striking, then there will be under-reaction in security prices. Conversely, when information is low in credibility but highly attention grabbing, then there will be overreaction in security prices.

Although their model makes use of assumptions that disallow prices to move back to equilibrium: namely there is a single investor, a single asset, and arbitrage opportunities may persist due to the unpredictability of asset prices and the possibility that investor sentiment can persist (an explanation documented in De Long et al., 1990 and Shleifer and Vishny 1997); it does provide some insight into how these psychological biases, when integrated, may affect investor sentiment and therefore stock market behaviour. What is still needed in order to confirm their model in practice is a real test of how investors react to different types of information and to determine what kinds of informational traits make that information more or less striking.
As stated by Griffin and Tversky's (1992), investors tend to put too little emphasis on highly credible yet discreet information and too much emphasis on highly noticeable yet unreliable information, and this causes conservatism. Doukas and McKnight (2005) tested that statement using a sample of 3,084 stocks in Europe and found empirical support for Barberis et al.'s (1998) model.

The limitation of Doukas and McKnight's (2005) findings is one that haunts most studies finding support for behavioural models: one has to use proxies for concepts like information strength and weight as there is no readily available and direct means of measuring these constructs. It may be that the proxies used are not linked to those constructs being measured but rather some other variable.

3.2.3.5. Overconfidence bias

The average person overestimates his or her ability, whether it is investment ability or otherwise, and there is a substantial amount of evidence within cognitive psychological literature supporting that statement (Odean, 1998). Evidence of overconfidence has been found in various professions around the world, ranging from medical practitioners (Baumann, Deber, & Thompson, 1991) and entrepreneurs (Cooper, Woo, & Dunkelberg, 1988), to investment bankers (Stael von Holstein, 1972) and other investment professionals such as security analysts and economists (Ahlers & Lakonishok, 1983; Froot & Frankel, 1989).

A related finding within the overconfidence literature is that experienced investors tend to be more overconfident than relatively inexperienced investors. Additionally that trait seems to be more extreme when the subject matter is difficult (Griffin & Tversky, 1992), requires judgement, and where feedback on decisions is delayed and uncertain (Einhorn, 1980).

Consequently one can easily see how such a behavioural heuristic may bias an investor's forecasts and investment decisions, especially given the fact that one's decisions are often based on judgement, experience, and subjective information that can easily be skewed by the individuals or institutions that provide it. Additionally, feedback on investment decisions or forecasts is often slow and subject to noise (Odean, 1998).

It is therefore implied that investors will generally overweight their information and judgements and it will be done even more by experienced investors who may sway the judgements of other, less experienced investors. Although Prast (2004) does not attribute the bias as having an influence on under- or overreaction, it may well be a contributing factor.
For example, it may lead the market to become excessively optimistic or pessimistic when it is in an upward or downward trend, which may lead to inflated or deflated market prices. Researchers such as Odean (1998) and Daniel et al. (1998) created behavioural models where overconfidence played a significant role in overreaction and both under- and overreaction behaviour in stock returns.

3.2.3.6. Behavioural models: overconfidence bias

Odean (1998) employed three different models where three different types of overconfident investors were analysed in a market where information is distributed differently. Although he made several conclusions around the effects of overconfidence on several market factors such as depth, volatility, and trading volumes, he found that the presence of overconfidence may lead to overreaction in the following situations:

1. When small amounts of information is distributed to many different traders; and
2. When information is publicly disclosed to traders who interpret it differently to one another.

However, Odean’s (1998) model was unable to explain initial under-reaction and therefore momentum profits.

3.2.3.7. Self-attribution bias

Although the overconfidence bias in Odean’s (1998) model was able to explain overreaction behaviour, it was unable to explain the under-reaction behaviour on its own. Another related behavioural bias - self-attribution - has been used within the literature to explain the under-reaction evidence. Self-attribution bias is where people tend to process information in a way that favours their beliefs and can even occur when they are making a conscious effort to be objective (Prast, 2004).

Like overconfidence, self-attribution bias has been documented extensively within psychological literature. The literature maintains that on the one hand, individuals tend to associate information that validates their beliefs or actions with their ability, while on the other hand they associate information that conflicts with their actions to external noise or sabotage (Daniel et al., 1998).

From a traditional finance perspective, all things being equal, any bias due to overconfidence should be eliminated through one’s rational learning process. One’s rational learning process should overcome overconfidence bias as people would presumably fail more than they expect to, given their overconfidence.
But, according to Hirshleifer (2001), self-attribution bias hinders the rational learning process. Additionally, he stated that the overconfidence and self-attribution biases are static and dynamic counterparts because self-attribution bias causes individuals to become and remain overoptimistic about their ability. If investors attribute expected market movements to their skill and unexpected movements to sabotage or market ‘noise’ then investors would typically become too confident in their abilities.

Although Prast (2004) refers to that behavioural heuristic as only being a contributing factor to the dynamics of overconfidence, thereby inferring its possible influence on overreaction behaviour in stock returns; Daniel et al. (1998) used self-attribution bias as an integral part of their behavioural model. What they found was self-attribution bias could drive lagged overreaction behaviour in stock prices as any information that confirms an investor’s own views or estimates may trigger further overreaction to the investor’s previous signal.

If self-attribution bias is indeed prevalent within the market then it implies that investors are not completely rational as assumed by EMH theorists. Daniel et al. (1998) stated that when the bias is prevalent then investors may be said to be quasi-rational in that they optimise any and all information available to them, however they over-assess the accuracy of their private information and their price adjustment process is biased in a manner that puts them in the best light.

3.2.3.8. Behavioural models: overconfidence and self-attribution bias

While Odean (1998) did not provide insight into both empirical findings of initial momentum and subsequent reversals in stock prices, as his study does not reconcile the under-reaction evidence with the overreaction evidence, he did provide some insight into how overconfidence might influence prices in a way that is consistent with some of these empirical findings; specifically with regards to the success of contrarian investment strategies.

Daniel et al. (1998), on the other hand, went a step further and distinguished between public and private information. They stated that if investors are overconfident about their ability to generate, analyse and interpret information, then they will overweight the information or estimates that are generated by them, known as private signals, and underweight the information or estimates that are generated by the public, known as public signals. Additionally, they define an overconfident investor in that manner.

When utilising the overconfidence assumption and the asymmetry in weightings between private and public signals within their model, Daniel et al. (1998) found that overconfident
informed investors may cause an initial overreaction to information and as more public information comes into the market, so it slowly adjusts to the ‘correct price. As such, their results were found to be consistent with overreaction behaviour, which a long-term (three to five years) contrarian strategy attempts to take advantage of.

There are two differences between Odean’s (1998) model and Daniel et al.’s (1998) model. Firstly, Daniel et al.’s (1998) model assumed that investors are overconfident about their own private information yet they are tentative about public information. Consequently, investors overweight their private information and underweight public information. As such, they find results that are consistent with both the under- and overreaction hypotheses.

Secondly, Daniel et al. (1998) made use of a second psychological bias – self-attribution whereby individuals’ adjustments to their overconfidence are biased upwards, thereby causing further overreaction and positive serial correlation in returns over the short-term (six to twelve months). Consequently, Daniel et al.’s (1998) model was not only found to be consistent with the overreaction hypothesis, but also the under-reaction hypothesis and therefore successful, yet contradictory investment strategies.

In contrast to Barberis et al. (1998), Daniel et al. (1998) made use of two different, yet not conflicting behavioural heuristics – overconfidence and self-attribution bias. Barberis et al. (1998) stated that it is possible for all four behavioural biases (representativeness, conservatism, overconfidence, and self-attribution bias) to be present and come to similar conclusions in both Daniel et al. (1998) and Barberis et al. (1998).

Daniel et al. (1998) used self-attribution bias as an integral part of their behavioural model. What they found is self-attribution bias can drive lagged overreaction behaviour in stock prices as any information that confirms an investor’s own views or estimates may trigger further overreaction to the investor’s previous signal.

Daniel et al. (1998) went on to say that such a reaction is therefore consistent with the empirical evidence whereby market prices initially exhibit momentum behaviour and see a subsequent reversal. Their model explains why there may be under-reaction or overreaction, followed by lagged momentum in stock prices that pushes them even further past their true intrinsic value and the subsequent reversal in prices that brings them back to their true intrinsic or equilibrium value.

The assumptions made in Daniel et al. (1998) around investors’ behaviour and psychological biases imply investors are not completely rational, as was previously assumed by EMH theorists. In their model, investors are said to be quasi-rational in that they optimise any and
all information available to them, with one exception: they over-assess the accuracy of their private information and their price adjustment process is biased in a manner that puts them in the best light.

3.2.3.9. The availability heuristic and salience bias

Two related biases presented within the literature are the availability and salience biases. The basic thought behind the availability heuristic is that people tend to estimate the probability of an outcome based on the ease with which it comes to mind (Prast, 2004). Salience bias occurs where people tend to focus on information that is mentioned often and therefore stands out. Thus the probability of a scenario that easily comes to mind may be exaggerated as a result of the availability heuristic and therefore a result of salience bias.

These heuristics are well documented within psychological literature. Slovic, Fischhoff, and Lichtenstein in 1988 (cited in Bell & Raiffa, 1988) found that people tend to exaggerate the probability of more publicised scenarios, which they stated are those scenarios that easily come to mind as a result of their publicity. Taylor and Fiske (1975) confirmed the finding when their subjects tended to exaggerate the impact people facing them had on the conversation as opposed to those people that did not face them. As such, they concluded that the more salient or available something is, the higher its impact on people’s minds.

Daniel, Hirshleifer, and Teoh (2002:178) suggested that the evidence points to the possibility that while people weight some signals too heavily, they neglect others. What it means in a market setting is that on average, the market will under-react to new information as there is a smaller pool of risk bearers possessing this new signal.

3.2.3.10. Behavioural models: availability heuristic and salience bias

Daniel et al. (2002) presented the availability and salience biases as a fundamental explanation for market mispricing. In keeping with that line of thought, Cooper, Gutierrez, and Hameed (2004) stated that there is an increased amount of media coverage on the stock market during recessions as opposed to boom periods and as a result, investors may overreact to information during these times, thereby causing initial overreaction and subsequent reversals in security prices.

3.2.3.11. The adjustment and anchoring biases

Epley and Gilovich (2006) asserted that one method people use to make a decision under uncertainty is to create a reference point or anchor and then make the necessary
adjustments to the anchor to arrive at an estimate or forecast. As such, adjustment and anchoring bias refers to the method of forming estimates, however this biases the estimates as the adjustments made are insufficient (Kahneman and Tversky, 1974). Kahneman and Tversky (1974) showed that in contrast to the rationality assumption, people tend to inappropriately adjust their forecasts when using a reference point.

Epley and Gilovich (2006) found that the anchor people tend to use creates friction in the adjustment process, thereby leaving their estimates too close to the anchor value. Evidence of adjustment and anchoring bias has been documented in both an experimental setting (Jacowitz & Kahneman, 1995) and a field setting (Mussweiler & Strack, 2004). As such, one can see how such a bias can be said to cause under- or overreaction to information depending on the relative standing between the forecasted value and reference value of the given variable - in the case of this study it would be price.

3.2.3.12. Behavioural models: adjustment and anchoring biases

From an investment perspective, the adjustment and anchoring bias has been presented as a possible source of momentum profits in Campbell and Sharpe (2009) when they found that expert forecasts of monthly economic releases tended to be biased toward the previous month’s forecasted values.

George and Hwang (2004) used the adjustment and anchoring bias in explaining the momentum profits observed within the literature. They hypothesised that investors set the 52-week high as their anchor or reference point when determining what the correct adjustment to their estimates should be. The thought here was that investors will under-react to positive or negative information about stocks that are close to, or far from their 52-week high respectively. As good or bad news eventually prevails, so the stock price moves towards its true intrinsic value. As a result, under-reaction produces momentum in stock prices.

They tested the adjustment and anchoring bias hypothesis by simulating a strategy that purchased stocks whose current price is closest to the 52-week high and selling stocks whose price is furthest from that reference point. Additionally, they compared their strategy profits to those produced by Jegadeesh and Titman’s (1993) simple momentum strategy and found their profits to be superior over the period 1963 to 2001. As such they concluded that the evidence is consistent with under- and overreaction behaviour resulting from the anchoring bias.
3.2.3.13. Behavioural models: market composition

Thus far, the literature that makes use of behavioural psychology to explain the under- and overreaction effects has only been discussed. However, there are other models whose basis also comes from psychology, but where the focus is not on the individual’s internal processes but rather on a macro level.

These models integrate the social interactions of investors and the way in which the market is comprised in order to explain the under- and overreaction phenomena. Specifically, theories where the composition of the market, the interactions between market participants, and the way in which information is disseminated throughout the market have also been used to explain the under- or overreaction effects.

Barberis and Shleifer (2003) looked into the effects of style investing on market prices. Style investing is where investors prefer to allocate funds to different styles rather than individual securities; where a ‘style’ is a group of assets with similar characteristics, such as high or low P/E ratios. Barberis and Shleifer (2003) set up a model where they assumed the market is comprised of fundamental investors and style investors.

These style investors essentially use a momentum strategy and allocate funds at the style level rather than an individual security level. As such, they move funds into styles that have performed well in the past and move funds out of styles that have performed badly in the past.

Barberis and Shleifer (2003) found if the market consists of these types of investors then stock returns will be positively auto-correlated in the short run and negatively auto-correlated in the longer run as prices revert back to fundamentals.

Teo and Woo (2004) tested the model in the US stock market from 1978 to 1999 and found evidence consistent with style momentum. Their style level momentum factor was able to predict the profitability of stock-level momentum strategies. Additionally, earlier research has provided indirect evidence of style investing effects on stock price behaviour. Moskowitz and Grinblatt (1999) found evidence of industry momentum, while Lewellen (2002) found momentum in securities with similar size and book-to-market variables.

3.2.3.14. Behavioural models: market composition and information diffusion effects

Like Daniel et al. (1998) and Barberis et al. (1998), Hong and Stein (1999) set up a model that explained both the under- and overreaction phenomena where certain EMH
assumptions were relaxed. However, their three assumptions did not infer any internal bias in the way people interpret information. Specifically, they assumed that:

1. There are only two types of investors in the market: news watchers and momentum traders;
2. Market participants are "boundedly rational" (Hong & Stein, 1999:2143). Each market participant is only able to process a portion of all publicly available information - news watchers condition their decisions on privately observed information only and not on current or past prices, while momentum traders make forecasts based on current and past price data only; and
3. Private information diffuses slowly across the news watcher population and therefore it is not rapidly incorporated into the price estimates of those market participants.

There are other models that provide a case for momentum traders playing a significant role in price formation (Goetzmann & Massa, 2000). In addition, it is not a farfetched assumption as Froot, Scharfstein, and Stein (1992) show how heterogeneity in investor horizons and information can cause investors to trade on past price data, while Grossman (1995) shows it may also be the case in an incomplete market.

Hong and Stein (1999) demonstrated with the use of these assumptions that it is possible for stock prices to exhibit both under-reaction and overreaction, without market participants being overconfident, hesitant, or optimistic about the future prospects of stocks. By assuming information diffuses slowly across the news watcher population and that groups of investors do not make use of past price data, they showed how there may be under-reaction to new information.

With momentum traders added, Hong and Stein’s (1999) model also shows how the initial under-reaction turns into overreaction. The basic price behaviour resulting from their model is that news watchers initially push the price in a positive or negative direction, although not enough, thereby causing under-reaction. Momentum traders and news watchers then bring the price to equilibrium.

However, as more and more generations of momentum traders start implementing their strategy, so the price overshoots its equilibrium price as determined by the initial news event, thereby causing overreaction. There is then a subsequent adjustment as news watchers bring the market price back to what fundamentals inferred.

Although the model seems incomplete in that it is assumed there are no fully rational arbitragers within the market, Hong and Stein (1999) did go on to relax their assumptions by
adding an arbitrageur group of investors. By doing so, their results still held as long as it was assumed that the arbitrageur group of traders have set risk tolerance levels.

Furthermore, Hong et al. (2000) tested Hong and Stein’s (1999) model by determining whether a momentum strategy works best when focussed on stocks for which there is either low analyst coverage or that have small market capitalisations, which are both assumed to be a proxy for a slow rate of information diffusion. Hong et al.’s (2000) sample of NYSE/American Stock Exchange (AMEX), over the period 1980 to 1996, demonstrated that a negative relationship existed between small stocks, momentum profits, and analyst coverage. These findings were further underscored by the findings of Doukas and McKnight (2005).

An interesting aspect to note about Hong and Stein’s (1999) model is that unlike the behavioural models presented earlier, they are able to explain the empirical observation that a momentum strategy seems to be abnormally profitable over a six to twelve month holding period (Jegadeesh & Titman, 1993). Hong and Stein (1999) stated that according to their calculations one would expect the strategy to be profitable when momentum traders have an investment time horizon of between twelve and eighteen months and related it to the implied average holding period on the NYSE of twenty to twenty-four months.

3.2.3.15. Behavioural models: market composition and the disposition effect

As stated by Grinblatt and Han (2002), one of the well-documented behavioural phenomena found among investors is the disposition effect. That is, investors are generally more inclined to hold onto loser stocks than they are to hold onto winner stocks (Shefrin & Statman, 1985). Grinblatt and Han (2002) analyse the effect it may have on market prices and create an equilibrium model whereby the market is composed of both rational investors and a fixed proportion of investors who are subject to the disposition effect.

Under these assumptions disposition investors have a higher demand for losing stocks than for winnings stocks, which results in price under-reaction. The reason being that these past winner stocks are undervalued in the market, due to the selling pressure by disposition investors, while past loser stocks are overvalued, due to the buying pressure from the same investor segment. However, due to the rational investor segment, market prices eventually revert back to their fundamentals and therefore past winners tend to outperform past losers.

Grinblatt and Han (2002) test their model by analysing the cross-sectional returns on NYSE/AMEX stocks between 1962 and 1996. They found that their capital gains variable, a capital gains overhang assumed to proxy unrealised capital gains or losses, was able to
predict future returns on their momentum portfolio even after accounting for differences in risk. Once their capital gains effect was controlled for, their momentum profits disappeared.

3.3. EMH explanations for momentum strategy profits

Unlike the behavioural explanations for momentum profits, the EMH explanations that are presented below are ones in which the traditional assumptions of investor rationality, access to information, and high competition are adhered to. As a result, these explanations reject the proposition that the market is inefficient and accept that the returns on momentum strategies can be attributed to some economically meaningful risk factor/s.

In general, the literature (Hong & Stein, 1999) that takes an EMH conforming perspective, does so by highlighting methodological drawbacks within the previous literature showing abnormal momentum profits, derived from either the use of inappropriate or biased data, or an inappropriate test methodology whereby certain factors such as risk or transaction costs are not sufficiently taken into account. This section presents the literature that has been broadly grouped as EMH explanations for the profitability of momentum strategies.

3.3.1. Misspecification of asset pricing models

A consequence of the EMH is that one should be able to trace any return on a risky security to some meaningful risk factor or factors (Hong & Stein, 1999). As a result any model used to represent an efficient market relies on it being correctly specified. That is, the validity of the model is reliant on:

1. It sufficiently taking the level of risk inherent within the security into account; and
2. All risk factors which have an impact on the stock’s returns are incorporated into the model (Jensen, 1978).

Consequently when a model is used to test the efficiency of the market, such as the CAPM or APT, it should be specified correctly in order for the results of the test to be valid. However, until a model can be proven to be a true reflection of an efficient market, one’s tests have to incorporate an if and then hypothesis. That is, one must hypothesise that if the model is specified correctly, then the market is (in)efficient based on the data used.

Even if overwhelming support against the EMH is provided, based on the appearance of abnormal momentum profits, one cannot conclude that these abnormal profits are truly present as one’s efficient market models might not be correctly specified.
For that reason, misspecification problems are another strong support for the EMH as it argues that such profits are illusionary and result from misspecified market models. Indeed, the seminal paper of De Bondt and Thaler (1985) posed the problem as being a serious drawback to their results. As such, the support for the EMH is actually a methodological issue which all tests for the EMH face when an efficient market model is used.

Unfortunately, there is still no known model that can be presented as perfectly representing an efficient market. Hence, one cannot unconditionally conclude that there are abnormal profits from momentum or contrarian strategies, leading to a significant limitation to this and previous studies.

3.3.2. Time-varying systematic risk

A related support for the EMH is the question of whether the risk-adjusted returns on momentum strategies have taken the time-varying nature of risk into account. As stated earlier, the evidence for momentum strategy profits in excess of that explained by risk is widely available. However, previous studies generally make use of an unconditional CAPM or a Fama-French three-factor model.

These models do not take into account the fact that the systematic risk of stocks and their sensitivity to the market (or the benchmark used) changes over time. For that reason researchers such as Conrad and Kaul (1998), Berk et al. (1999), and Chordia and Shivakumar (2002) argued that momentum profits are still a result of purchasing high expected return stocks and selling low expected return stocks. As such, these researchers argue that the momentum strategy exploits the incremental changes in risk and the sensitivity to the benchmark portfolio. It is implied that momentum profits are a result of cross-sectional time variability in expected returns (Chordia & Shivakumar, 2002).

The main thought underpinning the time-varying systematic risk explanation is that risk premiums and the systematic risk of stocks change over time. Berk et al. (1999) argued that profitable stocks are those that exploit profitable investment opportunities, however as these investments are made and as the firm's asset portfolio changes over time, so too does the systematic risk of the firm.

Conrad and Kaul (1998) analysed the profitability of both momentum and contrarian investment strategies, implemented on the NYSE and AMEX, and concluded that cross-sectional variation in returns may account for both strategies' profits. Berk et al. (1999) and Chordia and Shivakumar (2002) also found evidence of momentum strategy profits resulting from time-variation in expected returns.
Berk et al. (1999) studied the relative importance of firm-specific variables in explaining changes in systematic risk. In their model, the value of a firm is dependent on interest rates, the number of projects underway, and the systematic risk of these projects. If the turnover of these projects is slow, then the persistence of the firm’s asset base and its systematic risk results in positively correlated returns.

Chordia and Shivakumar (2002) on the other hand used a set of lagged macroeconomic variables related to the business cycle in predicting stock returns. They found that momentum strategies systematically varied in their sensitivity to these macroeconomic variables. Moreover, when they controlled for the effect, they found that abnormal momentum strategy profits were no longer present. As such, they concluded that time-variation in systematic risk is the main cause for momentum profits and as such, the momentum strategy does not show evidence of inefficient markets.

A theory that falls within the risk explanation is the uncertain information hypothesis proposed by Brown, Harlow and Tinic (1988). They hypothesised that when market participants are surprised by new information, the systematic risk of the stock increases as a result of the increased uncertainty in that stock. Hence a risk averse investor would rationally require a higher rate of return for the increase in risk.

In addition, Schiereck, De Bondt, and Weber (1999) stated that past performance, size, and the level of share prices have been used as proxies for risk in past literature, therefore by forming portfolios based on past performance, one may actually be forming a portfolio based on risk. However, Rey and Schmid (2007), after adjusting for risk, still found evidence of overreaction and the subsequent price reversals on the Swiss stock market.

Grundy and Martin (2001) acknowledged the invariable exposure to time-varying systematic risk when implementing a momentum strategy. However, unlike the studies cited above, Grundy and Martin (2001) found that the Fama-French three-factor model was unable to explain the mean returns on their momentum strategy after controlling for dynamic risk exposure. Like Chordia and Shivakumar (2002), Griffin et al. (2003) study the possibility of macroeconomic variables explaining momentum strategy profits. However, unlike Chordia and Shivakumar (2002), they do not find any evidence of that being the case.

Nagel and Lewellen (2006) took a slightly different angle when testing the time-variation explanation. They argued that the variation in betas and the equity premium would have to be impossibly large in order for the time-variation in systematic risk to be a plausible explanation. Additionally, they found that although betas vary significantly over time, they do not vary enough to explain the size of momentum profits observed. As a result they
concluded that although time-variation in betas does have an impact on one's asset-pricing tests, the impact is relatively small and therefore cannot be the only explanation for momentum profits.

3.3.3. Bid-ask bounce effects

Ball, Kothari, and Wasley (1995) stated that although the theories explaining market behaviour have changed over time, one thing that has remained constant is the methodology employed to test various trading strategies. All studies that test the profitability of trading strategies have done so with the use of simulation techniques using historical data rather than actually implementing the strategy in reality. As a result, there are several issues that arise, which call the validity of the results into question. Specifically, the practical aspects, known as market microstructure effects, are generally not taken into account.

Market microstructure theory refers to a branch of economics that studies the effects the mechanics of trading have on trading costs, prices, volume, and trading behaviour (O'Hara, 1995). Bid-ask bounce refers to one of the market microstructure effects that may influence the calculated returns in simulation studies. It occurs as a result of transactions being executed at different places within the bid-ask spread.

With respect to contrarian studies, the price of a stock will generally take place at the ask price when more investors wish to sell than to buy. If on the next day, there is a balance between buyers and sellers, trades should occur around the mid-point of the spread, thereby showing a return reversal, when the stock has not moved (Bowman & Iverson, 1998).

Bid-ask bounce is said to bias studies into momentum effects when the price of a stock at the end of the formation period is the same as its price at the beginning of the holding period (Conrad & Kaul, 1993). Thus many studies such as Gunasekarage and Kot (2007) skipped a day, a week, or even a month between the formation and holding periods, thereby reducing the possibility of bid-ask bounce occurring.

Ball et al. (1995) showed that when these effects are taken into account, the abnormal profits found using contrarian strategies are reduced significantly. Although not all abnormal profits were reduced, bid-ask bounce did have a significant effect and therefore it has the potential to cause illusionary profits for both momentum and contrarian simulation studies.

Another issue related to the bid-ask bounce effect is the actual transaction price at which trades would be executed. In a typical study, price data is taken from large-scale databases, which utilise closing prices recorded each day. However, according to Ball et al. (1995),
these closing prices are only estimates of the actual closing price as they are generally taken from the last trade of the day, either bid or ask, or the average bid-ask price in the absence of trades in that stock. As such, one may not be able to execute trades at these prices and therefore return calculations may be inaccurate (Ball, Kothari, & Wasley, 1995).

Conrad et al. (1997) showed that a change in the price within a short-term simulation study is made up of a true change and a measurement error. As a result, they showed that even if there is no autocorrelation between the true price changes, observed changes may exhibit some negative autocorrelation. After controlling for the market microstructure effect, Conrad et al. (1997) found that the short-term profits observed using a contrarian strategy on the NASDAQ were eliminated, thereby allowing them to conclude that there was no evidence in their sample of an overreaction effect.

Park (1990) on the other hand found that the short-term returns within his sample could not be explained entirely by the bid-ask bounce effect. One should note however that the effect becomes less important when long investment horizons are being evaluated (Venter, 2009). In addition, the bid-ask bounce issue can be exacerbated when shares are traded relatively infrequently where in one week, the bid price is recorded and in the next week, the ask price is recorded or vice versa.

Bowman and Iverson (1998) found that the bid-ask bounce effect was restricted to the smaller, more illiquid stocks in their sample. In addition, where the spread is sufficiently large, which is more likely in stocks that are not very active or are relatively illiquid, the bid-ask bounce has more room to cause illusionary profits (Scowcroft & Sefton, 2005).

3.3.4. Transaction costs

As stated by Jegadeesh and Titman (1993), one should always determine whether the abnormal profits from some set of trading rules, in this case momentum strategy rules, still exist after taking into account any transaction costs that would be incurred when implementing the strategy. The authors further stated that it is important from a practical perspective, however it can be argued that it is also important from a theoretical perspective where one relaxes the traditional ‘no transaction cost or taxes’ assumption.

Since the presence of market frictions is well accepted, an economically more sensible version of the efficiency hypothesis says that prices reflect information to the point where the marginal benefits of acting on information do not exceed the marginal costs (Fama, 1991:1575).
Hence the no-arbitrage principles, upon which neoclassical finance is based, do not hold in so far as they are not profitable to act upon. The reason being that arbitragers will have no incentive to act upon arbitrage opportunities where these opportunities do not create riskless profits or profits that more than compensate for all risk incurred or where these opportunities do not provide sufficient profits after accounting for transaction costs.

Lesmond et al. (2004) re-examined momentum strategy profits in light of possible trading costs and found that momentum strategies tend to incur high trading costs in their sample. They argued that momentum strategies tend to sell smaller, less liquid stocks, which tend to have higher transaction costs. They concluded that abnormal momentum profits are not present once these costs have been taken into account. However, it should be noted that they based their conclusion on a six-month formation period by six-month holding period (six-by-six) momentum strategy and therefore it is uncertain as to whether they would have come to the same conclusion when using a longer time horizon such as a six-by-twelve or twelve-by-twelve strategy.

Subsequent to Lesmond et al. (2004), Li, Brooks, and Miffre (2009) discovered conflicting evidence in the UK stock market. Li et al. (2009) found that when using a host of different strategies, combinations of three, six, and twelve month formation and holding periods, abnormal momentum profits are still present in six of the nine strategies tested. Authors such as Korajczyk and Sadka (2004) and Hanna and Ready (2005) have also found significant momentum profits after accounting for transaction costs.

Hanna and Ready (2005) found statistically and economically meaningful abnormal profits from momentum strategies, while Korajczyk and Sadka (2004) also studied the effect of transaction costs on abnormal momentum profits. Korajczyk and Sadka (2004) concluded that although abnormal momentum profits are present, they only persist for a relatively small scale investment (less than $200 million). Intrinsically it seems that although transaction costs tend to be a driving factor for abnormal momentum profits, it is not the only explanation.

### 3.3.5. Data mining bias

When an anomaly of the EMH is observed, a natural reaction by EMH supporters is to question the validity and reliability of the data used. One of the main issues in this regard is known as data mining bias. Data mining bias refers to the process whereby one searches a data set until a statistically significant pattern is found.
Although Jegadeesh and Titman (2001) stated that the data mining explanation is one of the harder issues to completely address, due to data availability limitations, it can now be argued that it is no longer the case. Firstly, now that nearly two decades have passed since the first documented case of momentum strategy success (Jegadeesh & Titman, 1993), far more from the sample data is available to researchers. Additionally, the anomaly has been documented by many other researchers in many different time periods and in many different markets around the world. As such, the results of Jegadeesh and Titman’s (1993) seminal study have largely been validated both in- and out-of-sample.

Indeed, Jegadeesh and Titman (2001) and many other researchers, such as Rowenhorst (1998), Schiereck et al.(1999), Fraser and Page(2000), Kang et al.(2002), Gunasekarage and Kot (2007), and Rey and Schmid (2007), have tested the momentum strategy in various markets and have generally come to similar results. Additionally, this study will add further evidence in this regard that may either validate or contest their results from a SA market perspective.

3.4. Bull and bear market states: implications for the momentum investment strategy

The theory and evidence surrounding momentum investment strategies and the under- and overreaction hypotheses were discussed in the previous sections. The literature that more directly assesses the main topic of this paper will be addressed in this section. Specifically, the previous literature that has studied the under- and overreaction effects over bull and bear sub-periods, using momentum investment strategies, will be presented here.

3.4.1. Research into varying market states and their contribution to under- and overreaction evidence

Researchers have been concerned with how momentum profits vary over different market states and different periods for four main reasons. Firstly to determine whether these profits are due to data mining bias or some anomalous period where markets were somehow inefficient (Jegadeesh & Titman, 2001); secondly to determine whether momentum profits are due to macroeconomic risk, as hypothesised by Chordia and Shivakumar (2002); thirdly to gain more understanding of the dynamics of bull and bear market states as studies into various phenomena tend to be inconsistent across these phases such as reduced diversification benefits in bear markets found by Butler and Joaquin, (2002); and stronger weekend effects during bear market phases documented by Arsad and Coutts(1996).
Lastly, these studies provide more insight into the workings of the market and the way in which explanatory psychological biases may fluctuate and/or explain the different price behaviour over different market states (Siganos & Chelley-Steeley, 2005).

3.4.1.1. Data mining bias

Given the evidence presented in section 2.7.2, the data mining bias explanation seems unlikely. Specifically, the momentum anomaly has been found both over different geographical areas and over different time periods. Statistically and economically significant momentum profits have been observed in Europe (Rowenhorst, 1998), the US (Jegadeesh & Titman, 1993), Asia (Chui, Titman, & Wei, 2005), SA (Fraser & Page, 2000), and also other emerging markets (Griffin et al., 2003). Moreover, subsequent to Jegadeesh and Titman’s (1993) initial analysis of the US stock market, the same researchers found momentum profits in the US over a more recent time period in Jegadeesh and Titman (2001).

From a SA perspective however, there is far less empirical evidence for or against the presence of momentum profits. Only two studies have been conducted that investigate this topic. Griffin et al., (2003) on the one hand found momentum evidence in SA over the period September 1990 to December 2000.

Griffin et al. (2003) did not focus on SA shares only but rather took an international perspective and studied these effects in 39 countries, both developing (such as Brazil, Mexico, India, and SA) and developed (such as Australia, Japan, the US, and the UK). Fraser and Page (2000) subsequently concurred and found significant momentum profits from December 1977 to September 1997.

Although this provides strong evidence against the data mining bias explanation, value can still be gained from further studies over other periods in the SA market due to:

1. The limited number of studies in this area from a SA perspective; and
2. The testing of the statement that markets should become efficient as more investors become aware of repetitive market behaviour.

3.4.1.2. Macroeconomic risk

The second and arguably more relevant reason for exploring the momentum phenomena over different market states is to see whether macroeconomic risk explains these momentum profits. The argument, although consistent with Chordia and Shivakumar’s (2002) initial study where they came up with the hypothesis and evidence to accept it, was found to be inconsistent with the international evidence presented by Griffin et al. (2003).
Griffin et al. (2003), found that macroeconomic variables assumed to mimic macroeconomic risk were unrelated to the momentum profits they observed. Additionally, significant momentum profits were observed in both good and bad market cycles and were therefore inconsistent with the business cycle risk explanation.

The reason for the inconsistency between the evidence documented in Griffin et al. (2003) and the business cycle risk explanation is that if a momentum strategy inherently chooses securities that are riskier during certain segments of the business cycle, then one can safely assume that the same strategy would choose stocks that are less risky in others. Consequently if the macroeconomic risk explanation reflects reality, then a momentum strategy should not be abnormally profitable throughout the business cycle.

3.4.2. Insights into investor psychology and bull and bear market states

There are various papers studying momentum investment strategy returns during different sub-periods, with little consensus. Schiereck, De Bondt, and Weber (1999) examined the contrarian and momentum investment strategy in Germany and found the momentum strategy to be profitable no matter the state of the market; although they do not draw any conclusion as to the strength of these momentum profits during the various sub-periods.

Griffin et al. (2003) also found statistically significant momentum profits regardless of the state of the market, however their momentum profits tended to be larger during bear periods. Rey and Schmid, (2007) corroborated that evidence in the Swiss market, while Cooper et al. (2004) and Wang, Jiang, and Huang (2009) found that momentum profits were generally stronger during bull markets in the US and Taiwan respectively.

3.4.2.1. Evidence for larger profits during bull periods

Although a number of studies (Schiereck, De Bondt, and Weber, 1999; Griffin et al., 2003; Cooper et al., 2004; and Wang et al., 2009) provide conflicting evidence over different markets and market states, they are able to provide some insight into the workings of investor psychology and how it may or may not affect stock price behaviour. For example, Cooper et al. (2004) and Antonios and Patricia (2006) found empirical support for the behavioural model of Daniel et al. (1998) when they both found momentum profits to be larger following bull periods. As discussed in section 3.2.3.8, Daniel et al. (1998) model is linked to investor overconfidence.

Daniel et al. (1998) posited that the momentum effect originates from the continued reaction by informed investors to the arrival of confirming news. Thus when the market moves higher,
investors become overconfident in their ability, which boosts overreaction and therefore momentum profits. Therefore, to the extent that the aggregate market position is long, a bull period causes increased overconfidence as investors attribute these gains to their skill, thereby causing higher momentum profits.

Another model that is consistent with Cooper et al.’s (2004) and Antonios and Patricia’s (2006) findings is that of Hong and Stein (1999). In Hong and Stein’s (1999) model, investors tend to under-react to information, which only gradually diffuses throughout the market place. The gradual diffusion of information through the marketplace coupled with the presence of momentum traders, causes initial under-reaction, followed by overreaction.

Hong and Stein (1999) also found that as they decrease momentum investors’ risk aversion, so their delayed overreaction increases, thereby increasing momentum gains. Thus to the extent that risk aversion and wealth are negatively associated, as posited by Campbell and Cochrane (1999), their model predicts that momentum profits will be stronger in a bull market phase.

3.4.2.2. Evidence for larger profits during bear periods

In Kaminsky and Schmukler’s (1999) analysis of the Asian Crisis, they concluded that prices overreact more strongly as a crisis worsens, indicating an overreaction to bad news and more so during a bear period. It may be a result of investors being less likely to use good news in a bear market state than they are to use bad news in a bull market state.

As discussed in Balsara et al. (2006) the tempered use of good information during a bear market state may cause an even slower rate of information diffusion across the market, which, as stated earlier, can lead to market under-reaction. The result may be that instead of correctly tempering negative information with positive information when making forecasts and decisions, investors discount that positive information during bear periods, thereby causing either under-reaction to good news, or overreacting to bad news.

Another possible explanation put forward by Siganos and Chelley-Steeley (2005) is that investors who have been realising losses, which will occur especially during a bear market, tend to under-react or hesitate to current information, thereby causing stronger momentum profits. Investors’ hesitation or under-reaction may be a result of pessimism and as stated by Siganos and Chelley-Steeley (2005) is consistent with the representativeness heuristic and Du’s (2002) behavioural model.

Du’s (2002) model assumed that investors are likely to demonstrate higher hesitation when selling a stock due to the potential losses they face or already incurred. Hesitation therefore
leads to initial under-reaction, followed by a subsequent adjustment in the same direction. It does not however predict the subsequent price reversals found in De Bondt and Thaler (1985).

Another theory that explains market overreaction and its subsequent reversals on the behavioural front is that of Daniel et al. (2002). They stated that investors may overreact to news, especially during bear market phases as a result of what they call salience bias. That is, investors overreact as a result of the abundance of the news that makes these signals more striking to investors.

Daniel et al. (2002) stated that market commentary is more prevalent during recessions and as such, one tends to see higher momentum profits during a bear period. Balsara et al. (2006) found that the momentum strategy works best especially during bear markets, while Rey and Schmid (2007) found support for this.

Both Balsara et al. (2006) and Rey and Schmid (2007) distinguish between low and high volatility stocks and found that the higher the volatility during these bear periods, the higher the profits from the momentum portfolios. Furthermore, Maheu and Mc Curdy (2000) stated that bull markets can be characterised as having relatively low volatility while bear markets have relatively high volatility. Consequently an explanation for the differences in profits from the momentum strategy, which is consistent with higher profits during bear periods, is that it is not the state of the market that necessarily has an impact, but rather that volatility or uncertainty somehow has an effect on momentum strategy profits.

3.4.2.3. Evidence for profits regardless of the market state

Kaminsky and Schmukler (1999) and Keijer and Prast (2001) found evidence of momentum investment strategy success. Keijer and Prast (2001) found that there was overreaction to good news during the telecommunications hype (1 October 1999 to 1 March 2000) on the Amsterdam Stock Exchange. As stated by Prast (2004), the overreaction evidence in both bull and bear periods provides support for the presence of cognitive dissonance in the market. That in turn results in under-reaction to regime opposing news during bull and bear periods alike as investors hesitate or do not respond to good news in a bear period or bad news in a bull period.

Although Prast (2004) implied the evidence is supportive of models utilising cognitive dissonance, it also indicates that many of the psychological biases presented in section 3.2.3 are also present. Thus it is expected that the momentum strategy will do well no matter the state of the market.
One model that conforms to the indifference of returns to market states is that of Kim (2002). In Kim’s (2002) behavioural model, momentum arises as a result of investors buying shares that are rising and selling shares that are falling. As such, if investors are trading to the same degree in both directions, the model predicts that momentum profits should not be affected by the state of the market.

There are both theories and evidence which point to several different conclusions. Consequently, this paper will attempt to see which theory, behavioural or otherwise, best fits in the SA stock market context. As such, this paper may provide further information and evidence of the presence or absence of under- and/or overreaction effects in SA.

3.5. Summary

There are several efficient market anomalies that have been observed in various markets around the world. Evidence of momentum and contrarian investment strategy success is one such anomaly and its evidence is widespread. In trying to come to terms with this market anomaly, researchers have generally provided two sets of explanations: behavioural explanations and efficient market explanations.

The important difference between these two sets of explanations is centred on investor rationality and the efficient flow of information throughout the market. The behavioural line maintains that there is either under- or overreaction in the market as a result of the inefficient use and flow of information in the market due to behavioural and social biases. In turn, under- or overreaction in the market causes deviations in the equilibrium price of securities.

While there seems to be some consensus in the behavioural explanations literature with regards to under- and overreaction causing momentum strategy success, there is far less consensus about the cause of under- and overreaction. Specifically, this paper has discussed several behavioural models, presented in the literature, that explain under- and overreaction using one or more behavioural, social, or informational biases.

Conversely, the efficient market explanations support the EMH and in some way these explanations state that the perceived abnormal momentum portfolio profits are illusionary and rather a result of risk, market microstructure effects, transaction costs, inadequate market models, or data mining.

As a result of the wide range of possible explanations for momentum strategy profits, further evidence is required to focus the literature on the explanations that represent empirical
evidence. Researchers have conducted similar research in various markets around the world with abnormally profitable strategies being found over bull and bear market states.

These papers have provided support for some of the efficient market explanations, while others have provided support for some of the behavioural explanations. However, similar research is yet to be conducted in a SA stock market context and as such, this paper attempts to do so in the chapters that follow.
Chapter 4
Research Methodology

4.1. Introduction

The presence of under- and/or overreaction effects imply that stock returns should exhibit positive and/or negative auto-correlations over time (Conrad et al., 1997). Lo and MacKinlay (1990:178) noted that the contrarian investment strategy is still a convenient tool for exploring the auto-correlation properties of stock returns. Because the momentum strategy employs the exact opposite set of trading rules, other than the duration of formation and holding periods, it is logical to assume that it will also be a good tool in analysing the under- and overreaction effects.

Thus, in order to see whether, and how strongly, under- and overreaction is present within the Top 40 Index and how the behaviour, if it is present, is influenced by bull and bear market dynamics, a momentum investment strategy is examined over bull and bear sub-periods. Additionally, given the behavioural models presented earlier in section 3.2.3, it will be interesting to see whether these momentum profits vary over bull and bear sub-periods and by how much. It should provide an indication of the extent to which these behavioural models are applicable in a SA stock market context.

This chapter presents the methodology used in this study to determine whether momentum strategy profits are affected by the state of the SA market, namely bull and bear markets as measured by the general movement in stock market prices. The structure of the chapter is discussed in the following paragraphs.

The research question and the objectives of this study are presented in more detail in section 4.2 so as to put the later sections into context when explaining how this question has been addressed. It is followed by a brief overview of the research methodology employed in section 4.3.

The research strategy, which will detail the research paradigm taken and the research method used within this study, is presented in section 4.4. Section 4.5 discusses the research instrument used. That is, it will detail the data requirements of this study and the reasons for these data requirements. It will be followed by a description of the target population and the sampling strategy employed.

Section 4.6 informs the reader from where the data was sourced. Section 4.7 will then provide an in-depth description of how the data was analysed by specifying the various steps.
taken. The statistical tests used will be briefly presented in section 4.8. Section 4.9 will then explain the various ethical issues considered throughout this study. Section 4.10 details the limitations of the research methods used while section 4.11 will conclude this chapter by summarising its main points.

4.2. Research question

The main research question addressed in this study is the following: is the anomalous evidence of inefficient market behaviour, represented through momentum strategy profits, more or less pronounced in a bull or a bear market phase in the SA stock market?

Three main observations have been identified within the literature: firstly, there is evidence of market under- and overreaction in various countries including SA. Secondly, when the evidence is found, researchers generally attribute the effects to behavioural and social psychological elements within the market, or to model misspecification problems, or a theory that conforms to the traditional view of efficient markets, such as differences in risk. Thirdly, model misspecifications aside past price paths may be affected by behavioural, social, and informational biases that may vary over different market states.

A natural development in this area of research is to look at different sub-periods as proposed by Cubbin et al. (2006), not only to see whether the market anomaly is consistently present but also to see if different market states have an impact on the under- or overreaction, as measured through momentum investment strategy profits. By doing so, one may gain further insight into the workings of the anomaly and its possible explanations.

4.2.1. Setting the hypotheses

To answer the question posed in the previous section, five sub-questions need to be answered:

1. Does a twelve-by-six momentum strategy produce positive returns, when implemented on the Top 40 Index?
2. To what extent are the returns in one above affected during bull formation periods?
3. To what extent are the returns in one above affected during bear formation periods?
4. To what extent are the returns in one above affected during bull holding periods?
5. To what extent are the returns in one above affected during bear holding periods?

If under- and/or overreaction is present in the market, it is expected that there will be momentum or reversals in stock prices and therefore stock returns. A zero cost momentum
portfolio should therefore provide an indication of under- and/or overreaction. From the sub-questions posed above, three hypotheses have been formulated. The first hypothesis to be tested is then:

1. $H_0$: The abnormal return, as measured by the portfolio alpha, on the average winner-minus-loser portfolio is equal to zero. By testing this hypothesis, one is able to determine if there was a momentum or contrarian effect within that time period;

In order to see whether momentum profits in SA, documented by Fraser and Page (2000) and Griffin et al. (2003), are influenced by the state of the market, one needs to compare the returns on momentum portfolios over different sub-periods, which are categorised as being either in a bull market or a bear market. Thus, the last two hypotheses are:

2. $H_0$: The abnormal return on the average winner-minus-loser portfolio with a bull formation period is equal to the abnormal return on the average winner-minus-loser portfolio with a bear formation period; and
3. $H_0$: The abnormal return on the average winner-minus-loser portfolio with a bull holding period is equal to the abnormal return on the average winner-minus-loser portfolio with a bear holding period.

One should note that in this study, abnormal returns are calculated using the CAPM, whereby the benchmark return is regressed on the momentum portfolio return. The intercept or alpha term is considered the abnormal return on that portfolio if it is found to be statistically significant at the 95% confidence level.

4.2.2. Research objectives

By testing each of the hypotheses described above, this study attempts to meet five objectives. Firstly, this study should provide some indication of the validity of the EMH in a SA stock market context. Although it has been tested extensively in the US and other foreign markets, it has been tested again here but from a SA stock market perspective and only as a consequence to the more important objectives of the study.

It should be noted that the results of this study will only provide an indication of market efficiency or inefficiency as transaction costs and inter-temporal variations in risk, as evidenced by Chordia and Shivakumar (2002), have not been taken into account.

Secondly, this study retests the results of past studies that show a momentum strategy to be abnormally profitable both in SA (Griffin et al., 2003 and Fraser & Page, 2000) and abroad so as to determine the robustness of their results over time for the previous studies on the
SA stock market, and over different geographical locations for international studies. It will help determine whether these results were due to data mining bias or not. By doing so, this study may also show evidence for or against the thought that the market should become efficient as investors make note of repetitive anomalous stock price behaviour.

Another contribution of this study will be to provide evidence for or against the notion that momentum in stock returns is a result of macroeconomic risk. As stated by Griffin et al. (2003:2536), “if a strategy is risky, then there should be at least some states in which the strategy underperforms.”

The fourth and most important objective of this study is to provide some insight into the behaviour of the SA stock market over distinct periods of market stress. By doing so, this study should provide further insight and/or evidence for or against behavioural and social psychological factors within the SA stock market and how these factors may change over different market states.

Lastly, this study should provide the ‘defensive investor’ with some empirical evidence of how the performance of a momentum investment strategy may change, if at all, during different market states in SA. A ‘defensive investor’ as defined by Graham (2006:22) is one interested chiefly in safety plus the freedom from bother.

4.3. Overview of the research methodology

The quantitative research strategy adopted here is a simulation technique whereby secondary data is used and a twelve-by-six month momentum strategy is assessed. A momentum investment strategy is simulated whereby an investor would condition his/her investment choices based on a stock’s past twelve-month return performance and limit his/her investment choice to stocks that form part of the Top 40 Index. Specifically, a stock is purchased if it was within the top five performing stocks within the Top 40 Index sample over the past twelve months known as the strategy’s portfolio formation period and a stock is sold short in the event that it was within the bottom five performing stocks over the same formation period.

The investor would enter into equally weighted positions in these stocks, one week after the portfolio formation period, known as the gap period, so as to reduce any bias that may enter into the study due to possible bid-ask bounce effects as documented by Jegadeesh (1990). These positions are then held for six months, known as the holding or test period, with no portfolio rebalancing unless a stock falls out of the Top 40 Index during the holding period.
The performance of a momentum strategy during bull and bear periods on the JSE/FTSE Top 40 index
M.R. Devonport

The simulation will be conducted ex-post and therefore daily returns of stocks within the Top 40 Index will be used for the period starting on 3 July 2002 and ending on 8 August 2012. Daily stock returns will be calculated and linked geometrically for each stock over the sample period. Stocks will then be ranked every week based on their previous 12 month returns.

The stock that is ranked 1 is the best performing stock over the past 12 months, while the stock that is ranked 2 is the next best performing stock and so on. The first ranking date will be on 3 July 2002, the second ranking date will then be a week later on 9 July 2002. If the start or ending day of the ranking period falls on a weekend or a public holiday where the market was not open for trading, then the start or end, whatever the case may be, would be on the next trading day.

As the reader can see, the simulation entails overlapping periods. It is done in order to increase the amount of observations available for the analysis that follows as in Jegadeesh and Titman, (1993). As a result, it may be easier to see this study as simulating the portfolios of 52 different momentum investors but with the same investment rules, each creating their investment periods one week after the previous investor.

Once the simulation has been conducted and each of the momentum portfolio returns have been calculated (winner, loser and winner-minus-loser portfolios), these momentum strategy portfolio returns are analysed over the entire sample period and over each of the bull and bear sub-periods. It is done with the use of averages, t-tests to test the significance of the differences in averages, and regression analysis to control for systematic risk as defined by the CAPM.

There is a need to quantify the size of the momentum strategy returns relative to the systematic risk incurred during bull and bear holding periods and as such a regression equation that calculates portfolio alphas in conjunction with a t-test on the average portfolio alpha lends itself nicely to such an analysis. It not only allows for greater comparability with other studies, most notably Cooper et al., (2004); Siganos and Chelley-Steeley (2005); and Wang et al., (2009) but it also allows the various bull and bear sub-periods to be compared on a risk-adjusted basis.

To do all of this, two sets of data were required:

1. Top 40 Index constituents' daily returns for the sample period. Because reliable data is available, secondary data is used over the sample period from 3 July 2002 to 8 August 2012; and
2 Daily Equally Weighted Top 40 Index returns for the sample period. The Equally Weighted Top 40 Index was only launched on 1 July 2010 and as a result, the index was manually created by reweighting the Top 40 Index from a value weighted index to its equally weighted counterpart.

Now that the reader has a general understanding of the methodology employed here, a more comprehensive explanation of the various nuances will be presented in the sections that follow.

4.4. Research strategy

A brief overview of the research methodology was provided in the preceding section. Now the research strategy employed will be discussed in detail. Specifically, the research paradigm will be discussed, followed by a discussion of the research method used and why the method was chosen.

4.4.1. Research paradigm

The very nature of the proposed research study calls for a quantitative research paradigm. A quantitative research paradigm is considered appropriate due to the fact that the purpose of this study is to determine the extent of under- and overreaction in the SA stock market, specifically within approximately the top 40 stocks as measured by market capitalisation, and the effect bull and bear states have on under- and/or overreaction. One should note that the Top 40 Index is not made up of exactly 40 stocks as a result of dual-listed stocks. As such, this index generally consists of between 41 and 43 stocks at any one time.

As stated earlier in this section, analysing an investment strategy that attempts to take advantage of under- and overreaction effects in the market is considered to be a convenient and useful tool in analysing such effects (Lo and MacKinlay, 1990). In order to accurately do so, one would have to use quantitative data of these portfolios together with their benchmarks.

4.4.2. Research method

The research approach used here is a quantitative one utilising a simulation technique. A simulation study entails creating an artificial environment that allows for the various dynamics of that environment to be observed within controlled conditions.

Meier, Newell, and Pazer (1969:1) describe simulation in business as the operation of a numerical model that represents the structure of a dynamic process. Given the values of
initial conditions, parameters and exogenous variables, a simulation is run to represent the behaviour of the process over time.

The approach is appropriate due to the following advantages:

1. The most important advantage is that it allows for a long period of time to be studied without having to gather primary data over that same period of time. As a result, this study was able to meet the research objectives within its time constraints;
2. Simulation techniques allow researchers to experiment with certain events or phenomena that cannot be done in the real world for various reasons, one of which is the cost of doing it in reality;
3. Phenomena or events can be examined even when they happen too slowly or quickly to observe in reality. As such, the time required to employ the strategy in reality in order to create enough data points for a reliable and valid conclusion has been reduced significantly, thereby making this study viable;
4. There is a certain degree of flexibility to manipulate variables or factors within the simulation study, which allows further understanding of the phenomena in question; and
5. Simulation studies allow researchers to simplify reality so as to gain more insight into a phenomena or event. By doing so, confounding variables or factors can be removed, thereby providing a more accurate understanding of that phenomena. Elron (1983) stated that the best simulation does not have to resemble reality in the most accurate way but rather the real benefit lies in the ability to simplify the complex reality of the real world and as a result, provide further understanding.

Although there are many advantages to utilising a simulation technique in this study, there is also a severe drawback:

1. Although the complexity of real life is reduced, by doing so, there is a possibility that it is oversimplified and relevant information is lost in the process. As such, an oversimplified understanding or skewed understanding of a phenomena or event can be gained. As a result a good simulation study is one where there is a balance between simplification and the application of real world dynamics so as to provide real world understanding. Consequently, one should always keep those factors that have been simplified in mind when drawing conclusions from a simulation study.
4.5. Research instrument

In order to analyse the performance of a momentum investment strategy, a relatively long period of time is required and as such, secondary data is used. More specifically two daily data sets over the sample period, from 3 July 2002 to 8 August 2012, were required:

1. Stock returns for all Top 40 Index constituents; and
2. Equally Weighted Top 40 Index returns.

4.5.1. Daily stock returns for the FTSE/JSE Africa Top 40 Index constituents

These returns should be derived from either the daily opening or closing bid or ask prices in order to reduce the possible bid-ask bias (Jegadeesh & Titman, 1993) while also taking any dividends into account. In this study the closing price was used as bid price and ask price data was not available. It is unknown whether the closing price data used was the bid price or the ask price but it is likely that it was a mixture of both. From these prices and any cash dividend distributions, daily stock returns were computed for each stock over the sample period.

4.5.2. Daily FTSE/JSE Africa Top 40 Index returns

In order to create the portfolio benchmark, the Top 40 Index constituents were used to recreate the Equally Weighted Top 40 Index over the sample period. It was done due to the fact that the Equally Weighted Top 40 Index was not available prior to 1 July 2010. From the recreated index, benchmark returns were calculated.

It should be noted however that the benchmark created is only an approximation of the Equally Weighted Top 40 Index as changes in the individual index constituents could only be determined at discrete points in time, at the end of each quarter (i.e. March, June, September, December) from March 2004 to December 2011.

The Top 40 Index rules state that the index is reviewed quarterly and that any changes to the index will only happen quarterly. There are certain exceptions to the rule though. As such, any changes to the index that may have happened between the review dates are missing from the data. Additionally, there was no knowledge of the index constituents between 2002 and 2004, nor was there knowledge of the index constituents for all quarters in 2010. Therefore in order to attain return data over these periods, it was the previous quarter constituents were used.
4.5.3. Daily data requirement

Daily data was chosen for three reasons. Firstly, daily variables allowed for momentum portfolios to be created on a weekly basis. This provided more data points, thereby increasing the power of the $t$-tests and the regression analysis used for each of the average momentum portfolios.

Secondly, as stated by Howe (1986), daily return data holds statistical properties assumed within a regression analysis. Although Howe (1986) does not say what statistical properties he is referring to, it is assumed that he is making reference to both the increased number of data points available and the increased likelihood that daily data may exhibit a normal distribution.

Lastly, although daily data would increase the possible bias due to bid-ask bounce, infrequent trading, and non-synchronous trading (Chowdhury & Michello, n.d.), by geometrically linking the returns over a twelve and six month period, these biases will be reduced. Moreover, selecting large, frequently traded stocks further reduces the potential for these effects to bias the results.

4.5.4. Sampling strategy

As a result of this research being focussed on the JSE, and the need to reduce bias from smaller, less liquid stocks, the portfolios tested over the sub-periods were based solely on the top 40 stocks on the JSE as measured by their market capitalisation. The top five stocks based on their past returns within the Top 40 Index were allocated to the winner portfolio, while the bottom five stocks were allocated to the loser portfolio in order to create a zero cost momentum portfolio.

Due to the methodology that will be employed in this study (see section 4.7 below), and the fact that JSE indices were rebased and reweighted with the introduction of the FTSE/JSE Africa Index Series on 21 June 2002, the period over which the analysis was conducted was from 3 July 2002 until 8 August 2012. It was done to reduce any bias that may have been introduced because of the change in index. Additionally, the sample period allowed for enough data points to conduct a regression analysis in addition to providing at least one bull market phase and one bear market phase so that the two different market phases or states could be compared.

As was stated earlier, this study only requires secondary data. Additionally, as a result of the small number of stocks that are traded frequently on the JSE, it is assumed that the Top 40
Index stocks over a sample period of nine years and seven months from 3 July 2002 to 8 August 2012 was sufficient in order to assess the momentum strategy used in this study.

4.5.5. Target population and sample selection

The target population in this study was the Top 40 Index over a period of nine years and seven months as opposed to the Siganos and Chelley-Steeley (2005) methodology where a much larger sampling frame was used: all UK companies listed on the Master Index File of the London Share Price Database, which ranged from 1,489 and 2,444 companies in any year of their sampled period, over a period of approximately 25.5 years.

Although the sampling frame and time period of this study is much smaller than that of Siganos and Chelley-Steeley (2005), it uses weekly overlapping investment periods like Chan, Hameed and Tong (2000), while Siganos and Chelley-Steeley (2005) used non-overlapping periods. This allowed for a larger number of data points and consequently increases the statistical power of the tests conducted and as a result, reduces small-sample biases (Jegadeesh & Titman, 1993). Thus, the current study does not fall short of Siganos and Chelley-Steeley’s (2005) amount of observations but only the time frame and the sample size used.

Consequently, this study’s results may be less representative of the past as the performance of the strategy is not analysed over a long period of time, such as 25 years. However, it is presumed that a nine-year period is sufficient to incorporate the different market states and is therefore sufficient to meet the objectives of this study.

Additionally, the smaller sampling frame of Top 40 Index stocks is also presumed to be sufficient given the nature of the SA stock market. That is, the SA stock market is made up of a relatively small amount of frequently traded stocks when compared to the UK stock market. Thus, the issues that arise from bid-ask bounce, infrequent trading, and the increased computational requirements far outweigh the benefits of using a larger sampling frame in the SA stock market.

To facilitate the simulation study specified in the data analysis section below, the following criteria were used to select the sample of stocks from the Top 40 Index. The stock should:

1. Be listed on the JSE main board for at least three years prior to the formation period;
2. Have complete data for at least three years prior to the formation period, which is consistent with Fraser and Page (2000) as well as Chan (1988);
3. Have data up to and including the gap period; and
4. Have been one of the index constituents within the Top 40 Index at some point leading up to the start of the formation, which is 53 weeks prior to the start of the test period.

To account for possible survivorship bias, a stock that falls out of the Top 40 Index during the holding period was presumed to have been sold on that day and returns are calculated as such. The replacement stock would then be assumed to have been purchased on the same day at the same weight within the portfolio than the stock that was dropped.

4.6. Data collection method

Stock return data was sourced from McGregor BFA, while index constituent data was sourced from SATRIX. Each of these institutions holds price data as a business service to market professionals and for the institution’s own research agendas. The sources are deemed to provide reliable stock market data due to the fact that they are used by economists, portfolio managers, investment analysts, journalists and other investment professionals.

4.7. Data analysis

Although an overview of the research method and the data and sample selection has been discussed, an in-depth presentation of how the data was analysed is still to be provided. This section will do that by providing the steps taken to analyse the data and provide valid and reliable results. The data analysis procedure that follows has been broken down into six steps.

4.7.1. Step 1: rank sample stocks

Stocks that meet the sample inclusion criteria, stated earlier, are ranked in ascending order based on their past 12-month daily geometrically linked return, also known as formation period returns. A stock’s daily return is calculated as:

\[
R_{i+1} = \left( \frac{P_{i+1}}{P_i} + \frac{D_i}{P_i} \right) - 1
\]

Where:

\[R_{i+1}\] = the return on the stock at day \(i+1\);
\[P_{i+1}\] = the price of the stock at day \(i+1\);
\[P_i\] = the stock price at day \(i\);
\[D_i\] = the dividend distributed at day \(i+1\); and
= the price of the stock on day $i$.

These daily returns are linked together to get the actual 12-month return on the stocks by:

\[ \frac{1}{12} \left( \sum_{i=1}^{12} \left( \frac{p_i}{p_{i-1}} - 1 \right) \right) \]

The above linking is repeated each week throughout the entire sample period in order to attain a weekly ranking throughout the sample period. The weekly ranking takes place on either a Wednesday or Thursday to ensure that any weekend effects that may be present are reduced.

4.7.2. Step 2: create the momentum portfolios

Once all sampled stocks have a ranking in each week over the sample period, a week gap period is left between the formation and holding periods in order to reduce any bias that may result from bid-ask bounce, price pressure, and lead-lag effects (Jegadeesh and Titman, 1993). Although many studies, such as Siganos and Chelley-Steeley (2005), leave a month gap between formation and holding periods, this methodology only makes use of a single week gap period in order to increase the number of observations within the sample. Additionally, the duration of the gap period has been deemed satisfactory by many researchers in reducing the bias (Jegadeesh, 1990).

Furthermore, one should note that because the Top 40 Index constituents are being used and the data is not intraday data, it is likely that the bias resulting from these market microstructure effects will be reduced. This is because these stocks are the largest and most liquid on the JSE and therefore the bid-ask spreads are relatively small and these stocks are traded regularly.

After the week gap period, \textit{winner} and \textit{loser} portfolios are created by holding the top five performing stocks ranked 1 to 5, known as the winner portfolio; and selling short the bottom five performing stocks, ranked 36 to 41/2 known as the loser portfolio, in the formation period. Because the strategy makes use of overlapping periods, the portfolio formation process is repeated each week throughout the sample period.

4.7.3. Step 3: determine portfolio performance

These portfolios are then held for approximately six months (182 days) so that a six-month return variable is calculated on both the winner and loser portfolios. The returns on the loser portfolios are then subtracted from the returns on their counterparts to attain the return on the momentum (winner-minus-loser) portfolio.
At this point, there are several statistics that will be calculated to analyse the performance of the momentum portfolios over the full sample period. It is done in order to test the first hypothesis presented earlier: The abnormal return on the average winner-minus-loser portfolio is equal to zero.

The analyses performed here include performance measures and risk measures. The performance measures include:

1. A simple average geometrically-linked six-month return on the momentum portfolios; and
2. A t-test to determine:
   a. Whether the return on the momentum portfolios (winner, loser and winner-minus-loser) are statistically different from zero; and
   b. Whether the returns on the momentum portfolios are statistically different from the benchmark portfolio.

The risk measure is the calculation of the momentum portfolios' alphas through the use of several regression analyses of the form:

\[ r = \alpha + \beta r_b + \epsilon \]

Where:

- \( r \) = the daily return on the momentum portfolio;
- \( \alpha \) = the portfolio's alpha term and the measure of the portfolio's abnormal return, as estimated by the CAPM;
- \( \beta \) = the sensitivity factor of the momentum portfolio to the benchmark portfolio return;
- \( r_b \) = the return on the benchmark portfolio; and
- \( \epsilon \) = the error term which can be attributed as white noise or events that impact the individual stocks within the momentum portfolios.

Once all the momentum portfolio alphas have been calculated, a t-test is conducted at a 95% confidence level on the average momentum portfolio alpha to determine whether it is statistically different from zero. The t-test is essentially the test of the first hypothesis. If the average portfolio alpha is different from zero and statistically significant, then the first hypothesis is not accepted at the 95% confidence level.
4.7.4. Step 4: allocate portfolios into bull and bear phases

This paper studies the effects of the formation and the holding period market states on the profitability of the momentum strategy. As such, instead of categorising portfolios on either bull or bear formation periods, portfolios are categorised into the following four categories:

1. Portfolios with bull formation periods;
2. Portfolios with bear formation periods;
3. Portfolios with bull holding periods; and
4. Portfolios with bear holding periods.

Bull and bear periods are determined by the benchmark return over that twelve or six month formation or holding period respectively. When the average benchmark return is positive, the period is categorised as being a bull period, while an average decrease in the benchmark is categorised as a bear period.

4.7.5. Step 5: determine the effect of market states

To determine the effect of both formation and holding period states on the profitability of momentum portfolios, the arithmetic average returns and arithmetic average alpha term on the winner, loser and winner-minus-loser portfolios in each category are calculated. Returns and alpha terms for each category are then differenced and t-tests are conducted on the differenced return variable and the differenced alpha term variable to determine whether these averages are statistically different from one another.

This step will test the second and third hypotheses. If the difference between the average alpha for the bull formation period portfolios and the average alpha for the bear formation portfolios is different from zero and statistically significant, then the third hypothesis is not accepted at the 95% confidence level.

4.7.6. Step 6: robustness test

As stated earlier, there was a lack of Top 40 Index constituent data from 2002 to 2004 and again in 2010. As a result, a robustness test is also conducted whereby steps one to five are repeated on the sample, excluding the years where there are gaps in the data. Specifically, the robustness test period is from March 2004 to December 2010.

4.7.7. Formation and holding periods chosen
Like many other studies, Jegadeesh and Titman (1995) analysed 16 variations of momentum strategies by altering the formation and holding period durations. However, the momentum strategy chosen here was a twelve-by-six formation and holding period strategy. This is in slight contrast to the methodology employed by other researchers such as Siganos and Chelley-Steeley (2005). The reasons for using a single twelve-by-six momentum strategy are based on the literature reviewed and the purpose of this study.

Firstly, when one reads the literature, it becomes apparent that many optimal variations of the momentum strategy exist, depending on the market studied and the timeframe used. While Jegadeesh and Titman (1993) found the strategy is optimised when using twelve-by-three months in the US, other studies found the strategy to be optimal over other formation and holding periods such as a nine-by-nine in Canada (Assogbavi & Leonard, 2008). However, consistent with Conrad and Kaul’s (1993) observations, each one of these studies still found a twelve-by-six strategy to be abnormally profitable and anything between three and twelve months’ formation and holding periods generally provided abnormal profits.

From a SA market perspective, Fraser and Page (2000) found that a twelve-by-one strategy produced abnormal profits on the JSE, while Griffin et al. (2003) found a six-by-six month strategy was also profitable on the JSE, although they do not test for the optimal period. Cubbin et al. (2006) on the other hand found that when a contrarian strategy is employed on the JSE, it only becomes profitable from the eighth holding month and provides negative profits until that month. Conversely, a momentum strategy would then have only been profitable until the eighth holding month. Therefore it is assumed that a momentum strategy with a twelve-month formation period and a holding period that ranges between three and eight months will be appropriate here.

Secondly, although one of the objectives of this study is to test the profitability of a momentum strategy on the JSE, it is an ancillary objective and is therefore not the main focus here. As such, this study does not set out to determine the optimal formation and holding periods but rather the optimal market state. By utilising a single strategy one is able to reduce the computational requirements needed for this study, while still meeting each of the objectives set.

Thirdly, by employing a shorter holding period, one is able to test far more momentum portfolios over the entire sample period and its bull and bear sub-periods. As a result, a single twelve-by-six month strategy is deemed appropriate in meeting the objective set out here.
4.7.8. Buy and hold versus rebalancing the portfolios

The momentum strategy used here does not rebalance the portfolio during the test period. This is because Jegadeesh and Titman (1993) did not find significantly different results from either a buy and hold strategy or a strategy that rebalances monthly. In fact, Jegadeesh and Titman (1993) found the buy and hold strategy produced slightly higher returns than the rebalancing strategy.

4.7.9. Assessing strategy profits/losses

In order to test for the under-reaction effect, momentum portfolios were set up as described earlier. Daily holding period returns on the winner and loser portfolios were calculated and an average daily geometrically linked six-month return obtained for each of the winner and loser portfolios over the entire sample period. The winner and loser portfolio returns relating to each of their test periods were then differenced, thereby providing several \( \text{winner minus loser return} \) figures, one for each portfolio’s test period.

An arithmetic average of these data points was then found and a \( t \)-test conducted in order to assess if these averages were statistically different from zero. The same analysis was conducted on the average alpha term on the momentum portfolios. If the null-hypothesis is not accepted then the average abnormal return on the momentum portfolios is different from zero, and it will be concluded that a return continuation or reversal (depending on the sign of the average return and alpha term) was present over the entire sample period.

4.7.10. Analysing bull and bear differences using a \( t \)-test

In order to assess whether the proposed momentum strategy performance is similar during bull and bear formation and holding periods the same analysis as described above was conducted for four distinct categories, namely when the Top 40 Index was exhibiting a general:

1. Increase over the formation period;
2. Decrease over the formation period;
3. Increase over the holding period; and
4. Decrease over the holding period.

These categories represent the respective bull and bear formation and holding periods on the momentum portfolios. Once the various average returns and average alpha terms were found on each momentum portfolio category, a paired sample \( t \)-test was conducted to
ascertain whether the averages of each formation period and holding period category are equal. Should the null-hypothesis be rejected, it would be concluded that a momentum investment strategy is affected by the state of the market.

If the average bull formation period category return and alpha term is statistically larger than the average bear formation period category return and alpha term, this may provide additional evidence of investors overreacting to information following a bull period, more so than when following a bear period. If however the average bear formation period category return and alpha term is statistically larger than the average bull formation period category return and alpha term, then this will provide evidence of investors overreacting to information following a bear period, more so than following a bull period.

Depending on which average return and alpha term is largest, this study will provide evidence of there either being an additional risk factor that is affected by the state of the market, or it will provide evidence of an increased or decreased rate of information diffusion during the respective periods. It may also provide evidence of there being a behavioural bias or heuristic, such as conservatism, that is more or less affected by the state of the market.

It should once again be noted that the purpose of this study is not to prove or disprove any theory in this area of research but rather to add to the body of knowledge with regards to what evidence there is for the under- and overreaction anomaly and the effects of market states on that anomaly in the SA market context.

4.8. Description of statistical tests used

Now that a thorough description of the research method has been provided, this section briefly discusses the statistical tests used within the research methodology in order to highlight their strengths and weaknesses. As such, this section will explain why these tests were deemed appropriate and will provide some of the limitations to the methodology used here. These limitations will however be repeated within the limitations section that follows.

4.8.1. Student’s t-test

The t-test is one of the more common ways to test whether the means of two groups are statistically different from one another. Because obtaining a sample mean value that is exactly the same as the population parameter is highly unlikely one needs to determine whether the difference between the sample mean and its expected value, given the hypothesis, is a result of chance alone. The t-test allows for such an analysis and does so
relative to the variability of these means. As such, it determines the probability of the difference being due to chance (Trochim, 2006).

In this study the \(t\)-test is used to determine whether the average returns on each of the momentum strategy categories are significantly different from one another. When one wants to test the hypothesis that two sample means are different, some variation of a \(t\)-test is generally used. A \(p\)-level is also generally reported in conjunction with the \(t\)-test. The statistic determines the probability of error involved in accepting the hypothesis. The same methodology is used in other studies of this nature such as Cooper et al. (2004), Siganos and Chelley-Steeley, (2005) and Wang, Jiang, and Huang (2009) when determining whether their average bear portfolio returns are different from their average bull portfolio returns.

There are many variations of the \(t\)-test, the most appropriate one being a function of the assumptions one can make about the sample and its population. The variation of the \(t\)-test used here is the paired comparisons test. The purpose of the test, like the independent samples \(t\)-test, is to determine the statistical significance of the difference in means between two samples. However, the difference here lies in the fact that the samples are dependent, which allows the \(t\)-test to identify and exclude the within-group variation or error from the analysis. The sample means in this study are seen to be dependent due to the various momentum portfolios being created with overlapping periods.

In addition to the general assumptions that are made when utilising any \(t\)-test, there are other assumptions that should also be met. The test is used when the following assumptions hold:

1. When one wants to conduct tests on two means;
2. These means are assumed to be dependent; and
3. The differences between observations have a distribution that is approximately normal.

Although these assumptions should hold, the test is relatively robust to departures from its assumptions. As such, the fact that stock returns are generally not normally distributed should not bias the results significantly as long as there are more than 30 observations that create the return averages.

4.8.1.1 Advantages of a \(t\)-test

The \(t\)-test used in this study has several advantages:

1. It can be used when the mean and standard deviation of the population are unknown and two groups are being compared;
2. The t-test used here is an example of repeated measures designs and as a result, the test is more powerful, thereby providing a smaller error term and therefore a larger t-value; and
3. A more robust test results in the ability to utilise a smaller sample and still find reliable and valid results.

4.8.1.2. Limitations of a t-test

Although the t-test has several advantages, it, like many other statistical tools, also has several disadvantages. Two disadvantages to using the t-test are:

1. The test is a repeated measure design and as a result it has less degree of freedom, which in turn means that one requires a higher t-score to reach significance. As a result, by using the test there is a trade-off between power and degrees of freedom. In general, the higher the correlation between two groups, the greater the advantage of utilising a paired sample t-test; and
2. When utilising a t-test, one needs to assume the population parameter is normally distributed. It is a serious limitation to this study as stock returns are generally not normally distributed.

4.8.2. Regression analysis

A regression analysis is one of the most useful statistical tools for business analysts and researchers alike as it can be applied in so many different situations. There are two broad reasons for conducting a regression: to explain a relationship between two (simple regression) or more (multiple regression) variables, or to predict a continuous dependent variable with the use of another single or multiple variables.

It should be noted that a regression does not allow one to prove or disprove a causal relationship but to show that there is some amount of association between variables. The purpose of a regression is to quantify the relationship between variables and to determine association between them.

The basic concept behind the regression equation is that it attempts to create a straight line, in the case of a linear regression used here, that minimises the distance, or error between that line and the observations. As such, the basic equation for a regression is:

\[ y = \alpha + \beta x \]

Where
The performance of a momentum strategy during bull and bear periods on the JSE/FTSE Top 40 index
M.R. Devonport

\[ y = \alpha + \beta x + \epsilon \]

\( y \) = the independent variable, which is the variable being explained or predicted;
\( \alpha \) = a constant amount, which is the base case for the dependent variable that, given the independent variables, is equal to zero;
\( \beta \) = the effect the independent variable has on the dependent variable, otherwise known as the slope;
\( x \) = the explanatory variable; and
\( \epsilon \) = the error term, otherwise known as noise that reflects other factors that influence the independent variable. Stated another way, the term represents the amount of variability in the dependent variable that is not explained by the independent variable.

What the regression does is create an estimate of the constant (\( \alpha \)), the slope (\( \beta \)) and the error term (\( \epsilon \)) utilising the observed dependent and independent variable data.

4.8.3. Regression assumptions

Like the t-test, there are various assumptions that are made by the regression equation and as a result, these assumptions should hold true if the regression's results are to be valid and reliable. Specifically, the following assumptions should hold when conducting a regression analysis:

1. The relationship between variables is linear, although nonlinear relationships can be made linear by suitable mathematical transformations;
2. Independence of error term;
3. The dependent variable is normally distributed for any value of the independent variable and by extension, the error term is also normally distributed; and
4. Stationary variance of the error term, otherwise known as homoscedasticity.

4.8.3.1. Linearity

A standard regression assumes that the relationship between variables, the independent variable/s and the dependent variable, is linear. Although the regression procedures are not affected greatly by deviations from that assumption, it is generally recommended that one always determines whether it holds true, at least in part. That is because a nonlinear relationship between variables will be understated by the regression equation.
4.8.3.2. Independent error terms

The error terms should be independent of one another. If that is not the case, then one is able to predict one error term from other error terms. As a result, one should be able to improve the predictions of the dependent variable.

4.8.3.3. Variables are normally distributed

In order to calculate confidence intervals of one's predictions, it is necessary to know the probability distribution of the error terms. It is generally assumed that the error terms have a normal distribution.

4.8.3.4. Error terms are stationary

The assumption that error terms are stationary is concerned with the variation of the sample around the population regression line. A regression assumes that the variation of the dependent variable is the same for any value of the independent variable/s. The assumption is also known as constant error variance or homoscedasticity. It implies that the variance of the dependent variable is the same for both small and large values of the independent variable/s.

4.8.4. Advantages of regression analysis

There are several advantages to using a regression analysis when it is applicable. Specifically:

1. Regression techniques enable researchers to quantify a relationship between variables;
2. The regression equation is relatively robust to violations of its assumptions and the equation can be adjusted to overcome the problem of nonlinearity;
3. Regression techniques are able to account for many different variables simultaneously and quantify each variable's relationship with the dependent variable;
4. Interpreting a regression is relatively easy, particularly when variables have not been transformed; and
5. Irrelevant variables do not bias the results of the regression equation.

4.8.5. Limitations of regression analysis
The performance of a momentum strategy during bull and bear periods on the JSE/FTSE Top 40 index

M.R. Devonport

The main limitation to all regression techniques is the fact that one cannot be sure of any causal relationship between the independent variable/s and the dependent variable. Consequently, the only conclusion that can be drawn is that there is or is not a linear relationship between the independent variable/s and the dependent variable. Whether the relationship is a result of some other variable or causal in nature cannot be determined by a regression equation (Trochim, 2006).

Regression analysis requires a fair amount of data in order for the results to be robust and repeatable. Many researchers such as Dallal (2001) recommend at least ten to twenty times as many observations as there are variables in order for the regression results to be robust. Additionally, the technique is prone to data mining bias as many researchers may be tempted to input many different variables in order to find some significant relationship.

Another issue with regression analysis is that it can be sensitive to outliers and therefore sensitive to observations that have been skewed due to unreliable data or some irregular event.

4.9. Ethical considerations

By conducting this study, there are various ethical issues that will need to be considered so as to provide a piece of research that is of good quality and meets the ethical standards of the University of Johannesburg. Specifically, the ethical considerations are as follows:

1. Data needs to be sourced from a reliable source so that any conclusions drawn from their analysis is correct and well founded. Additionally, the data that is used should not be tampered with in any way that would distort the true information contained within it;
2. Valid statistical procedures should be followed so that the results of these procedures are of good quality. Therefore, these results should be reliable and valid as all assumptions made within the statistical procedures used should be adhered to;
3. Any and all results attained from the research must be reported so that the research does not lead the readers into thinking something that is not entirely true and well founded; and
4. The interpretations that are made based on the statistics and literature should be valid. Specifically, there are several limitations to the proposed research methodology and sampling strategy, which will be explained in the next section. Consequently, various ethical issues would need to be addressed when interpreting the results of the study. In order to do so, it is proposed that these limitations be stated clearly, wherever they may be relevant, throughout the research report. These limitations should be in terms
of the ability to generalise throughout the SA equity market and in terms of other factors that may have confounded the results.

4.10. Limitations

As was stated previously, the nature of the SA stock market is that there are a relatively small number of stocks that are frequently traded when compared to more developed markets such as that in the US and the UK. As a result, this study only utilises the largest stocks on the JSE as a sampling frame.

Utilising only large stocks on the JSE as a sampling frame was deemed appropriate to meet the objectives of this study and reduce the bias that may result from the small firm effect, infrequent trading, and other market microstructure effects. However, the use of the small sampling frame does limit the scope of this study and therefore has several implications in terms of generalisability. Specifically:

1. Each industry or market sector is not represented appropriately, if at all, in the Top 40 Index stocks over the entire sample period and in each sub-period. Thus the results may reflect a specific industry momentum rather than a stock specific momentum or the lack thereof; and
2. It is not possible to generalise past the SA context where either the behavioural or EMH theory explanation is assumed to be the cause of momentum profits, or the lack thereof. The reason being, the composition of the market in terms of the types of investors and the way in which they react to information in SA may be different from other parts of the world. As such, one can only relate these findings to what has been found in other markets.

Additional limitations of this study are:

1. The results of this study will only provide an indication of market (in)efficiency as transaction costs and inter-temporal variations in risk, as evidenced by Chordia and Shivakumar (2002), have not been taken into account;
2. By using parametric statistics, certain assumptions are made around the distribution of the population parameters. These assumptions may not hold true, thereby providing spurious results;
3. The benchmark created is only an approximation of the Equally Weighted Top 40 Index as changes in the individual index constituents could only be determined at discrete points in time; and
4. Lastly, the use of daily data would increase the possible bias due to bid-ask bounce, infrequent trading, and non-synchronous trading (Chowdhury & Michello, n.d.).

4.10.1. Transaction costs and inter-temporal variations in risk

Due to the fact that transaction costs are not accounted for within the research methodology, the results of this study must be interpreted in that light. Specifically, it may be necessary to reduce the portfolio returns by some percentage in order to take these costs into account. However, Rey and Schmid (2007) noted that such a methodology is crude and is more of an approximation. Thus the results of this study should be interpreted with care.

Another limitation of the methodology employed in this study is that it does not take into account the fact that certain macroeconomic instruments that measure market conditions can explain a significant part of abnormal momentum profits. Chordia and Shivakumar (2002) argued that variations in macroeconomic factors and therefore risk are the main source of momentum profits.

The methodology employed here is a single factor model that does not take time-variation in risk into account and therefore that explanation cannot be ruled out here where positive abnormal momentum profits are found.

4.10.2. The use of parametric statistics

It should be noted that although most of the research conducted in this area is of a parametric nature and has been conducted in a similar manner to that proposed for this study, Mun et al. (2000) explained that there is a danger in using parametric statistics. They stated that a non-parametric analysis is better suited to this type of study due to the evidence of some serious violations of the assumptions presumed in a parametric type of analysis. That is with specific reference to the assumption that stock returns are normally distributed.

Specifically, if stock prices and indices do indeed follow a random walk pattern as stated by the EMH, any regression of a non-stationary data series on another non-stationary data series would result in a spurious regression model with low explanatory power. They continued to explain that in previous studies where stock price data is used, non-parametric analysis has been found to provide as good, if not better results as parametric studies. As stated previously, this is due to the fact that non-parametric analysis does not require a known distribution and therefore it is seen to be better specified when using financial and stock price data.
However, this is in contrast to the vast majority of studies looking at momentum strategy profits that utilised parametric statistics, including Jegadeesh and Titman (2001). The main point to note in this regard is that a *t*-test is relatively robust to violations to its normality assumption where more than 30 observations are available. This study has far more than 30 observations for all variables being analysed. As a result the analysis performed is also relatively robust to the possibility that the data is not normally distributed.

4.10.3. Benchmark

The benchmark created is only an approximation of the Equally Weighted Top 40 Index as changes in the individual index constituents could only be determined at discrete points in time (March, June, September and December) from March 2004 to December 2011.

The Top 40 Index rules state that the index is reviewed quarterly and that any changes to the index will only happen quarterly. However, there are certain exceptions to the rule and although they don’t happen often, they do happen. Any changes to the index that may have happened between the index review dates are missing from the data. Additionally, there was no data on the index constituents between 2002 and 2004, nor was there knowledge of the index constituents for all quarters in 2010.

As stated previously, in order to control for the bias, two sample periods were analysed: a robust sample period and the full sample period. As will be explained in Chapter 5, where there are differences in the results between the two samples, the interpretation of these results is focussed solely on the robust sample period.

4.10.4. The use of daily data

The last limitation of this study is the fact that daily stock price data was used. It has been found that daily data may increase the possible bias resulting from bid-ask bounce and infrequent trading, although using the Top 40 Index should minimise the problem (Chowdhury & Michello, n.d.).

By geometrically linking the returns over the twelve and six-month periods, these biases will be relatively muted however. Moreover, selecting large, frequently traded stocks further reduces the potential for these effects to bias the results, although the limitation should still be noted when reviewing the results of this study.
4.11. Summary

The purpose of this study was to determine whether the state of the market has an effect on the profitability of a momentum strategy. As such the research objectives were fourfold:

1. To provide some indication of the validity of the EMH in a SA stock market context;
2. To retest the hypothesis of past studies to determine whether these results were due to data mining bias or not;
3. To provide some insight into the behaviour of the SA stock market over distinct periods of market stress; and
4. To provide the ‘defensive investor’ with some empirical evidence of how the performance of a momentum investment strategy may change during different market states in SA.

Although many of these issues have been tested extensively in the US and other foreign markets, it is tested again here but from a SA stock market perspective.

The quantitative research methodology employed is a simulation technique whereby a twelve-by-six month momentum strategy is employed on the Top 40 Index. Secondary stock price data was attained from McGregor BFA, which is a reputable organisation that provides price data as a business service to many market professionals in SA and for their own research agendas. The top five performing stocks are purchased in equal weights and the bottom five performing stocks are sold in equal weights following a week gap period. The gap period is employed in order to reduce any bias that may arise as a result of infrequent trading, bid-ask bounce and other market microstructure effects.

The portfolio is not rebalanced over its six-month duration as it is generally found that it has little effect on the profitability of momentum portfolios (Jegadeesh and Titman, 1995). A single twelve-by-six momentum strategy was chosen as a result of its performance within studies that found it to be abnormally profitable in SA and abroad. Additionally, it was deemed unnecessary to test more than one strategy as this study’s objectives are not to find the most profitable strategy but rather to find out whether the state of the market has an effect on the profitability of a momentum strategy.

These momentum portfolios are created every week to create overlapping portfolios that allow for a larger number of return observations. The performance of these portfolios is assessed by categorising them into one of four categories based on the general market performance during the portfolio’s formation and test periods.
The formation or holding period is categorised as being a bull period when there was a general increase in the benchmark over that period. Conversely, the formation or holding period is categorised as being a bear period when there was a general decrease in the benchmark over that period.

The average momentum portfolio return and the average alpha term for each momentum portfolio category are calculated and a \textit{t-test} is conducted on the differences between the formation categories and the holding period categories respectively. It is done to determine whether the average returns and the average alphas in each category are significantly different from one another.

Although there are several advantages to using these statistical techniques, there are also several assumptions that have been made in order for these methods to be valid and reliable. As a result, there are some limitations that need to be taken into account. The most important of which is that returns are generally not normally distributed.

The normality limitation is not overcome in this study; however it is relatively robust when using a \textit{t-test} and regression equation where there are more than thirty observations. Therefore the central limit theorem holds in this study as there are far more than thirty observations for all variables assessed.

In addition to the limitations imposed by the statistical tests used here, there are other limitations of this study that should be noted. That is, the sampling frame is relatively small when compared to other studies and as such, the generalisability of this study suffers in that one cannot generalise past the sampling frame of Top 40 Index stocks.

Another significant limitation is that inter-temporal variation in macroeconomic factors and therefore risk in addition to transaction costs are not taken into account. Therefore the results of this study should be tempered by that fact by potentially reducing the returns of the momentum investment strategy. One also cannot rule out the potential for macroeconomic factors to be the cause of momentum strategy profitability.
Chapter 5
Results and findings

5.1. Introduction

The purpose of this research is to determine whether under- and overreaction evidence, represented by a momentum investment strategy, is more or less pronounced during bull or bear market states. By doing so, further understanding may be gained into the potential causes of under- and overreaction in a SA stock market context.

The most pertinent literature surrounding this research question was discussed in Chapter 2 and Chapter 3, while the research methodology utilised was discussed in the preceding chapter. In Chapter 4 it was stated that this study uses a quantitative research paradigm, whereby a simulation was conducted to: firstly determine whether there was momentum over the sample period; and secondly to determine whether the bull and bear sub-periods had any influence on these momentum returns.

The main research hypotheses tested are as follows:

1. H₀: The abnormal return on the average winner-minus-loser portfolio over the entire sample period is equal to zero. By testing this hypothesis, one is able to determine if there was a momentum or contrarian effect within that time period;
2. H₀: The abnormal return on the average winner-minus-loser portfolio with a bull formation period is equal to the abnormal return on the average winner-minus-loser portfolio with a bear formation period; and
3. H₀: The abnormal return on the average winner-minus-loser portfolio with a bull holding period is equal to the abnormal return on the average winner-minus-loser portfolio with a bear holding period.

It should be noted that because a momentum investment strategy is made up of both a formation and a holding period, both periods were analysed to determine whether a change in market state in either period yielded significantly different momentum returns.

This chapter describes the sample used to conduct the analysis in section 5.2 and presents the results attained in section 5.3. The results are discussed in the order in which the main hypothesis tests were performed.

Section 5.3.1 first presents and discusses the results of the analysis performed to determine whether there was momentum in stock returns over the entire sample period. Section 5.3.2
discusses the market states in the formation period and their impact on momentum in stock returns in the holding period. Section 5.3.3 discusses whether the market states in the holding periods had any effect on the momentum in stock returns in those periods. Lastly, section 5.4 and section 5.5 conclude this chapter with a summary of the salient points.

5.2. Description of the sample

The sample period used in this study was from 3 July 2002 to 8 August 2012. However, the Top 40 Index constituents are not known from 3 July 2002 to 22 March 2004 and again from 22 March 2010 to 19 March 2012. The reason being that the information was not made available by McGregor BFA or SATRIX. As such, the analysis was conducted with and without these periods. The period that includes the sub-periods 3 July 2002 to 22 March 2004 and 22 March 2010 to 19 March 2012 is referred to as the “full sample period” while the period that excludes these sub-periods is referred to as the “robust sample period”.

There are very slight differences between the two sample periods. While the six-month average benchmark return for the holding periods within the full sample period was 10.12%, the six-month average benchmark return for the holding periods within the robust sample period was 11.52%, as illustrated in Table 1 below.

Table 1: Benchmark returns over the sample period

<table>
<thead>
<tr>
<th></th>
<th>Full Sample Period (2002/07/03 – 2012/02/08)</th>
<th>Robust Sample Period (2003/03/26 – 2012/03/17)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Return over Formations (12-month)</td>
<td>21.78%</td>
<td>24.11%</td>
</tr>
<tr>
<td>Average Return over Holding Periods (six-month)</td>
<td>10.12%</td>
<td>11.52%</td>
</tr>
<tr>
<td>Standard Deviation in Returns over Formation Period (12-month)</td>
<td>19.67%</td>
<td>21.46%</td>
</tr>
<tr>
<td>Standard Deviation in Returns over Holding Period (six-month)</td>
<td>12.97%</td>
<td>14.19%</td>
</tr>
<tr>
<td>Number of Portfolios Created</td>
<td>432</td>
<td>286</td>
</tr>
</tbody>
</table>

Source: McGregor BFA

Figure 1 below is a graphical representation of how the index changed in value over the full and robust sample periods, where the robust sample period is the highlighted section of the figure. There was a strong upward trend over the sample period chosen. As such, there are many more bull periods than bear periods. Figure 2 also illustrates the upward trend by depicting the annual benchmark returns over the full and robust sample periods. It also provides an indication of the number of bull and bear periods within the sample analysed.
The performance of a momentum strategy during bull and bear periods on the JSE/FTSE Top 40 index
M.R. Devonport

Figure 1: Change in the benchmark index level over the sample period

Source: McGregor BFA
*Base date for this index is 2 May 2002.

Figure 2: Six-month benchmark return

Source: McGregor BFA

The full sample period yielded 343 bull formation periods, 89 bear formation periods, 355 bull holding periods and 77 bear holding periods. The robust sample period yielded 233 bull formation periods, 53 bear formation periods, 236 bull holding periods and 50 bear holding periods, which are displayed in Table 2.

Table 2 below also presents the number of overlapping portfolios that were created over the full and robust sample periods in addition to the number of bull and bear formation and holding portfolios that were available within each sample period.
Table 2: Number of bull and bear periods

<table>
<thead>
<tr>
<th>Portfolios with Bull Formation Periods</th>
<th>Full Sample Period (2002/07/03 – 2012/02/08)</th>
<th>Robust Sample Period (2004/03/26 – 2012/03/17)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Portfolios with Bear Formation Periods</td>
<td>343</td>
<td>233</td>
</tr>
<tr>
<td>Portfolios with Bull Holding Periods</td>
<td>89</td>
<td>53</td>
</tr>
<tr>
<td>Portfolios with Bear Holding Periods</td>
<td>355</td>
<td>236</td>
</tr>
<tr>
<td>Portfolios with Bull Formation and Bull Holding Periods</td>
<td>77</td>
<td>50</td>
</tr>
<tr>
<td>Portfolios with Bull Formation and Bear Holding Periods</td>
<td>276</td>
<td>193</td>
</tr>
<tr>
<td>Portfolios with Bear Formation and Bear Holding Periods</td>
<td>67</td>
<td>40</td>
</tr>
<tr>
<td>Portfolios with Bear Formation and Bull Holding Periods</td>
<td>79</td>
<td>43</td>
</tr>
<tr>
<td>Portfolios with Bear Formation and Bear Holding Periods</td>
<td>10</td>
<td>10</td>
</tr>
</tbody>
</table>

Source: McGregor BFA

5.3. Analysis of data

Now that the sample used in this study has been discussed, this section presents the results that are used to support or reject the three main hypotheses tested in this study.

5.3.1. Hypothesis 1

“H₀: The abnormal return on the average winner-minus-loser portfolio is equal to zero.”

The results of the performance and risk measures discussed below led to the rejection of the null hypothesis that the average return on a momentum winner-minus-loser portfolio is equal to zero. A discussion of why the conclusion has been made is presented below.

5.3.1.1. Performance measures

In order to determine whether the abnormal average return on the winner-minus-loser portfolios is equal to zero, a t-test was calculated on the difference between the average benchmark return and the average winner, average loser, and average winner-minus-loser momentum portfolio returns. Table 3 below presents the results for the full and robust sample periods.

There was a slight difference in results when differentiating between the full and robust sample period. Specifically, the loser portfolio returns were statistically different from the
benchmark returns in the full sample period, while they were not statistically different from
the benchmark returns in the robust sample period. As a result, the robust sample period is
focussed on the analysis that follows.

The null hypothesis is rejected for the winner and winner-minus-loser portfolios and
accepted for the loser portfolio over the robust sample period. That is because the winner
and winner-minus-loser portfolios are statistically significantly different from their benchmark
with t-statistics of 2.51 and -8.50 respectively, while the loser portfolio returns are not with a
t-statistic of -1.40. These results indicate that there was momentum in winner stock returns,
which lead to the positive returns in the winner-minus-loser portfolios, while there was little
momentum in the loser stocks.

Table 3: Momentum profitability over the sample period

<table>
<thead>
<tr>
<th>Portfolio Type</th>
<th>Period</th>
<th>Return</th>
<th>t-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Winner Portfolios</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Full Sample Period</td>
<td>2002/05/08 – 2012/02/08</td>
<td>15.17%</td>
<td>4.01</td>
</tr>
<tr>
<td>Robust Sample Period</td>
<td>2003/03/26 - 2012/03/17</td>
<td>15.99%</td>
<td>2.51</td>
</tr>
<tr>
<td><strong>Loser Portfolios</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Full Sample Period</td>
<td>2002/05/08 – 2012/02/08</td>
<td>7.04%</td>
<td>-3.04</td>
</tr>
<tr>
<td>Robust Sample Period</td>
<td>2003/03/26 - 2012/03/17</td>
<td>9.75%</td>
<td>-1.40</td>
</tr>
<tr>
<td><strong>W - L Portfolios</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Full Sample Period</td>
<td>2002/05/08 – 2012/02/08</td>
<td>3.24%</td>
<td>-8.37</td>
</tr>
<tr>
<td>Robust Sample Period</td>
<td>2003/03/26 - 2012/03/17</td>
<td>2.21%</td>
<td>-8.50</td>
</tr>
<tr>
<td><strong>Benchmark Portfolio</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Full Sample Period</td>
<td>2002/05/08 – 2012/02/08</td>
<td>10.03%</td>
<td>N/A</td>
</tr>
<tr>
<td>Robust Sample Period</td>
<td>2003/03/26 - 2012/03/17</td>
<td>11.67%</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Source: McGregor BFA
*Statistically significant t-statistics are presented in bold.

Although the momentum strategy yielded positive returns over the sample period, one still
needs to determine whether these returns are a result of portfolio risk or are indeed
abnormal. In order to do this, the risk measure, portfolio alpha discussed in Chapter 3, is
employed.

5.3.1.2. Risk measures

To account for differences in risk, the first measure employed was to determine the average
winner, loser, and winner-minus-loser portfolio alphas. That is, individual portfolio alphas
were calculated and a $t$-test conducted on the average alpha term for each category of momentum portfolio to determine whether these portfolios were able to yield positive and statistically significant alphas.

It was found that the results for the full and robust sample periods were very similar with the winner and winner-minus-loser portfolios significantly outperforming the benchmark on a risk-adjusted basis. The average alpha for the winner and winner-minus-loser portfolios in the full (robust) sample period was 0.0298% (0.0246%) and 0.0296% (0.0221%) respectively. In contrast to the winner and winner-minus-loser portfolios, the loser portfolio significantly underperformed the benchmark with an average alpha in the full (robust) sample period of -0.0293% (-0.0195%).

Table 4 illustrates that over the full sample period, the apparent momentum in winner stock returns are not solely a result of differences in risk. That is because the alpha terms for the winner portfolios are positive (0.0246%) and statistically significant at the 95% confidence level ($t$-statistic of 3.87). Similarly, the loser portfolio’s underperformance (or over-performance when shorting the portfolio) cannot be attributed to a difference in risk, with an average portfolio alpha of -0.0195% ($t$-statistic of -3.75). Because these results are statistically significant the null hypothesis that the portfolio alpha is not different from zero is rejected. Although these alphas seem practically insignificant, one should note that they are calculated on daily return data and are therefore both statistically and practically significant.

Table 4: Average momentum portfolio alpha

<table>
<thead>
<tr>
<th>Sample Period</th>
<th>Winner Alpha</th>
<th>t-stat</th>
<th>Loser Alpha</th>
<th>t-stat</th>
<th>W-L Alpha</th>
<th>t-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full sample period</td>
<td>0.0298%</td>
<td>6.42</td>
<td>-0.0293%</td>
<td>-7.43</td>
<td>0.0296%</td>
<td>7.91</td>
</tr>
<tr>
<td>Robust sample period</td>
<td>0.0246%</td>
<td>3.87</td>
<td>-0.0195%</td>
<td>-3.75</td>
<td>0.0221%</td>
<td>4.45</td>
</tr>
</tbody>
</table>

Source: McGregor BFA

*Statistically significant $t$-statistics are presented in bold.

These results suggest the presence of under- or overreaction on the Top 40 Index. However, one should note that these alphas are only averages and that over the sample period there were times where the winner-minus-loser portfolios yielded negative and statistically significant alpha terms. Figure 3 presents the size of the various winner-minus-loser portfolio alpha terms over the full and robust sample periods.
It is concluded that over the long-term, a momentum investment strategy outperformed the market on a risk-adjusted basis and the outperformance was chiefly driven by the winner component of the portfolio. However, it should be noted that there are times where the investment strategy underperformed the market.

Moreover, it is concluded that the SA stock market was inefficient over the period studied as momentum was still present after accounting for risk. The question therefore is when did the strategy outperform the benchmark and what caused the market to under- or over-react?

5.3.2. Hypothesis 2

"H_0: The abnormal return on the average winner-minus-loser portfolio with a bull formation period is equal to the abnormal return on the average winner-minus-loser portfolio with a bear formation period."

The results of the performance and risk measures discussed below led to the rejection of the null hypothesis that the returns on the average winner-minus-loser portfolios with bull formation periods are equal to the returns on the average winner-minus-loser portfolios with bear formation periods. A discussion of why this conclusion was made is presented below.

5.3.2.1. Performance measures

The previous section presented the finding that although in general there was momentum over the sample period, the momentum was not consistently present. That is, not all of the
momentum portfolios provided positive and statistically significant alpha terms. The second hypothesis is intended to determine whether the outperformance of a momentum portfolio is affected by the state of the market prior to its holding period.

In order to determine the possible effect of the market state prior to the holding period of a momentum portfolio, a *t-test* was conducted on the difference between the portfolios with a bull formation period and the portfolios with a bear formation period. Table 5 and Table 6 below illustrate the results of these tests on the full and robust sample periods respectively.

The analyses of the full and robust sample periods show slightly different results. As such, the interpretation will focus on the robust sample period. The robust sample period results indicate the following:

1. Following a bull formation period, a portfolio comprising previous winner stocks significantly outperformed the benchmark with a return of 17.64% (*t-statistic* of 3.33) versus 11.41%. However, the same portfolio underperformed the benchmark following a bear formation period with an average return of 8.72% versus 12.81%, albeit the underperformance is not statistically significant with a *t-statistic* of -0.97;

2. Following a bull formation period, a portfolio of loser stocks yielded a positive average return of 8.28%, which significantly underperformed the benchmark (11.41%), while the same portfolio yielded positive (16.22%) but not statistically different (*t-statistic* of 0.7) returns to the benchmark portfolio (12.81%) post a bear formation period;

3. Following a bull formation period, a momentum portfolio holding previous winner stocks and shorting previous loser stocks provided positive returns on average (3.50%), however it significantly underperforms the benchmark with a *t-statistic* of -6.77. That is in contrast to the same portfolio following a bear formation market state, where, although it significantly underperformed the benchmark with a return of -3.46% versus 12.81%, it provided negative portfolio returns;

4. The return on the winner-minus-loser portfolio following a bull formation period is driven by the return on the winner portfolio and reduced by the return on the loser portfolio; and

5. The state of the market prior to the holding period of momentum winner and momentum winner-minus-loser portfolios had a significant impact on the returns on these portfolios; while the state of the market during the formation period of the loser portfolio did not significantly affect the performance of the loser portfolio.
Table 5: Difference in market states during formation (full sample period)

<table>
<thead>
<tr>
<th>Formation</th>
<th>#</th>
<th>Winner Average Return</th>
<th>t-stat</th>
<th>Loser Average Return</th>
<th>t-stat</th>
<th>W – L Average Return</th>
<th>t-stat</th>
<th>Benchmark Average Return</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bull</td>
<td>343</td>
<td>15.13%</td>
<td>4.10</td>
<td>5.38%</td>
<td>-4.14</td>
<td>3.96%</td>
<td>-6.09</td>
<td>9.31%</td>
</tr>
<tr>
<td>Bear</td>
<td>89</td>
<td>15.33%</td>
<td>0.84</td>
<td>13.42%</td>
<td>0.20</td>
<td>0.50%</td>
<td>-6.26</td>
<td>12.81%</td>
</tr>
<tr>
<td>Difference</td>
<td>254</td>
<td>-0.20%</td>
<td>-0.07</td>
<td>-8.03%</td>
<td>-3.05</td>
<td>3.46%</td>
<td>2.60</td>
<td>-3.50%</td>
</tr>
</tbody>
</table>

Source: McGregor BFA

* The statistically significant t-statistics are shown in bold.

Table 6: Difference in market states during formation (robust sample period)

<table>
<thead>
<tr>
<th>Formation</th>
<th>#</th>
<th>Winner Average Return</th>
<th>t-stat</th>
<th>Loser Average Return</th>
<th>t-stat</th>
<th>W – L Average Return</th>
<th>t-stat</th>
<th>Benchmark Average Return</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bull</td>
<td>233</td>
<td>17.64%</td>
<td>3.33</td>
<td>8.28%</td>
<td>-2.49</td>
<td>3.50%</td>
<td>-6.77</td>
<td>11.41%</td>
</tr>
<tr>
<td>Bear</td>
<td>53</td>
<td>8.72%</td>
<td>-0.97</td>
<td>16.22%</td>
<td>0.70</td>
<td>-3.46%</td>
<td>-5.40</td>
<td>12.81%</td>
</tr>
<tr>
<td>Difference</td>
<td>180</td>
<td>8.92%</td>
<td>2.40</td>
<td>-7.94%</td>
<td>-1.86</td>
<td>6.96%</td>
<td>3.89</td>
<td>-1.40%</td>
</tr>
</tbody>
</table>

Source: McGregor BFA

* The statistically significant t-statistics are shown in bold.

Although risk is still to be taken into account, the following can be concluded:

1. There tended to be momentum in stock returns following a bull period, however a winner-minus-loser portfolio may not yield returns in excess of the benchmark as the loser portfolio may still provide positive returns following a bull period; and
2. The state of the market in the formation period had a significant impact on the momentum in the winner portfolio returns.

Although the impact the state of the formation period has on the performance of the momentum portfolios has been discussed, risk still needs to be taken into account. The next section will present the results when risk has been accounted for.

5.3.2.2. Risk measures

To consider risk in the analysis above, a t-test was conducted on the differences in the average alphas of those portfolios with bull formation periods and those portfolios with bear formation periods. Table 7 and Table 8 below present the results for the full and robust sample periods respectively. The analysis of the full and robust sample periods have slightly differing results and as such, the analysis that follows is focussed on the robust sample period only.
The results of the risk adjusted performance of the winner, loser, and winner-minus-loser portfolios are comparable to the points noted in the performance measures discussion above. Specifically, the following points are of significance:

1. Winner and winner-minus-loser portfolios significantly outperformed the benchmark with average portfolio alphas of 0.0324% and 0.0267% respectively. That is in contrast to the loser portfolio, which underperformed against the benchmark on a risk-adjusted basis with an average portfolio alpha of -0.0209%. However, that was only the case where the formation period was bullish;

2. Where the formation period was bearish, the performance of the winner, loser and winner-minus-loser portfolios did not significantly differ from the benchmark on a risk-adjusted basis with t-statistics of -0.60, -1.09 and 0.18 respectively;

3. The state of the market during the formation periods did not have a statistically significant impact on the underperformance of the loser portfolio against the benchmark as the average difference in the portfolio's alpha over the two market states had a t-statistic of -0.56; and

4. When winner and winner-minus-loser portfolios had bull formation periods, they tended to outperform the benchmark on a risk-adjusted basis with average portfolio alphas of 0.0324% (t-statistic of 4.74) and 0.0267% (t-statistic of 4.81) respectively. However, when their formation periods were bearish, they did not outperform the benchmark on a risk adjusted basis with t-statistics of 0.60 and 0.18 respectively. As such, the state of the market during the formation period of these portfolios had a significant impact on the outperformance of these portfolios.

Table 7: Difference in alpha terms for bull and bear formation period portfolios (full sample period)

<table>
<thead>
<tr>
<th>Formation</th>
<th>#</th>
<th>Average Alpha</th>
<th>t-stat</th>
<th>Average Alpha</th>
<th>t-stat</th>
<th>Average Alpha</th>
<th>t-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bull</td>
<td>343</td>
<td>0.0313%</td>
<td>6.25</td>
<td>-0.0305%</td>
<td>-6.76</td>
<td>0.0309%</td>
<td>7.33</td>
</tr>
<tr>
<td>Bear</td>
<td>89</td>
<td>0.0243%</td>
<td>2.06</td>
<td>-0.0248%</td>
<td>-3.09</td>
<td>0.0246%</td>
<td>3.02</td>
</tr>
<tr>
<td>Difference</td>
<td>254</td>
<td>0.0069%</td>
<td>0.54</td>
<td>-0.0056%</td>
<td>-0.61</td>
<td>0.0063%</td>
<td>0.69</td>
</tr>
</tbody>
</table>

Source: McGregor BFA

* The statistically significant t-statistics are shown in bold.
Table 8: Difference in alpha terms for bull and bear formation period portfolios (robust sample period)

<table>
<thead>
<tr>
<th>Formation</th>
<th>#</th>
<th>Winner</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>Loser</th>
<th></th>
<th></th>
<th></th>
<th>W-L</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Average Alpha</td>
<td>t-stat</td>
<td>Average Alpha</td>
<td>t-stat</td>
<td>Average Alpha</td>
<td>t-stat</td>
<td>Average Alpha</td>
<td>t-stat</td>
<td>Average Alpha</td>
<td>t-stat</td>
<td></td>
</tr>
<tr>
<td>Bull</td>
<td>233</td>
<td>0.0324%</td>
<td>4.74</td>
<td>-0.0209%</td>
<td>-3.63</td>
<td>0.0267%</td>
<td>4.81</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bear</td>
<td>53</td>
<td>-0.0096%</td>
<td>-0.60</td>
<td>-0.0133%</td>
<td>-1.09</td>
<td>0.0019%</td>
<td>0.18</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Difference</td>
<td>180</td>
<td>0.0420%</td>
<td>2.42</td>
<td>-0.0076%</td>
<td>-0.56</td>
<td>0.0248%</td>
<td>2.05</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Source: McGregor BFA

* The statistically significant t-statistics are shown in bold.

Given the performance and risk-adjusted performance analysis presented above, the null hypothesis that the return on the average winner-minus-loser portfolio with a bull formation period is equal to the return on the average winner-minus-loser portfolio with a bear formation period, is rejected.

One can conclude that the market state prior to the creation of the momentum portfolios had an effect on the portfolio’s returns. Now that the results from the analysis of formation period market state effects have been discussed, the section below focuses on the effect of the holding period market state.

5.3.3. Hypothesis 3:

“H₀: The abnormal return on the average winner-minus-loser portfolio with a bull holding period is equal to the return on the abnormal return on the average winner-minus-loser portfolio with a bear holding period.”

The results of the performance and risk measures discussed below led to the rejection of the null hypothesis in favour of the alternate hypothesis that returns on the winner, loser, and winner-minus-loser portfolios are affected by the state of the market during their holding periods. A discussion of why this conclusion was drawn is presented below.

5.3.3.1. Performance measures

Determining the effect of the holding period market state on the performance of a momentum investment strategy is done in a similar manner to that of hypothesis 2 discussed above. Specifically, t-tests are conducted on the difference between the average benchmark
returns and the average winner, loser and winner-minus-loser portfolio returns with bull and bear holding periods.

Additionally, \( t \)-tests were also conducted on the difference between the returns on winner, loser and winner-minus-loser portfolios with bull holding periods and their counterparts with bear holding periods. \textbf{Table 9} and \textbf{Table 10} below present the results. The analysis that follows is again focussed on the robust sample period results.

The results illustrated in \textbf{Table 9} and \textbf{Table 10} indicate the following:

1. Much like in the analysis of the formation period results, the holding period results show that when the holding period was bullish, the winner portfolio outperformed the benchmark with an average return of 24.83\% versus 16.75\% (\textit{t-statistic} of 7.44). Moreover, the loser portfolio underperformed the benchmark with a return of 13.76\% (\textit{t-statistic} of -2.41) and the winner-minus-loser portfolio yielded positive returns on average of 4.90\%;

2. However, unlike the previous analysis, when the holding period was bearish, the winner portfolio significantly underperformed the benchmark with an average return of -25.72\% versus -12.30\% (\textit{t-statistic} of -3.82). Additionally, the loser portfolio's returns were not statistically significantly different from the average return on the benchmark with a \textit{t-statistic} of 1.38. As such, there was a reversal in the returns on the winner portfolio when the holding period was bearish;

3. The winner, loser and winner-minus-loser portfolio returns were significantly affected by the state of the market during the holding period, as seen through the \textit{t-statistics} (15.04, 11.07, and 8.07 respectively) on the difference in these portfolios' average returns over bull and bear periods.

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|c|c|c|}
\hline
\textbf{Holding} & \textbf{#} & \textbf{Average Return} & \textbf{t-stat} & \textbf{Average Return} & \textbf{t-stat} & \textbf{Average Return} & \textbf{t-stat} & \textbf{Average Return} \\
\hline
\textbf{Bull} & 355 & 22.64\% & 8.58 & 10.02\% & -4.46 & 5.61\% & -12.47 & 14.22\% \\
\hline
\textbf{Bear} & 77 & -19.27\% & -3.87 & -6.73\% & 1.55 & -7.64\% & 0.99 & -9.30\% \\
\hline
\hline
\end{tabular}
\caption{Difference in market states during holding (full sample period)}
\end{table}

Source: McGregor BFA

* The statistically significant \textit{t-statistics} are shown in bold.
Table 10: Difference in market states during holding (robust sample period)

<table>
<thead>
<tr>
<th></th>
<th>#</th>
<th>Winner</th>
<th>Lose</th>
<th>W - L</th>
<th>Benchmark</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Average Return</td>
<td>t-stat</td>
<td>Average Return</td>
<td>t-stat</td>
</tr>
<tr>
<td>Bull</td>
<td>236</td>
<td>24.83%</td>
<td>7.14</td>
<td>13.76%</td>
<td>-2.41</td>
</tr>
<tr>
<td>Bear</td>
<td>50</td>
<td>-25.72%</td>
<td>-3.82</td>
<td>-9.20%</td>
<td>1.38</td>
</tr>
<tr>
<td>Difference</td>
<td>186</td>
<td>50.54%</td>
<td>15.04</td>
<td>22.96%</td>
<td>11.07</td>
</tr>
</tbody>
</table>

Source: McGregor BFA

* The statistically significant t-statistics are shown in bold

The winner portfolio may consist of more risky and less defensive stocks, while the loser portfolio may hold the opposite set of stocks. However, the relative riskiness of the portfolios needs to be examined before such a conclusion can be made. The next section presents the relative alpha terms of the momentum portfolios within the same categories.

5.3.3.2. Risk measures

In order to adjust for risk, the relative alpha terms of the various bull and bear holding period portfolios are examined. To do so, a t-test is conducted on the average alpha terms of the two categories of portfolios to determine whether these alphas are statistically different from zero.

A t-test is also conducted on the difference between the average alpha on the bull holding period set of portfolios and the average alpha on the bear holding period set of portfolios. The results of the analysis are presented in Table 11 and Table 12 below.

The results illustrated in Table 11 and Table 12 provides further support for the points presented earlier. Specifically:

1. The winner portfolio significantly outperformed the benchmark on a risk-adjusted basis when the holding period was bullish (t-statistic of 13.10) but it significantly underperformed against the benchmark when the holding period was bearish (t-statistic of -6.53);

2. The loser portfolio significantly underperformed against the benchmark during bull holding periods with an average alpha term of -0.0295% (t-statistic of -5.60), while it did not significantly differ from the benchmark on a risk-adjusted basis during a bear period with a t-statistic of 1.84; and

3. The winner-minus-loser portfolio significantly outperformed the benchmark during bull periods with an average portfolio alpha of 0.0429% (t-statistic of 10.51), while it
The performance of a momentum strategy during bull and bear periods on the JSE/FTSE Top 40 index

M.R. Devonport

significantly underperformed against the benchmark during bear periods with an average portfolio alpha of -0.0765% (t-statistic of -5.39).

The state of the market during the holding period had a significant impact on the under- or outperformance of the momentum portfolios as seen through the t-statistics on the difference between the portfolio returns over the two market states (9.24 for the winner, -3.59 for the loser and 8.08 for the winner-minus-loser portfolios).

Table 11: Difference in alpha terms for bull and bear holding period portfolios (full sample period)

<table>
<thead>
<tr>
<th></th>
<th>#</th>
<th>#</th>
<th>#</th>
<th>#</th>
<th>#</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average Alpha</td>
<td>t-stat</td>
<td>Average Alpha</td>
<td>t-stat</td>
<td>Average Alpha</td>
</tr>
<tr>
<td>Holding</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bull</td>
<td>343</td>
<td>0.0556%</td>
<td>15.82</td>
<td>-0.0398%</td>
<td>-9.95</td>
</tr>
<tr>
<td>Bear</td>
<td>89</td>
<td>-0.0890%</td>
<td>-6.35</td>
<td>0.0193%</td>
<td>1.81</td>
</tr>
<tr>
<td>Difference</td>
<td>254</td>
<td>0.1446%</td>
<td>10.01</td>
<td>-0.0591%</td>
<td>-5.21</td>
</tr>
</tbody>
</table>

Source: McGregor BFA

* The statistically significant t-statistics are shown in bold.

Table 12: Difference in alpha terms for bull and bear holding period portfolios (robust sample period)

<table>
<thead>
<tr>
<th></th>
<th>#</th>
<th>#</th>
<th>#</th>
<th>#</th>
<th>#</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average Alpha</td>
<td>t-stat</td>
<td>Average Alpha</td>
<td>t-stat</td>
<td>Average Alpha</td>
</tr>
<tr>
<td>Holding</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bull</td>
<td>233</td>
<td>0.0564%</td>
<td>13.10</td>
<td>-0.0295%</td>
<td>-5.60</td>
</tr>
<tr>
<td>Bear</td>
<td>53</td>
<td>-0.1255%</td>
<td>-6.53</td>
<td>0.0274%</td>
<td>1.84</td>
</tr>
<tr>
<td>Difference</td>
<td>180</td>
<td>0.1819%</td>
<td>9.24</td>
<td>-0.0568%</td>
<td>-3.59</td>
</tr>
</tbody>
</table>

Source: McGregor BFA

* The statistically significant t-statistics are shown in bold.

As a result, the null hypothesis that the returns on the momentum winner-minus-loser portfolio are not affected by the state of the market during its holding period is not accepted.

5.4. Conclusions drawn from the findings

Now that the results of the analysis have been presented, this section will discuss these findings as they relate to the objectives of this study and the literature reviewed in Chapter 3. As a result, this section is organised into four main sections:
The performance of a momentum strategy during bull and bear periods on the JSE/FTSE Top 40 index
M.R. Devonport

1. Conclusions around the consistency of momentum investment strategy success in the SA stock market;
2. Conclusions around the efficiency of the SA equity market;
3. Conclusions around the behaviour of the SA equity market as it relates to momentum investment strategy success; and
4. Conclusions around the success of a momentum investment strategy given changes in the overall performance of the market.

5.4.1. Consistency of serial correlation in stock returns

The fact that hypothesis one was not accepted at the 95% confidence level means that over the years, momentum in stock returns has been consistently present in the SA stock market. Winner stocks have tended to outperform the market and loser stocks have tended to underperform relative to the market.

Evidence of momentum behaviour has been found in this study over the nine-year period 2002 to 2012 and in other studies (Fraser & Page, 2000 and Griffin et al., 2003) over earlier periods such as 1973 to 1997 and 1990 to 2000 respectively. As a result one can conclude that this evidence is not due to data mining bias.

Moreover, it is concluded that the presence of a market anomaly and widespread evidence of its existence does not necessarily mean that it will disappear as more and more rational investors trade in light of this evidence.

5.4.2. South African stock market efficiency

Given that all three hypotheses were not accepted at the 95% confidence level and that momentum in stock returns is consistently present, one can conclude that the market for large SA stocks is not entirely efficient. This study has found that the CAPM is not able to explain all the profits earned on the momentum portfolios.

There is, on average, a positive alpha term on the winner and winner-minus-loser portfolios over the entire sample period and over the majority of the market state categories assessed here. As a result, in so far as the CAPM is representative of an efficient market and the Top 40 Index is representative of the SA stock market, it is concluded that the SA stock market is inefficient.
5.4.3. South African stock market behaviour

The explanations for the success of a momentum investment strategy were presented in Chapter 3. The first explanation that is consistent with the EMH was data mining bias. This explanation has obviously been ruled out due to the evidence provided by Fraser and Page (2000) and Griffin et al. (2003), together with the results of this study.

The second EMH explanation was macroeconomic risk and although this explanation was not accepted by Griffin et al. (2003), it cannot be ruled out by this study for two reasons. Firstly, this study does not control for macroeconomic risk as mimicked by various macroeconomic variables.

Secondly, positive abnormal returns resulting from the momentum investment strategy were not present in all market states, which is consistent with the macroeconomic risk explanation of Chordia and Shivakumar (2002). Specifically, although the winner component of the momentum strategy was abnormally profitable regardless of the formation period market state, it was not profitable where the holding period was bearish. As a result, changes in macroeconomic risk may be the cause of the apparent success of the momentum investment strategy tested in this study.

The macroeconomic risk explanation aside, the results of this study are consistent with the presence of investor overconfidence and therefore Daniel et al.'s (1998) behavioural model in that momentum returns tend to be strongest following bull formation periods. Daniel et al. (1998) posited that the momentum effect originates from the continued reaction by informed investors to the arrival of confirming news.

When the market moves higher, investors become overconfident in their ability, which boosts overreaction and therefore momentum profits. Consequently, to the extent that the aggregate market position is long, a bull period causes increased overconfidence as investors attribute these gains to their skill, thereby causing higher momentum profits.

Another behavioural model and hypothesis that is consistent with the results of this study is Hong and Stein (1999), and Campbell and Cochrane (1999). Specifically, Hong and Stein's (1999) model predicts that investors initially under-react to information, which gradually spreads throughout the market.

However, as more and more momentum traders enter the market, the initial under-reaction turns into overreaction. If one assumes that risk aversion and wealth are negatively associated (Campbell and Cochrane, 1999), then momentum profits should be stronger in a bull market phase, which is the case here.
5.4.4. Momentum investment strategy performance over different market states

The defensive investor can take two main points from the evidence presented here:

1. The momentum investment strategy is abnormally profitable, however investors should not generally take a short position in the loser portfolio as it detracts from the momentum strategy's absolute returns; and
2. The momentum strategy is generally more profitable following a bull formation period, however it is dependent on the holding period being bullish as the strategy is not profitable during a bear holding period.

5.5. Summary

This chapter presented the empirical results concerning the three hypotheses tests and the research questions. In general the results of these tests led to the rejection of the null hypothesis in all three cases. Specifically, it is concluded that the average return on the winner-minus-loser portfolios are not equal to zero and the returns on the momentum portfolios are significantly affected by the state of the market in both the formation and the holding periods.

It was found that on average, the winner, loser, and winner-minus-loser portfolios are capable of yielding positive risk-adjusted returns and that these returns tend to differ significantly given the state of the formation and holding periods. The winner portfolios significantly outperformed the benchmark on both an absolute and risk-adjusted return basis following a bull period; however the very same portfolio yielded very similar returns to the benchmark following a bear period.

Momentum in stock returns is only present following a bull period as the risk-adjusted returns on winner, loser, and winner-minus-loser portfolios are only statistically significant following a bull period. The state of the holding period also had a significant impact on momentum portfolio returns. Winner portfolios tended to produce large positive abnormal market returns in a bull period; however there was a complete reversal when the holding period was bearish. The opposite was true for the loser portfolio. There tended to be momentum in the loser stock returns during a bull period, while these returns turned positive during a bear period.

Now that these results are known, the next chapter will conclude this study by bringing together the findings and conclusions presented in all the other chapters. The limitations will
be reiterated and the empirical results presented above will be compared to the conclusions made by the literature reviewed.
Chapter 6
Findings, conclusions and recommendations

6.1. Introduction

The literature has been reviewed, methodology presented and findings discussed in the previous chapters. This chapter will conclude the paper by summarising the salient points. Specifically, the research question and objectives of the study are briefly revisited in section 6.2; the findings presented in Chapter 5 are discussed in section 6.3. Lastly, this chapter will conclude with some recommendations for further research that may contribute to this area of knowledge in section 6.4.

6.2. The research question

The main research question addressed in this study was to determine whether a momentum investment strategy employed on the Top 40 Index is more or less successful over bull and bear market states. Answering this question seeks to meet three main objectives.

Specifically, the research aimed to add to the current body of evidence for or against the under- or overreaction hypothesis in a SA stock market context. Secondly, this study aimed to determine whether the success of a momentum strategy is a result of changes in macroeconomic risk as hypothesised by Griffin et al. (2003). Thirdly, insight into the workings of the SA stock market was gained by determining how a momentum strategy’s profits vary over bull and bear market states and how these findings relate to past literature on the topic.

6.3. Summary of the findings

In order to answer the research question and meet the research objectives, three main hypotheses were tested and discussed in Chapter 5. The three null hypotheses tested were:

1. $H_0$: The abnormal return on the average winner-minus-loser portfolio is equal to zero;
2. $H_0$: The abnormal return on the average winner-minus-loser portfolio with a bull formation period is equal to the abnormal return on the average winner-minus-loser portfolio with a bear formation period; and
3. $H_0$: The abnormal return on the average winner-minus-loser portfolio with a bull holding period is equal to the abnormal return on the average winner-minus-loser portfolio with a bear holding period.
The performance of a momentum strategy during bull and bear periods on the JSE/FTSE Top 40 index

M. R. Devonport

It should be noted that absolute returns were not the only data analysed, risk was also taken into account by calculating an average alpha term, consistent with the CAPM, thereby calculating the average abnormal return on the various portfolio types.

In all three cases, the $H_0$ was rejected at a 95% confidence level. These results indicate that there was significant momentum within the Top 40 Index over the sample period. Additionally, based on the portfolio alpha terms analysed, the momentum in stock returns cannot be solely explained by risk, as measured by the CAPM, and therefore these results indicate the SA stock market was inefficient over the sample period.

The presence of momentum in the equity market has strong implications for the measurement and control of risk. Its presence means that returns over various periods are not independent and therefore the true variance of returns could be much greater than twelve multiplied by the monthly variance (Scowcraft & Sefton, 2005).

Based on the differences in portfolio performance over bull and bear formation and holding periods, a momentum investment strategy employed on the Top 40 Index tends to generate positive abnormal profits if the formation period is bullish, or if the strategy only comprises winner stocks. As such, the market state had a significant impact on the performance of the momentum portfolios and these portfolios are driven by the performance of their winner component. As a result, when the market is trending upward during the holding period, the overall momentum portfolio performance is positive, while the opposite is true when the market state is bearish during the holding period.

Those investors who follow a momentum investment strategy may benefit from these results through the knowledge of momentum in an emerging market such as SA’s because in general, emerging markets have a very low correlation with developed markets, thereby providing further diversification benefits to an international momentum portfolio (Chowdhury & Michello, n.d.). What’s more, Benjamin Graham’s (2006) defensive investors should also benefit from this study as it provides evidence for this ‘easy, rules-based’ investment strategy and its applicability in a bull market, while being ineffective in a bear market state.

Although the macroeconomic risk explanation was not accepted by Griffin et al. (2003), it cannot be completely ruled out by this study for two reasons. Firstly, this study does not control for macroeconomic risk as mimicked by various macroeconomic variables. Secondly, positive abnormal returns resulting from the momentum investment strategy were not present overall market states, which is consistent with the macroeconomic risk explanation of Chordia and Shivakumar (2002).
The performance of a momentum strategy during bull and bear periods on the JSE/FTSE Top 40 index

M.R. Devonport

The macroeconomic risk explanation aside, the results of this study are consistent with the presence of investor overconfidence and therefore Daniel et al.'s (1998) behavioural model as momentum returns tend to be strongest following bull formation periods. Daniel et al. (1998) posited that the momentum effect originates from the continued reaction by informed investors to the arrival of confirming news. As such investors and researchers should take this into account when making investment decisions as behaviour, particularly overconfidence and under-reaction, can have a significant effect on SA stock price behaviour.

Another behavioural model and hypothesis that is consistent with the results of this study is Hong and Stein (1999) and also Campbell and Cochrane (1999). Specifically, Hong and Stein's (1999) model predicts that investors initially under-react to information, which gradually spreads throughout the market. However, as more and more momentum traders enter the market, the initial under-reaction turns into overreaction. If one assumes that risk aversion and wealth are negatively associated (Campbell and Cochrane, 1999), then momentum profits should be stronger in a bull market phase, which is the case here.

6.4. Recommendations for further research

The limitations presented in this study create room for further research in this area. Specifically, research can be done into the effects of market states, taking transaction costs into account. One would do so by creating trading ranges and conducting the analysis in the same manner as in this study but measuring the returns post transaction costs. By doing so, one may gain further understanding of the practicality of employing a momentum strategy on the JSE.

Another area for future research is to determine the effect of market states on investors’ risk profiles. By doing so, one may gain further understanding into inter-temporal variations in risk and therefore the required rate of returns as predicted by the CAPM or some other efficient market model that is deemed appropriate.

Given the findings of this study it may also be relevant to determine what can be used as a proxy for behavioural and social biases in order to predict the potential for abnormal profits to be gained from momentum investment strategies. Such a finding would be a great addition from both a practical and theoretical perspective.
List of references


