The Profitability of Momentum Investing

Testing a Practical Momentum Strategy

by

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Declaration

By submitting this dissertation electronically, I declare that the entirety of the work contained therein is my own, original work, that I am the owner of the copyright thereof (unless to the extent explicitly otherwise stated) and that I have not previously in its entirety or in part submitted it for obtaining any qualification.

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Abstract

Several studies have shown that abnormal returns can be generated simply by buying past winning stocks and selling past losing stocks. Being able to predict future price behaviour by past price movements represents a direct challenge to the Efficient Market Hypothesis, a centrepiece of contemporary finance.

Fund managers have attempted to exploit this effect, but reliable footage of the performance of such funds is very limited. Several academic studies have documented the presence of the momentum effect across different markets and between different periods. These studies employ trading rules that might be helpful to establish whether the momentum effect is present in a market or not, but have limited practical value as they ignore several practical constraints.

The number of shares in the portfolios formed by academic studies is often impractical. Some studies (e.g. Conrad & Kaul, 1998) require holding a certain percentage of every share in the selection universe, resulting in an extremely large number of shares in the portfolios. Others create portfolios with as little as three shares (e.g. Rey & Schmid, 2005) resulting in portfolios that are insufficiently diversified. All academic studies implicitly require extremely high portfolio turnover rates that could cause transaction costs to dissipate momentum profits and lead the returns of such strategies to be taxed at an investor's income tax rate rather than her capital gains tax rate. Depending on the tax jurisdiction within which the investor resides these tax ramifications could represent a tax difference of more than 10 percent, an amount that is unlikely to be recovered by any investment strategy.

Critics of studies documenting positive alpha argue that momentum returns may be due to statistical biases such as data mining or due to risk factors not effectively captured by the standard CAPM. The empirical tests conducted in this study were therefore carefully designed to avoid every factor that could compromise the results and hinder a meaningful interpretation of the results. For example, small-caps were excluded to avoid the small firm effect from influencing the results and the tests were conducted on two different samples to avoid data mining from being a possible driver. Previous momentum studies generally used long/short strategies. It was found, however, that momentum

strategies generally picked short positions in volatile and illiquid stocks, making it difficult to effectively estimate the transaction costs involved with holding such positions. For this reason it was chosen to test a long-only strategy.

Three different strategies were tested on a sample of JSE mid-and large-caps on a replicated S&P500 index between January 2000 and September 2009. All strategies yielded positive abnormal returns and the null hypothesis that feasible momentum strategies cannot generate statistically significant abnormal returns could be rejected at the 5 percent level of significance for all three strategies on the JSE sample.

However, further analysis showed that the momentum profits were far more pronounced in "up" markets than in "down" markets, leaving macroeconomic risk as a possible explanation for the vast returns generated by the strategy. There was ample evidence for the January anomaly being a possible driver behind the momentum returns derived from the S&P500 sample.

Opsomming

Verskillende studies het gewys dat abnormale winste geskep kan word deur eenvoudig voormalige wenner aandele te koop en voormalige verloorder aandele te verkoop. Die moontlikheid om toekomstige prysgedrag te voorspel deur na prysbewegings uit die verlede te kyk is 'n direkte uitdaging teen die "Efficient Market Hypothesis", wat 'n kernstuk van hedendaagse finansies is.

Fondsbestuurders het gepoog om hierdie effek te benut, maar akademiese ondersteuning vir die gedrag van sulke fondse is uiters beperk. Verskeie akademiese studies het die teenwoordigheid van die momentum effek in verskillende markte en oor verskillende periodes uitgewys.

Hierdie akademiese studies benut handelsreëls wat gebruik kan word om te bepaal of die momentum effek wel in die mark teenwordig is al dan nie, maar is van beperkte waarde aangesien hulle verskeie praktiese beperkings ignoreer. Sommige studies (Conrad & Kaul, 1998) vereis dat 'n sekere persentasie van elke aandeel in die seleksie-universum gehou moet word, wat in oormatige groot aantal aandele in die portefuelle tot gevolg het. Ander skep portefeuljes met so min as drie aandele (Rey & Schmid, 2005), wat resulteer in onvoldoende gediversifiseerde portefeuljes. Die hooftekortkoming van alle akademiese studies is dat hulle portefeulleomsetverhoudings van hoër as 100% vereis wat daartoe sal lei dat winste uit sulke strategieë teen die belegger se inkomstebelastingskoers belas sal word in plaas van haar kapitaalaanwinskoers. Afhangende van die belastingsjurisdiksie waaronder die belegger val, kan hierdie belastingseffek meer as 10% beloop, wat nie maklik deur enige belegginsstrategie herwin kan word nie.

Kritici van studies wat abnormale winste dokumenteer beweer dat sulke winste 'n gevolg kan wees van statistiese bevooroordeling soos die myn van data, of as gevolg van risikofaktore wat nie effektief deur die standaard CAPM bepaal word nie. Die empiriese toetse is dus sorgvuldig ontwerp om enige faktor uit te skakel wat die resultate van hierdie studie sal kan bevraagteken en 'n betekenisvolle interpretasie van die resultate kan verhinder. Die toetse sluit byvoorbeeld sogenaamde "small-caps" uit om die klein firma effek uit te skakel, en die toetse is verder op twee verskillende monsters uitgevoer om myn van data as 'n moontlke dryfveer vir die resultate uit te skakel. Normaalweg toets akademiese studies lang/ kort nulkostestrategieë. Dit is gevind dat momentum strategieë oor die algemeen kort posisies kies in

vlugtige en nie-likiede aandele, wat dit moeilik maak om die geassosieerde transaksiekoste effektief te bepaal. Daar is dus besluit om 'n "lang-alleenlik" strategie te toets.

Drie verskillende strategieë is getoets op 'n steekproef van JSE "mid-caps" en "large-caps" en op 'n gerepliseerde S&P500 index tussen Januarie 2000 en September 2009. Alle strategieë het positiewe abnormale winste opgelewer, en die nul hipotese dat momentum strategieë geen statisties beduidende abnormale winste kan oplewer kon op die 5% vlak van beduidendheid vir al drie strategieë van die JSE monster verwerp word.

Verdere analiese het wel getoon dat momentumwinste baie meer opvallend vertoon het in opwaartse markte as in afwaartse markte, wat tot die gevolgtrekking kan lei dat makro-ekonomiese risiko 'n moontlike verklaring kan wees. Daar was genoegsaam bewyse vir die Januarie effek as 'n moontlike dryfveer agter die momentum-winste in die S&P500 monster.

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"The boundaries of my language are the boundaries of my world."

– Ludwig von Wittgenstein

Glossary and Abbreviations

active management: Holding portfolios that differ from their benchmark portfolios in an attempt to produce positive risk adjusted returns

AMEX: American Stock Exchange

anomalies: Security price relationships that contradict the Efficient Market Hypothesis

alpha: The return on an asset in excess of the asset's required rate of return; the risk-adjusted return

autocorrelation: The correlation of a time series with its own past values

autoregressive (AR) model: A time series regressed on its own past values, in which the independent variable is a lagged value of the dependent variable

autoregressive conditional heteroskedacity (ARCH): ARCH describes the condition where the variance of the residuals in one time series is dependent on the variance of the residuals in another period. When this condition exists, the standard errors of the regression coefficients in AR models and the hypothesis tests of these coefficients are invalid

basis point: One basis point equals 0.1 percent

beta: A standardized measure of systematic risk based on an asset's covariance with the market portfolio

Capital Asset Pricing Model (CAPM): An equation describing the expected return on any asset (or portfolio) as a linear function of its beta relative to the market portfolio

cointegration: Cointegration means that two time series are economically linked or follow the same trend. If two time series are cointegrated, the error term from regressing one on the other is covariate stationary and the *t*-tests are reliable

contrarian investing: Investing contrary to general market sentiment

conditional trading costs: Trading costs that are adjusted for certain factors such as market conditions, buying or selling positions, immediacy of trades, etc.

covariance stationary: Statistical inferences based on a lagged time series model may be invalid unless it can be assumed that the time series is covariance stationary. A time series is covariance stationary if it has a constant and finite expected value, a constant and finite variance and if it exhibits a constant and finite variance with regards to leading or lagged values

decile: One-tenth of a portfolio in terms of its net asset value (NAV)

data snooping bias: Concern that studies on historical (ex-post) data do not create a good fit for technical trading strategies that will work for forecasted (ex-ante)returns

earnings momentum: Phenomenon that stocks with high earnings in one period exhibit higher earnings in the following period

ex-ante returns: Expected or future returns

ex-post returns: Past or historical returns

formation period: The time in months of previous price series information before the current date used to make investment decisions for the upcoming holding period

firm-specific risk: See "unsystematic" risk

holding period: The time in months a security is held in a portfolio, or the time in months a portfolio of securities is held as a whole

industry: Group of companies that are related in terms of their primary business activities. Industry average ratios and returns etc. are often used as a benchmark for comparison between different companies in a certain industry

industry effects: Concept that stipulates that the overall performance or behaviour of an industry will explain a significant amount of the performance or behaviour of individual stocks located within that industry

J: Formation period in months

JSE: Johannesburg Stock Exchange

K: Holding period in months

large-cap: A company with large market capitalization (over $5 billion on US markets)

liquidity: The ability to trade a stock quickly and at quoted prices. For example, small illiquid stock positions can often not be converted to cash right away, leading to opportunity costs of imperfect execution. Liquid stock positions will not exhibit these problems

long position: The buying or holding of a security such as stock. The holder of a long position owns the underlying security and will profit if it appreciates in price

market capitalization: The market price of an entire company, computed by multiplying the number of shares outstanding by the market price of these shares

mid-cap: A company with medium capitalization ($1 billion to $5 billion on US markets)

market microstructure: Branch of finance concerned with the details of how exchange occurs in markets. Microstructure research examines the ways in which the working processes of a

market affects determinants of transaction costs, prices, quotes and volume (for example bid-ask bounce and liquidity effects)

momentum effect: The tendency of stocks that have performed well in one period to continue to perform well in subsequent periods

momentum indicators: Valuation indicators that relate either price or a fundamental (such as earnings) to the time series of their own past values

NASDAQ: National Association of Securities and Dealers Automated Quotation. It is the largest electronic screen-based over-the-counter equity securities trading market in the United States

Net Asset Value (NAV): The combined asset value of all share and cash positions of a portfolio

NYSE: New York Stock Exchange

passive management: An investment strategy such as a buy-and-hold strategy, usually investing in an index

portfolio turnover: The rate of trading activity in a fund's portfolio of investments, equal to the lesser of purchases or sales, for a year, divided by average total assets during that year

price reversals: A sudden change in the price direction of a stock

price momentum: Phenomenon that stocks exhibiting high price appreciation over previous periods are likely continue this trend over subsequent periods.

risk-free rate: The maximum return that can be earned in a market without taking on any risk. Usually the rate on Treasury securities.

robustness: A robust statistical technique is one that performs well even if the assumptions for the model used to analyse are somewhat violated

securities: Financial assets. These can be broadly classified as debt securities (e.g. bonds, Treasury Securities and debentures), equity securities (e.g. common stocks) and derivative contracts (e.g. futures and options). In this paper the term securities is used interchangeably for equity securities, shares or stocks

short position: Short selling is investing in the downside of the market. A stock is borrowed at a nominal fee and immediately sold in the market. The short seller gets the proceeds and repurchases the stock in the market at a later stage for a (hopefully) lower price and gives it back to the lender. He/she keeps the difference between the original price and the lower repurchase price

small-cap: A company with small capitalization (less than $250000 on US markets)

systematic risk: The variability of an asset's return that is due to macroeconomic factors that affect all risky assets. It is the portion of risk that cannot be eliminated by diversification

tax loss selling: Selling off securities that had undergone losses to reduce taxable income and therefore the amount of tax to be paid

technical analysis: A security analysis discipline for forecasting the future direction of prices through the study of past market data, primarily price and volume

unconditional trading costs: Trading costs that are fixed to a certain percentage of the trade's value

underreaction: An investor's delayed price reaction to the release of new information on the market

unsystematic risk (or non-diversifiable risk): The portion of risk that is unique to an asset and is due to individual characteristics. It can be eliminated by diversification

volatility: The total risk of a stock or a portfolio. It is measured in standard deviation (σ)

zero-cost strategy: Portfolios formed in a way that the long positions are financed by short positions equal in value

Chapter 1: Introduction

"Scientists investigate that which already is; Engineers create that which never has been."

-Albert Einstein

1.1 BACKGROUND

Various studies, predominantly on U.S. markets, document predictability in equity returns, in other words, stocks that have outperformed in the past continue to do so in the near future (For example, De Bondt and Thaler, 1987; Jegadeesh and Titman, 1993; Chan, Jegadeesh, & Lakonishok, 1996). These studies have found that an investment strategy based on buying past "winners" and selling past "losers" can generate statistically significant abnormal returns over holding periods of 3 to 12 months.

A heated academic debate started when Jegadeesh and Titman (1993) first documented the profitability of simple, trading rule-based momentum investing strategies on US equity markets. A myriad of studies followed, on US markets and internationally, most them confirming the findings of Jegadeesh and Titman (1993) (For example, Jegadeesh and Titman, 1996; Rouwenhorst, 1998; Schiereck et al., 1999). For example, Moskowitz and Grinblatt (1999) state: "The ability to outperform buy-and-hold strategies by acquiring past winning stocks and selling past losing stocks, commonly referred to as individual stock momentum, remains one of the most puzzling of these anomalies, both because of its magnitude ~up to 12 percent abnormal return per dollar long on a self-financing strategy per year."

The main critic of momentum investing is the Efficient Market Hypothesis (EMH), a fundamental theorem in contemporary finance. The EMH claims that past price information cannot be used to predict future price patterns, one of the core principles upon which momentum investing relies. Jegadeesh and Titman (2001) remark that "the momentum effect represents perhaps the strongest evidence against the Efficient Market Hypothesis". It is safe to say that momentum investing is one of the most disputed topics in investment finance academia today.

Momentum investing was used by investors and fund managers long before the academic debate even started. One of the most prominent examples is Gerald Tsai, who used a momentum approach to manage Fidelity's Capital Fund with great success throughout the bullish "Go-Go" years on Wall Street from 1958 to 1965 (Ellis & Vertin, 2001). Today momentum investing is utilized by many mutual fund managers and private investors. Momentum investing is a widespread investment style in the US and other equity markets (Taffler, 1999). Jeff Saunders, fund manager of the UK Growth Fund and the winner of the 1997 and 1999 Standard and Poor's Micropal award for the best UK mutual fund, publicly attributes his investment success to the principle of running the winners and cutting the losers (Saunders, 2004).

Tom de Lange[1] outperformed the FTSE/JSE All Share index over most of the past decade using a unique momentum investing strategy. He also conducted several back tests for different periods on JSE stock price data and found that he could earn abnormal returns in almost every randomly selected period in the history of the JSE, even when taking trading costs into account.

Momentum research to date investigates hypothetical trading strategies that are far from being implementable in practice. There exists sufficient evidence of successful practical implementations of

[1] De Lange is the CIO of Vega Capital, a South African boutique asset management firm based in Centurion, Pretoria.

size and value strategies[2]; but a similar practical implementation of a momentum strategy has never been formally documented (Keim, 2003).

1.2   PURPOSE OF THE STUDY

While the methodologies used by momentum researchers (e.g. Jegadeesh and Titman, 1993; Conrad and Kaul, 1998) to date were found to be able to earn abnormal returns it is questionable whether such strategies can be readily implemented in practice. On the other hand, it is likewise questionable whether practical strategies similar to the one used by De Lange (2009) yield abnormal returns when tested in an academic setting.

This paper will seek to test the practical approach followed by De Lange (2009) which relies on technical indicators and reflects the restrictions imposed by practical portfolio management and taxation considerations within a formal academic framework to establish whether momentum strategies are viable in practice.

While De Lange's results could be explained by factors such as data mining bias, this paper will seek to design and conduct a robust statistical test of De Lange's method. This will entail simulating De Lange's approach on two different sets of historical data and recording returns and risk measures.

This study is very relevant as little or no academic research has taken on such a perspective. Most published momentum studies focus on proving the existence of the momentum anomaly or investigating the sources of momentum profits, rather than testing the performance of realistic and implementable investment strategies based on the momentum effect (Rey & Schmid, 2005).

1.3   RESEARCH QUESTIONS AND HYPHOTHESES

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[2] For example, Dimensional Fund Advisors and LSV Asset Management have successfully implemented strategies based on academic research on the size and value effect.

The research questions and hypotheses of the study deal with the profitability of feasible momentum strategies.

Hypotheses:

H_0:   Feasible momentum strategies do not yield statistically significant abnormal returns.

H_a: Feasible momentum strategies yield statistically significant abnormal returns.

Rejection of the null hypothesis would lead to accepting the alternative hypothesis.

More general research questions pertaining to the subject area include:

- Are feasible momentum strategies profitable across different markets?
- Do the optimized technical momentum indicators used in practice deliver superior portfolio performance as opposed to simply ranking stocks in terms of past performance as done in most academic studies?
- Do the momentum returns persist through time and through different macroeconomic states?
- Are momentum profits robust with regard to trading costs?

The hypotheses and research questions will be refined in Section 6.1 and form the core focus of this dissertation.

1.4   SCOPE OF THE STUDY

This study is conducted in fulfilment of an MSc (Engineering Management) degree, which requires a relatively narrow focus on a subject area. It does not necessitate the creation of new theory. However, a formal framework for testing feasible momentum strategies such as the one used by De Lange (2009) has never been devised before, in essence requiring the creation of new knowledge and a new testing framework.

As this report is compiled from the perspective of engineering management, basic financial concepts terminology will be discussed in more detail than in the case of conventional papers stemming from this context.

Engineering can be defined as: "The application of scientific and mathematical principles to practical ends such as the design, manufacture, and operation of efficient and economical structures, machines, processes, and systems." Engineering management involves managing engineered solutions. In other words, engineering is concerned with applying theoretical knowledge to a practical problem. Managing portfolios is similar to managing any other complex system. Establishing whether feasible momentum strategies can earn abnormal returns is a practical problem that requires to be substantiated by academic theory in order to arrive at a result that can be used by practitioners.

This dissertation fuses the academic theory around momentum investing with a practical investment strategy and its results have practical and academic implications.
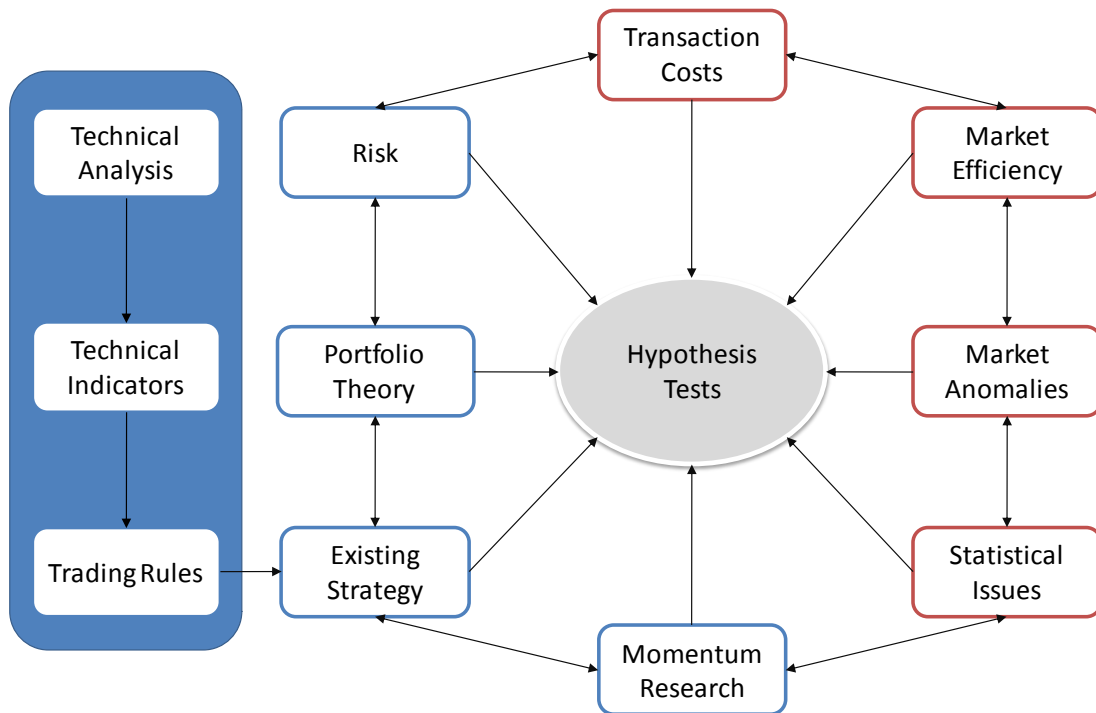
Figure 1: Research Area

The research area of this study is mapped in Figure 1 above. The field of technical analysis serves as a basis to the existing, practical momentum strategy used by De Lange (2009) that serves as the basis for

the hypothesis tests. Previous literature on momentum investing, market efficiency and previously documented market anomalies represent the academic setting of the study. Practical issues pertaining to the field of portfolio management such as the number of shares in a portfolio and the diversification of risk, alongside with statistical issues generally encountered with tests for abnormal returns and transaction costs guide the design of the empirical tests.

The scope of the study is to investigate whether a momentum strategy such as the one developed by De Lange (2009) will yield statistically significant returns on the JSE and when applied in another market.

1.5   RESEARCH METHODOLOGY

The research method design chosen for this study is mapped in Figure 2 below.
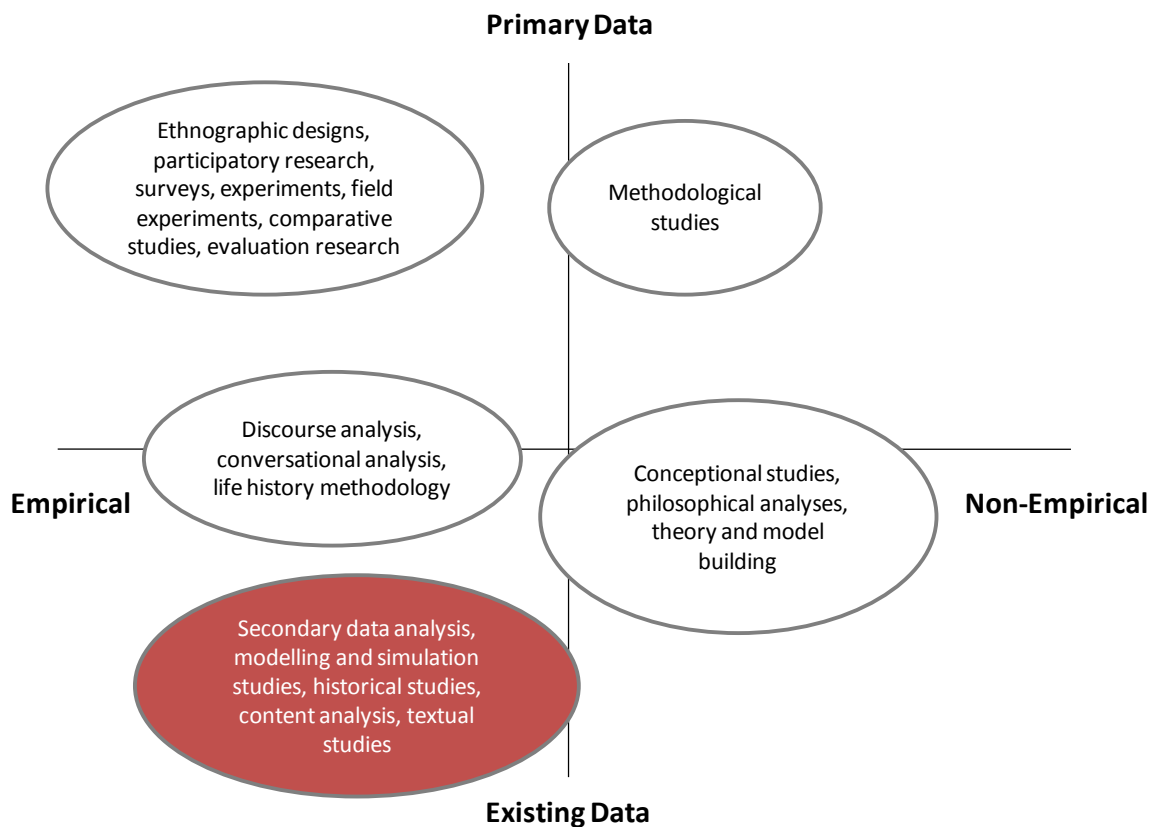
Figure 2: Mapping Research Design

Figure 2 above categorizes different types of research approaches as to the degree that they are empirical in nature and as to whether they employ primary (new) or existing data. This dissertation is empirical in nature and entails simulating feasible momentums strategies on historical data. It therefore falls into the lower left quadrant of Figure 2.

The dissertation is structured as follows:
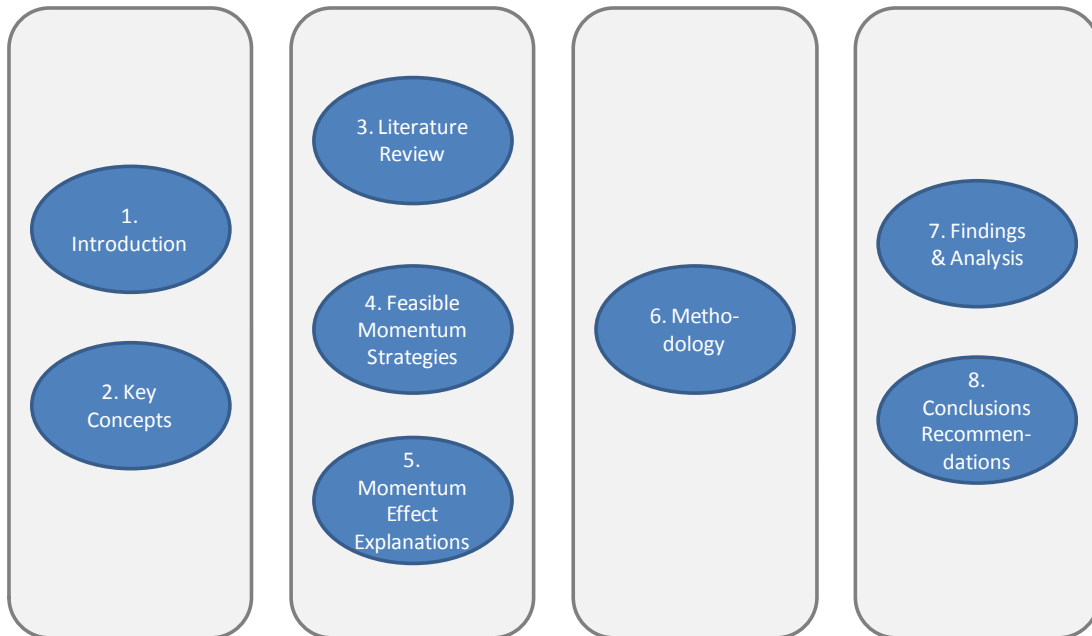
Figure 3: Dissertation Structure

The area of research, the aim and scope of the study are outlined in Chapter 1. In Chapter 2the study will be mapped from an academic as well as from an investment industry perspective. Key concepts that form the basis of the discussion throughout the study will also be introduced.

In Chapter 3 previous academic studies pertaining to momentum investing are discussed. In Chapter 4 the practical momentum strategy followed by De Lange (2009) is described and the latter is compared to the academic studies discussed in Chapter 3. In Chapter 5 possible explanations of the momentum effect are discussed and a set of guidelines for a robust empirical test is set forth.

In Chapter 6 the data and methodology used is discussed. It is shown how the data set and the methodology were chosen according to the guidelines in Chapter 5, the academic studies of Chapter 3 and the practical momentum strategy introduced in Chapter 4. The empirical results are presented and analysed in Chapter 7. The dissertation is concluded in Chapter 8 and suggests future research is suggested.

Chapter 2:   Key Concepts

"A successful man is one who can lay a firm foundation with the bricks others have thrown at him."

- *David Brinkley*

In this chapter the financial concepts necessary to facilitate the discussion throughout the study will be explained. The Efficient Market Hypothesis is formally introduced and a basic understanding of risk vs. returns is established. Finally differences between the two active investment strategies, fundamental and technical analysis, will be discussed.

2.1   EFFICIENT MARKET HYPOTHESIS (EMH)

The Efficient Market Hypothesis (EMH) is a central concept to this study. The EMH was devised by Eugene Fama in 1965 based on the articles by Kendall (1953) and Roberts (1959) and is still regarded as one of the most important concepts in contemporary finance.

2.1.1   History of EMH

Kendall (1953) analysed a sample of 22 UK commodity stock price series. He found that there were no predictable patterns in the price series and that they behaved in a truly random manner. The prices at any point were equally likely to increase, decrease or remain the same. In statistical terms this means that there is no autocorrelation between the stock's current prices and their previous prices. Roberts (1959) conducted similar tests on US stocks confirming the findings of Kendall (1953).

2.1.2   Rationale of the EMH

The EMH stipulates that only the arrival of new information can influence stock prices. Since information arrives randomly on the market, stock prices are also bound to behave in a random manner. If there was any way to develop a model that predicts future price movements it would be fully discounted in the market. If more returns could be generated by an investment at the same level of risk, all investors would allocate their funds to exploit this opportunity. The increased demand would increase the price to the equilibrium level.

2.1.3   Levels of Efficiency

The EMH suggests three levels of market efficiency.

1. *Strong form* market efficiency is the highest attainable level of market efficiency. All information, including insider's information is reflected by the security prices.

2. *Semi-strong form* market efficiency stipulates that all publicly available information is incorporated into asset prices. New information on assets is disseminated correctly and instantly. It is impossible to earn abnormal returns as all publicly available information is already discounted in the market. Earning abnormal returns is only possible by holding inside information.

3. *Weak form* market efficiency exists when all information contained in historical price series is correctly represented in asset prices. Consequently no abnormal returns can be earned by technical analysis that uses past price and volume information to predict future price movements. However insiders and fundamental analysts can earn abnormal returns.

The EMH represents the basis of a vigorous academic debate. Proponents of the EMH reject the claims of researchers of market anomalies and technical analysts suggesting that abnormal returns can be derived from analysing past price behaviour.

Basic portfolio theory will be discussed next, leading to the market model that will be used to measure abnormal returns.

2.2 PORTFOLIO THEORY

The fundamentals of modern portfolio theory were established by Professor Harry Markowitz in 1952. Markowitz (1953) proposed that all investors are risk averse and want to be compensated for taking on additional risk. He defined risk in terms of volatility, i.e. if an investor is faced with the choice between two assets that are expected to yield the same return but the one is more volatile than the other, the investor would opt for the less volatile asset as he can be more certain of the returns of the latter.

2.2.1 Diversification and Portfolio Risk

Markowitz (1953) introduced the concept of reducing portfolio risk by diversification. Every asset is characterized by its volatility and its correlation with other assets. This concept can best be explained by a simple analogy to wave theory:

If Wave 1 and Wave 2 are 90 degrees out of phase they will cancel each other out, a phenomenon known as destructive interference.
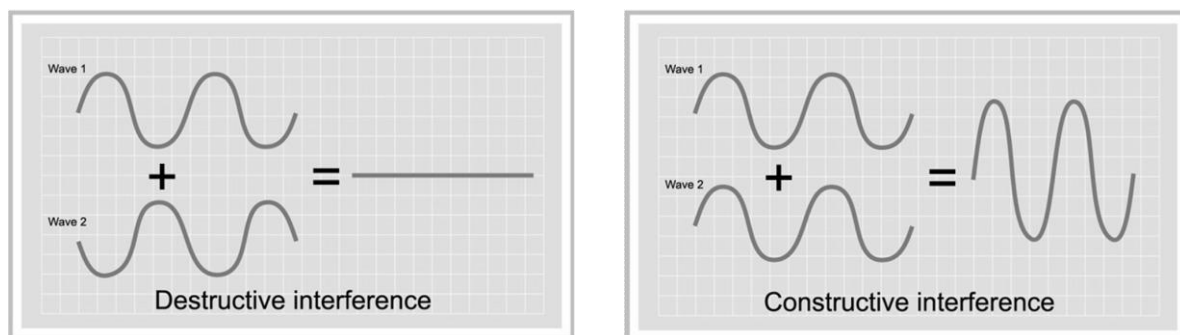
Figure 4: Wave Interference Analogy

However, if the two waves are in phase, constructive interference will occur and the amplitude of the fluctuations of the two waves will be superimposed.

According to Markowitz' portfolio theory assets behave in much the same manner. The wave amplitude can be compared to an asset's volatility and the phase angle can be compared to the asset's correlation with another asset or market return. The more out of phase the two waves are, the less the amplitude

of the superimposed wave. Similarly, the less correlated two assets are - the less their combined volatility. For example, the stocks of two companies might be differently related to changes in oil price. Should the oil price increase the one stock (say a green energy company stock) will increase and the stock of the other company (say a plastic manufacturer) will decrease. Combined, the one stock functions as "insurance" for the other, reducing their combined volatility.

2.2.2   Risk vs. Returns

In this section the concepts of diversification and expected returns will be combined in to create a basic understanding of how securities are priced in the marketplace. Investors will expect to be compensated for taking on more risk. A hypothetical portfolio consisting of asset A and asset B is illustrated in Figure 5 below.
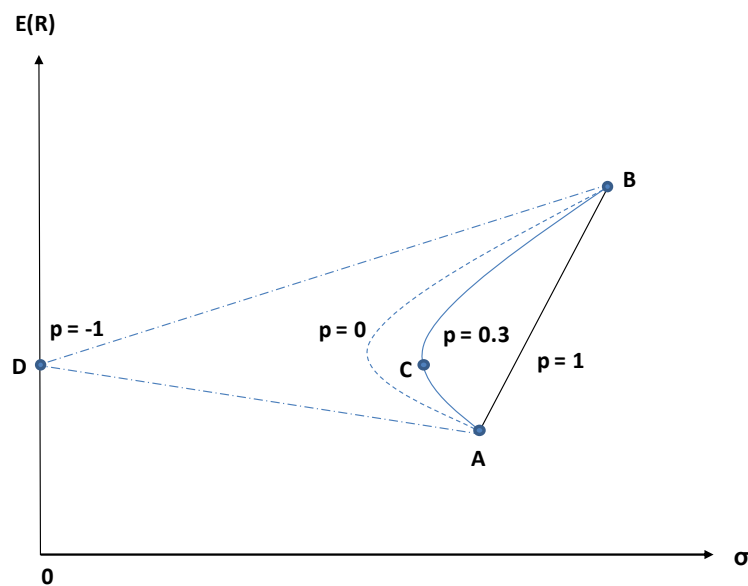
Figure 5: Effect of Correlation

Asset A has lower risk (measured by standard deviation) and has therefore a lower expected return compared to asset B which has higher expected returns at the expense of higher risk. The lines and curves in the figure represent the portfolio risk for different weights of asset A and asset B and different levels of correlation between the two. If the two assets are perfectly correlated ($\rho=1$), adding a higher percentage of asset B to a portfolio consisting mainly of asset A will result in an increase in portfolio

variance (moving along the line connecting A and B). Conversely, if the assets are perfectly negatively correlated (ρ=-1) a combination of A and B will be able to yield a return with no risk at all. If assets A and B are less than perfectly correlated (ρ=0.3), increasing the component of asset B in the portfolio will decrease portfolio variance up to a certain point (C) after which overall volatility will start to increase again.

2.2.3   Diversification

In the previous paragraph the unlikely case of a portfolio comprised of only two assets was discussed. When an increasing number of less than perfectly correlated assets are added to a portfolio, the overall portfolio standard deviation will decrease (See Figure 6). It seems intuitive that overall volatility will eventually decrease to zero if an infinite number of assets is added. It has been found, however, that volatility decreases logarithmically to a certain level (Evans & Archer, 1968).

Volatility [σ]

Unsystematic Risk

Systematic Risk

no. of Assets
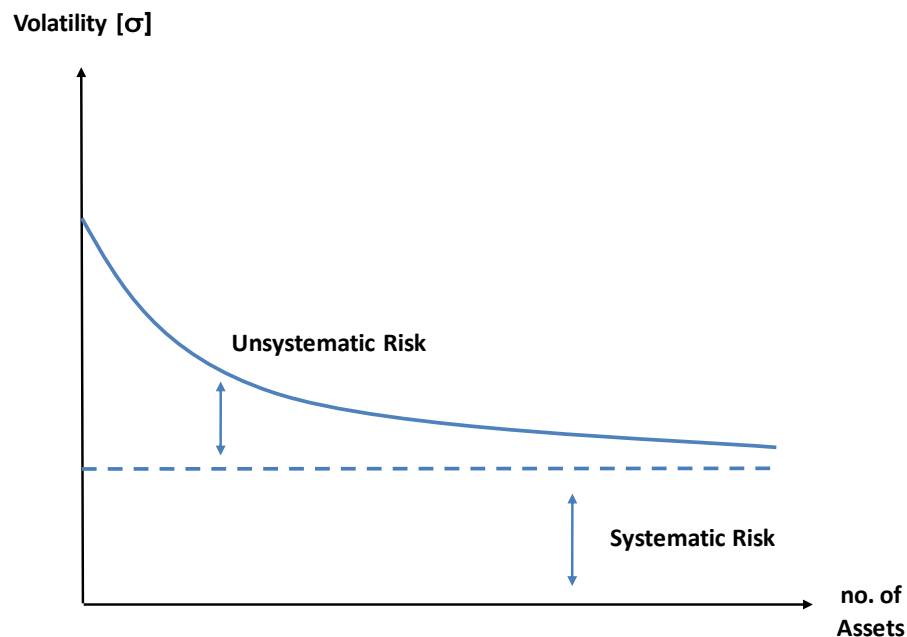
Figure 6: Systematic vs. Unsystematic Risk

This remaining level of risk is referred to as systematic risk or non-diversifiable risk. Systematic risk cannot be diversified away as it affects all assets in an economy equally; thus it is sometimes referred to as market risk.

2.2.4   The optimal Number of Shares in a Portfolio

Various studies investigate the optimum number of shares needed in a portfolio to be adequately diversified.

- Evans and Archer (1968) regard 10 shares to be enough. They state that their results "raise doubts concerning the economic justification of increasing portfolio sizes beyond 10 or so securities".
- Stevenson and Jennings (1984) indicate that a portfolio of 8 to 16 randomly selected shares will closely resemble the market portfolio (a portfolio consisting of all assets in the market) in terms of fluctuations and returns.
- Reilly (1985) finds that systematic risk is satisfactorily reduced between 8 and 12 shares.
- Gup (1983) indicates that proper diversification does not require investing in a large number of securities and industries. He concludes that almost all diversifiable risk is eliminated when the number of securities in a portfolio is increased to 9.

Under guidance from the literature quoted above, we can be reasonably assured that systematic risk will have been eliminated in portfolios consisting of 10 to 15 shares.

2.2.5   The Capital Asset Pricing Model (CAPM)

Although the CAPM will not be formally used in this study in its raw form, the beta measure set forth in this model will be used to assess the riskiness of the simulated portfolios.

The Capital Asset Pricing Model (CAPM) developed by William Sharpe in 1964 is regarded by many as the centrepiece of modern finance. Essentially the CAPM is a model that relates a stock's (or a portfolio's) systematic risk to the returns of a "market portfolio". It is important to note that only the *systematic* risk that remains after diversification is priced by the model as opposed to other models that price *total volatility* represented by standard deviation *(σ).*The rationale behind using systematic risk as a proxy for risk is that unsystematic risk can be diversified away at no cost and that it should therefore not be priced in the market.

The expected CAPM return of an asset or a portfolio of assets is governed by the equation:

$$E(R_i) = Rfr + \beta_i\,(R_m - Rfr)$$

Where:

- $E(R_i)$ = Expected return of asset *i* or portfolio *i*
- Rfr = Risk-free rate
- R_m = The return on the market portfolio

$$\beta_i = \frac{Cov(R_i, R_m)}{\sigma_m^2}$$

Where:

- $Cov(R_i, R_m)$ = The covariance of the asset or portfolio's returns with the returns of the market portfolio.
- σ_m^2 = The variance of the market portfolio[3].

The expected return on individual assets or portfolios is proportional to the returns of the market portfolio in excess of the risk-free rate. The beta coefficient measures to which extent the security moves together with the market.

The beta measure of an individual security or a portfolio is a measure of how risky the security or portfolio is relative to the market portfolio and is in essence a correlation coefficient (the covariance between the asset or the portfolio standardized by the market's variance). The market portfolio will, per definition, have a beta of 1. Portfolios and securities with betas larger than one are regarded riskier than the market portfolio and portfolios and securities with betas less than one exhibit less systematic risk than the market portfolio.

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[3] The market portfolio is defined as a portfolio holding direct proportions of all assets in the market.

The SML is the graphic representation of the CAPM (See Figure 7 below). It is very useful in providing a benchmark for evaluating investment performance and is often used in practice. All "fairly priced" assets in an efficient market should plot on the SML, that is, their returns can be explained by systematic risk. Point M represents the risk and return of the market portfolio. The market portfolio has a beta of 1. Riskier "fairly priced" assets have higher beta measures plot to the right of the market portfolio on the SML and have higher expected returns. Assets that are less risky have lower betas and therefore lower expected returns and plot to the left of the market portfolio.
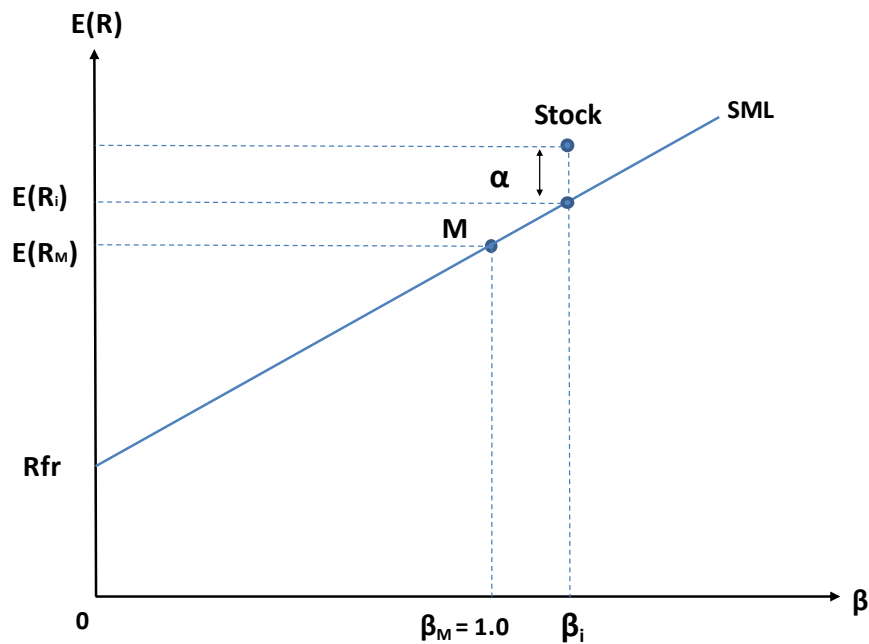
Figure 7: Security Market Line

If an asset plots above/below the SML, it is underpriced/ overpriced in term of systematic risk (Figure 7). An underpriced stock will plot above the SML, since it is expected to generate higher returns than an equal "fairly priced" asset at the same level of systematic risk. These expected excess returns are referred to as ex-ante (expected) alpha (α). The same concept holds for underperforming assets. If an asset plots below the SML, it is expected to generate too little returns for its level of systematic risk and is regarded to be overpriced.

Investors pursuing an active investment style typically seek to capture alpha, while passive investors invest in fairly priced assets and seek to receive market returns.

2.2.6   The Market Model

The CAPM is impractical as it requires the estimation of a host of different parameters that will not be discussed here. William Sharpe (1963) proposed a simplified model that is easier to estimate and therefore more commonly used in practice.

The Market Model uses ordinary least squares to regress the returns of a market-wide index against the returns of a security or a portfolio of securities according to the equation:

$$R_i = \alpha_i + \beta_i R_M + \varepsilon_i$$

Where:

- R_i = return of asset i
- α_i = intercept (the value of R_i when R_M equals zero)
- β_i = slope (estimate of the systematic risk for asset i)
- R_M = return on the market portfolio
- ε_i = regression error with expected value equal to zero (firm specific surprises)

The market model regression essentially yields the historical (ex-post) beta and alpha coefficients of the returns series used as an input to the regression. Beta is a measure of how much an individual security or portfolio is correlated to movements of the market and is interpreted in the same manner as the CAPM beta explained earlier.

Alpha represents the returns of a security or portfolio if market return equals zero. If the asset's/portfolio's alpha were zero, the regression line intercept would pass through zero and the asset

would generate an equal amount of returns as the benchmark[4] and therefore earn zero abnormal returns. Positive alphas represent risk-adjusted outperformance relative to the benchmark, while negative alphas indicate underperformance in terms of risk-adjusted returns.

It should be noted that the Market Model does not rely on any assumptions about investor behaviour as, for example, the CAPM. It simply reflects the linear relationship that exists between the returns of the market versus that of an individual security or a portfolio. This relationship is illustrated for a hypothetical "Momentum Portfolio" in Figure 8 below. Looking at the equation of the regression line it can be seen that the portfolio has a beta of 1.15 and an alpha of 1.61. If the market (S&P 500) moves by 1 percent the portfolio is expected to respond with a 1.15 percent movement. Consequently the portfolio is deemed to be more risky than the average share or portfolio in the market. If the market has zero returns, the portfolio will still return 1.61 percent (alpha) at zero systematic risk relative to the market index. The portfolio is said to be outperforming the market on a risk-adjusted basis or that it is earning abnormal returns. On the other hand, an alpha smaller than one means the portfolio will be underperforming the market on a risk-adjusted basis. A beta smaller than unity means the portfolio is less risky than the average portfolio or security in the market.

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[4] The benchmark is usually chosen to be a market-wide index
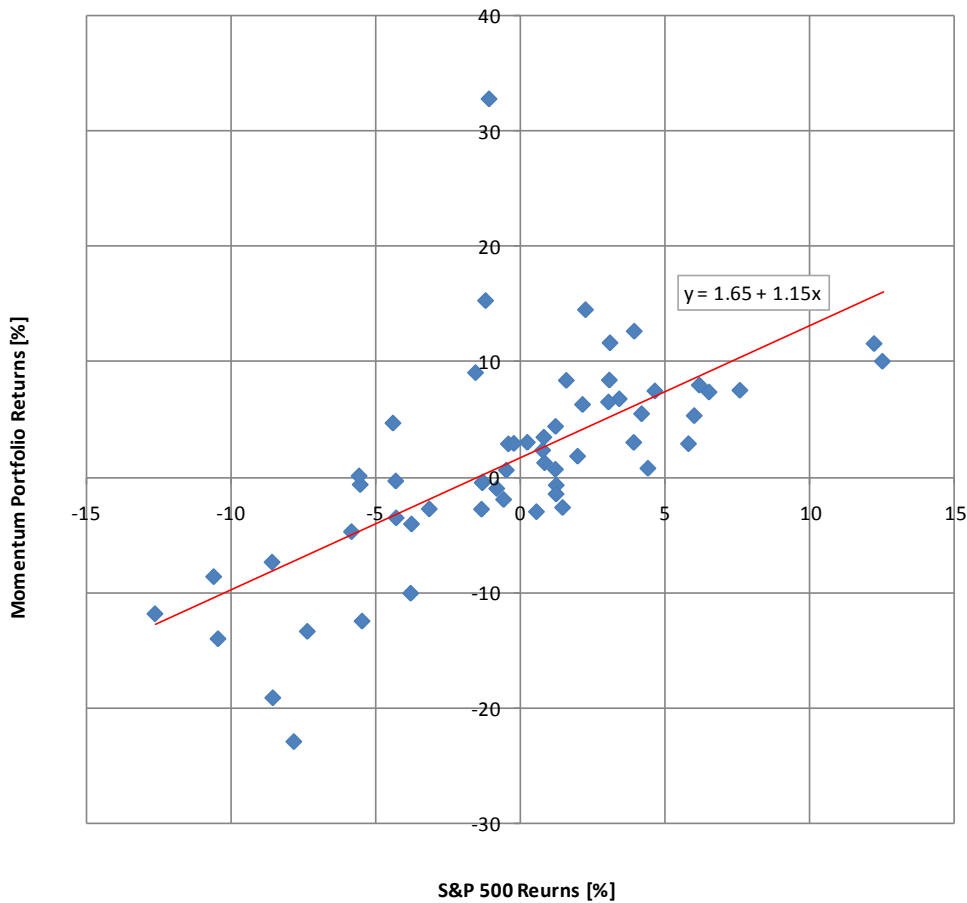
Figure 8: Example of Market Model Regression

The market model will be used to estimate risk-adjusted returns of momentum portfolios in later chapters. The beta measure will give an indication of the riskiness of the portfolios and alpha will be used to determine whether the strategies can earn abnormal returns. However, there are a few difficulties with the implementation of the market model that will be discussed next.

2.2.7   Market Model Coefficient Estimation

The market model regression can be conducted with relative ease. However, there are a few practical issues with estimating beta in this manner that could influence the results of a study using beta as a risk measure and alpha as a measure for abnormal returns.

REGRESSION ISSUES

The market model regression relies on three assumptions:

1. The expected value of the error term is zero.

2. The error terms are uncorrelated with the market returns.

3. The firm-specific surprises are uncorrelated across assets.

Failing to meet any of the above criteria would lead to unreliable alpha and beta estimates.

THE MARKET INDEX

In contrast to the assumptions made by the CAPM, the Market model does not assume a market portfolio containing all possible assets. Practical considerations dictate that an investable proxy such as a stock index be used as a benchmark for portfolio performance. Often all share indices are used, but if markets appear to be segmented, sector indices can be used (Bradfield, 2003).

LENGTH OF ESTIMATION PERIOD

Estimates that are generated using long periods of historical data can be irrelevant because the economic conditions and/or the markets and therefore the business risks may have changed significantly. Extensive research was conducted on the behaviour of beta with varying time periods. It was concluded that 5-year betas generated by monthly returns are the most stable (Bradfield, 2003). This translates into a regression with 60 data points (5 years of monthly returns).

BETA INSTABILITY

Research has shown that ex-post betas derived from market model regression are imperfect estimates for predicting future returns. Due to the mean reverting characteristics of the beta measure, extremely high negative or positive betas are likely to be overestimates (Kaplan Schweser, 2009) and need to be adjusted.

ADJUSTMENTS FOR THIN TRADING

Beta estimates need to be adjusted for thin trading should liquidity be an issue (Bradfield, 2003).

This section has dealt with pricing assets and measuring returns in terms of risk, leading up to the market model and a discussion of practical implementation issues. The next section will seek to map the intended study from a practical, investment industry perspective. A later chapter on literature review will map the study from an academic viewpoint.

2.3   EQUITY INVESTMENT STYLES

This section will seek to map momentum investing in the investment industry.

There are three main categories of investment styles:

- Value
- Growth
- Market-oriented

Value and growth investing are *active* investment strategies, that is, they seek to derive abnormal returns and therefore disregard the EMH.

Market-oriented investors are said to follow a *passive* investment strategy. They aim to mimic the behaviour of the market and therefore do not challenge the EMH.

2.3.1   Value Investing

Value investors focus on the numerator in the P/E or P/BV ratio, desiring a low stock price relative to earnings or book value of assets. The two main justifications for a value strategy are: (1) although a firm's earnings are depressed now, the earnings will rise in the future as they revert to the mean; and (2) value investors argue that growth investors expose themselves to the risk that earnings and price multiples will contract for high-priced growth stocks. The philosophy of value investing is consistent with behavioural finance, where investors overreact to the value stock's low earnings and price them too cheaply.

2.3.2   Growth Investing

Growth investors focus on the denominator of the P/E ratio, searching for firms and industries where high expected earnings growth will drive the stock price up even higher.

There are two main substyles of growth investing: consistent earnings growth and momentum. A consistent earnings growth firm has a historical record of earnings growth that is expected to continue into the future. Momentum stocks have had a record of high past earnings and/or stock price growth, but their record is likely less sustainable than that of the consistent earnings growth firms. The manager holds the stock as long as the momentum (i.e. the trend) continues, and then sells the stock when the momentum breaks.

Next, fundamental and technical analysis, two analysis styles often followed by active investors in practice, will be discussed and compared.

2.4   FUNDAMENTAL ANALYSIS

Fundamental analysis is a top-down scrutinizing process that usually consists of three levels, namely economic analysis, industry analysis and company analysis.

Economic analysis involves determining whether the overall economic conditions are suitable for investing in a certain asset class. In order to determine the state of the economy, macroeconomic variables such as interest rates, inflation, consumer spending, balance of payments, money supply etc. are analysed.

Industry analysis investigates the health of specific industries within an economy. If the industry as a whole is struggling, it is relatively more difficult for a stock within that industry to perform well than it is for a stock within a thriving industry.

Company analysis: After establishing the state of the economy and the industry, specific companies are analysed to determine their financial condition. This is done by analysing the companies' financial

statements and computing ratios that are compared to other companies' ratios within the same industry. There are five main categories of ratios: profitability, price, liquidity, leverage, and efficiency. The main objective of fundamental analysis is determining the theoretical "fundamental" value of a security through financial statement analysis and applying dividend discount models and risk models. If a security's market price is less than its fundamental value, it is regarded "undervalued" and is recommended for purchase. Conversely, if the security turns out to be above its fundamental value it is "overvalued" and should be sold short.

As mentioned previously, the semi-strong version of the EMH prohibits fundamental analysis to outperform the market. However, a number of asset managers and mutual funds have managed to consistently outperform the market in which is a direct violation of the EMH. Examples of such funds include Fidelity's Magellan fund (formerly managed by Peter Lynch) and Vanguard's Windsor fund (managed by John Neff). This is confirmed by a number of semi-strong efficiency tests. It was found that across the world a small number of mutual funds were in fact able to consistently outperform the market over significant periods of time.

2.5   TECHNICAL ANALYSIS

This section will explore the field of technical analysis, which forms a core element of the methodology used in the study.

Technical analysts predict the behaviour of individual securities and the market as a whole by analysing trading volume, past prices and market activity (Achelis, 2000). Contrary to fundamental analysis technical analysis refrains from establishing the intrinsic value of a security, but rather relies on trends and reversals to give an indication of future performance. Basing investment decisions on past volume and price data is a direct violation of the weak-form of the EMH. Most, but not all weak form tests of the EMH indicate that markets are in fact weak form efficient (Bodie, Kane, & Marcus, 2008).

The key difference between technical and fundamental analysis lies in the way how information dissemination within markets is interpreted. Fundamental analysts believe that prices react quickly and accurately to reflect the arrival of new information in the market. Technicians, to the contrary, believe

that information enters the market gradually over a period of time because market participants receive or interpret information about fundamental changes differently and at different periods of time. They surmise that as various groups of investors such as insiders, investment professionals and private investors receive information and buy and sell a security accordingly, its price gradually moves to a new equilibrium.

Price

Fundamental Analyst Takes Position in Market **(1)** **(2)** New Equilibrium Price

Old Equilibrium Price

Technical Analyst Identifies New Trend and Takes Action

New Information Enters Market

Time
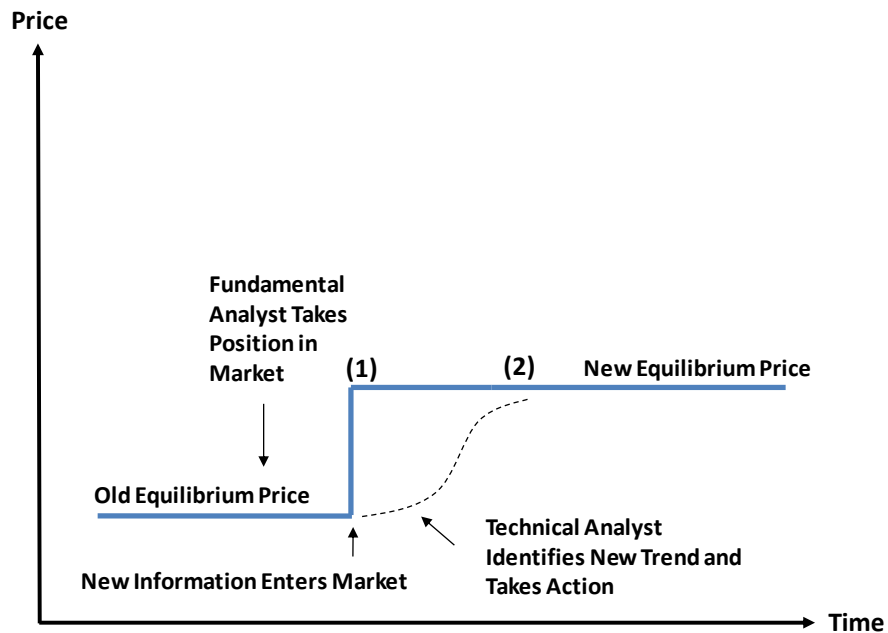
Figure 9: Perception of Information Dissemination between Technical and Fundamental Analysts

As illustrated in Figure 9, technicians look for the beginning of a shift in a trend (1), so they can get on the "bandwagon" early and benefit from the shift to the new equilibrium price (2) by buying the trend when it is up and selling it when it is down. If the shift was short (1), as believed by proponents of the EMH, deriving profits from shifts in trends would not be viable.

There are different approaches towards technical analysis, which can be broadly divided into four main groups, namely contrary opinion rules, follow the smart money rules, momentum indicators, and stock price and volume indicators.

- Contrarian investors typically assume that the majority of the market participants are wrong. So, for example, if the general market sentiment is highly optimistic the contrarian would regard this as a bearish sign and would be bullish when the market sentiment is pessimistic.

- Follow the smart money investors believe that there are a few superior investors that lead the pack and try to match their behaviour while there is still time.

- Momentum investors use trend-following indicators that are supposed to identify persistent market trends.

- Stock price and volume techniques are aimed at timing the market and are aimed at profiting from the irrational behaviour of other market participants.

2.6   MOMENTUM INDICATORS

An indicator is a mathematical formula that can be applied to a security's price, volume or even to another indicator (Equis, 2006). The resulting value is used to anticipate future changes in prices. Such indicators guide the trading decisions of momentum investors.

The specific indicators and their formulae used in this study are discussed under "methodology" in Chapter 6 to avoid repetition.

2.7   TECHNICAL TRADING RULES

Technical trading rules typically rely on indicator values. Some technical analysts apply indicators to charts and base their trading decisions upon visual inspection of the charts (hence technical analysts are often referred to as "Chartists").

The trading system developed by de Lange (2009) specifies threshold values for indicators which are used to trigger investment decisions. Specific "buy" and "sell" rules are defined which together establish a mechanized trading system that cannot be influenced by human emotion. A trading system similar to that of De Lange (2009) will be used in this study. This system will be discussed in more detail in Chapter 4.

2.8   CONCLUSIONS

In this chapter a basic understanding of abnormal returns was established and the market model that will be used to measure such returns was introduced. This chapter also explored the investment industry setting from which this study originates and it discussed the conflict momentum investing creates with Efficient Market literature. To summarize (also refer to Figure 10 below):

- The intended study will focus on price momentum, which represents a subset of the growth investment spectrum of active investing.
- The study stands in direct contrast to the weak form of the Efficient Market Hypothesis, as opposed to fundamental analysis which stands in contrast to the semi-strong form of the EMH.
- The trading system to be tested relies on technical momentum indicators and stems from the field of technical analysis.
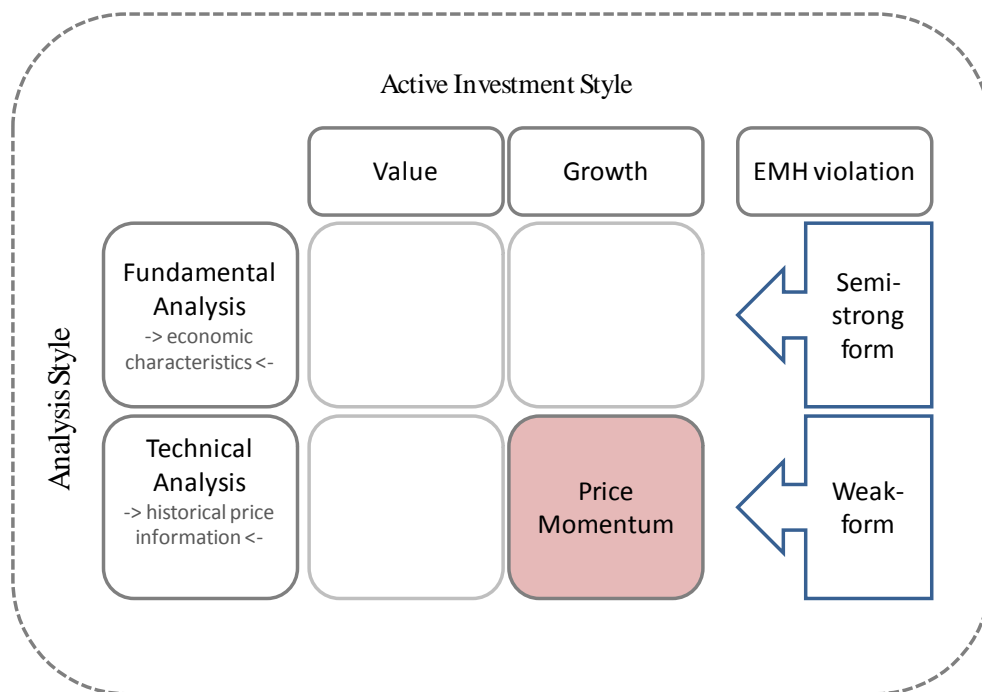
Figure 10: Mapping of Study in Practical Setting

The following chapter will explore previous studies on the momentum anomaly and will seek to map the intended study in its academic context.

Chapter 3: Literature Review

"He who loves practice without theory is like the sailor who boards the ship without a rudder and compass and never knows where he may cast."

- *Leonardo da Vinci*

The aim of this chapter is to map this study within the field of academia. A general overview will be given over relevant US, international and South African studies on momentum investing. The most authoritative studies and those closely related to the content of this dissertation are discussed. Note that this chapter focuses more on the methodologies followed in previous academic studies. Studies relating to the explanation of the momentum effect will be discussed in Chapter 5.

3.1 US STUDIES

Most in-depth studies on the momentum anomaly were conducted on US markets using AMEX and NYSE stocks as samples. In this section the most authoritative studies on momentum investing will be discussed. Most attention is given to the methodologies set forth by Jegadeesh and Titman (1993) and Conrad and Kaul (1998) because these studies form the basis of most other studies researching the momentum effect.

Jegadeesh & Titman (1993) conduct the first comprehensive study on the momentum effect and create a framework that is employed and referenced by numerous consequent studies. This study is regarded by many as the most authoritative piece of literature on the momentum anomaly.

Jegadeesh and Titman (1993) use a sample of NYSE and AMEX stocks covering the period from 1965 to 1989. The methodology used will be explained next: The stocks in the sample are ranked according to their returns over the past J months and are held for the following K months. J and K refer to the formation period and to the holding period in months, respectively. A set of 16 strategies were tested; for each J = 3, 6, 9 and 12 with K = 3, 6, 9 and 12.

The Jegadeesh and Titman (1993) methodology is illustrated in Figure 11 below. At the beginning of each month all stocks in the test sample are divided into ten equally weighted decile portfolios. The decile portfolios are formed according to the returns during the past J months and are ranked in ascending order.
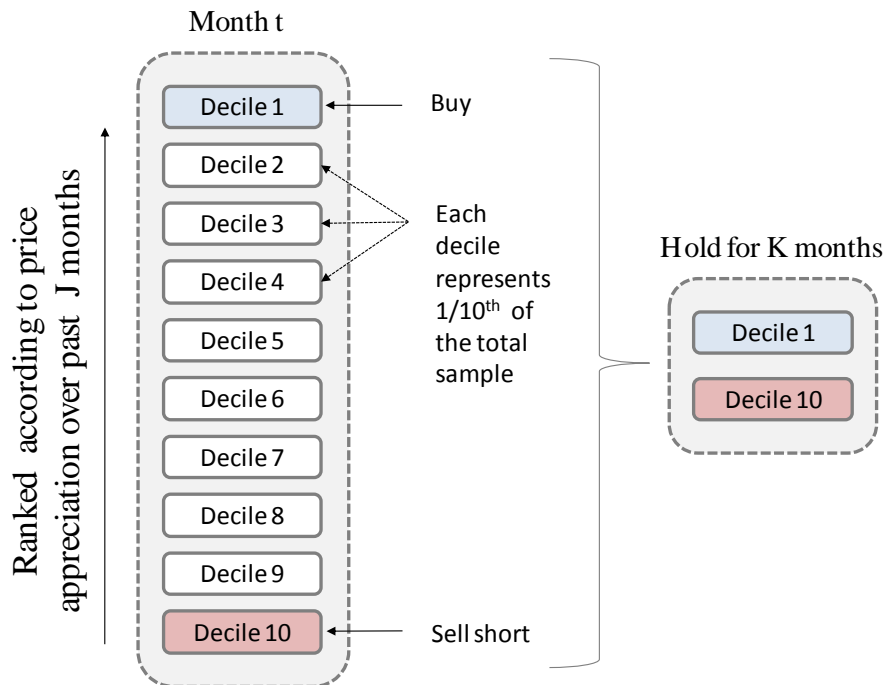
Figure 11: Jegadeesh and Titman (1993) Decile Formation Procedure

The top decile is referred to as the "winner" portfolio and the decile with the lowest returns is referred to as the "loser" portfolio. The "loser" portfolio is sold short and the "winner" portfolio is bought. All long and short positions entered K months ago are closed out at the end of every month and are replaced by the new "winner" and "loser" decile. In any given month t there are K different overlapping

portfolios, each created from buying "winner" deciles and short selling "loser" deciles formed in each month between month t and month t-(K-1). The returns of the short position are subtracted from the returns of the long position (the short position is profitable if loser decile returns are negative) to yield the returns of the overall long/short strategy.

In the Jegadeesh and Titman (1993) study all 32 zero-cost portfolio selection strategies yield positive returns. The most significant returns are generated by the K=3 and J= 12 strategy, which yields average monthly risk adjusted returns of 1.31 percent. All other strategies yield returns between 0 % and 1%.

Jegadeesh and Titman (1993) conclude that momentum was present on the NYSE and the AMEX in the period from 1965 to 1989 and suggest investor underreaction to firm specific information as a possible explanation.

Jegadeesh & Titman (1996) conduct an out-of-sample test for their 1993 study using a similar sample, but over the period from 1990 to1998. They find that the relative strength momentum strategies continued to be profitable in the same order as in the Jegadeesh and Titman (1993) study. This is a remarkable result at that time, as this study suggests that the Jegadeesh and Titman (1993) results were unlikely to be the result of data mining.

Conrad & Kaul (1998) investigate the profitability of 120 different rule-based trading strategies on the NYSE and the AMEX during 1926 to 1989. They find that merely 55 of these strategies have returns statistically significant different from zero, including eight basic momentum strategies.   The methodology and findings pertaining to their momentum strategies will be briefly discussed here.

Conrad and Kaul (1998) use a weighting scheme and methodology that differs from the one used by Jegadeesh and Titman (1993) in several aspects. They include every of the N shares contained in their test sample in their portfolios, as opposed to Jegadeesh and Titman (1993) who select only one "winner" and one "loser" decile from the whole sample. They assign each share a weighting according to its relative performance to the "market portfolio". The market portfolio in this case comprises all stocks contained in the test sample. If a share performs better than the market portfolio it receives a long weight scaled upwards by how much the share outperforms the market portfolio. In other words, the

greater the outperformance of a stock is relative to the market portfolio, the greater will be the position in that specific stock. The opposite applies for the short position. If a share significantly underperforms the market portfolio, it is assigned a relatively large percentage of the total short positions. The overall stock position weights are confined in such a manner that the sum of all long position is equal to all short positions, in effect creating a zero-cost strategy.

Conrad and Kaul (1998) test momentum strategies with holding and formation periods (K and J) of 1 to 36 months and they merely implement strategies with equal holding and formation periods. They split their sample into two parts, one ranging from 1926 to 1946 and the other from 1947 to 1989. Both sub-samples yield positive returns for holding/formation periods of 6, 9 and 12 months. The 1962-1989 sample is found to be profitable for holding periods of 6, 9, 12, and 18 months, which confirms the results of Jegadeesh & Titman (1993). The magnitude of the returns is also in the same order as in the original Jegadeesh & Titman (1993) study.

3.2   INTERNATIONAL STUDIES ON DEVELOPED MARKETS

Four studies will be discussed in this section. The study conducted by Rouwenhorst (1998) is considered an authoritative study on foreign markets. Schiereck et al. (1999) provide another well-regarded study on international equities. Ryan and Obermeyer (2004) conduct their test on Germany's top 100 shares only, which differs from other studies that do not differentiate stock according to market capitalization. The Rey and Schmid (2005) study is the only available study that focuses on the profitability of feasible momentum investing strategies optimized to reduce trading costs, also focusing on large caps only. Consequently the Rey and Schmid (2005) study is very relevant to this dissertation and will be discussed in some detail.

Rouwenhorst (1998) studies momentum profits across 12 European markets, namely: Austria, Belgium, Denmark, France, Germany, Italy, The Netherlands, and the UK using 2190 shares over the period 1978 to 1999. He intends to investigate whether the momentum anomaly documented by Jegadeesh and Titman (1993) was merely the result of data mining processes and therefore focuses on international returns continuation in and across markets at the individual share level. The method used to construct the portfolios is identical to the one used by Jegadeesh & Titman (1993). Since the sample spans across

multiple countries, all currencies were converted to Deutsche Marks. Rouwenhorst (1998) considers bid-ask bounce by constructing an additional set of portfolios delayed by one month relative to the ranking period. Rouwenhorst (1998) finds that all portfolios yield positive returns, varying from 0.64 percent to 1.35 percent per month. Confirming the results previously obtained by Jegadeesh and Titman (1993), the J=12, K=3 strategy is the most profitable.

Rouwenhorst (1998) conducts another test, in which he uses country specific samples instead of the combined sample of all 2190 international stocks using a J=6, K=6 strategy. All 12 countries except Sweden show profits that are significantly different from zero. He finds that the momentum effect is the most prominent in Spain, Netherlands, Belgium and Denmark in descending order. These results lead Rouwenhorst (1998) to the conclusion that the continuation of momentum can be explained by country effects.

Schiereck, De Bondt and Weber (1999) conduct their experiments in a similar fashion to Rouwenhorst (1998) but use a larger sample of stocks and use a slightly different ranking method. The study involves a sample of 375 companies listed in the Prime[5] segment of the Frankfurt stock exchange over a period between 1961 and 1991. Schiereck et al. (1999) rank the stocks in the sample according to their returns in excess of a market index over the past J months. They use formation periods of 1, 3, 6, and 12 months and measure formation period returns in two different ways. For the one, they record cumulative strategy returns in excess of the index returns. For the other they calculate the monthly compounded geometric returns of the respective strategy from which they subtract the monthly compounded index returns over the same period.

Schiereck et al. (1999) form winner and loser portfolios with 10, 20 or 40 shares containing the top and bottom 10, 20 or 40 ranked shares in terms of cumulative excess returns. Again a zero cost strategy is created by buying the winner portfolio and selling the loser portfolio short.

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[5] Prime Standard is a market segment of the German Stock Exchange that lists German companies which comply with international transparency standards.

Schiereck et al. find that all their momentum strategies were profitable. Progressively increasing the ranking period from 3 to 6 months increased the returns, but increasing the ranking period further to 12 months decreased the returns. This is in contrast to the findings of Jegadeesh and Titman (1993) for US markets. The two different methods of calculating returns did not influence the results and it was concluded that momentum was present in the Frankfurt Stock Exchange.

Ryan and Obermeyer (2004) use an approach similar to Jegadeesh and Titman (1993) on a sample of a replicated DAX 100 index, Germany's 100 largest and most liquid stocks during the period between 1990 and 1999. They find that the momentum profits generated are statistically significant even after transaction costs (For example, their J=6, K=6 strategy generates 4.21% annualized returns after allowing 1% transaction costs).

Rey and Schmid (2005) focus on the profitability of momentum investing and, in an attempt to maximize momentum profits, employ a trading strategy that differs slightly from the traditional approach used by Jegadeesh and Titman (1993). They restrict their sample to the shares contained in the Swiss Market Index (SMI), Switzerland's largest blue chips (between January 1994 and December 2004) and by limiting their trades to buying and short selling merely one share per month. In other words, Instead of buying the entire top decile and short selling the bottom decile every month, they merely buy the highest ranked momentum share, short sell the lowest momentum ranked share and close out the positions from t-K months ago.

Rey and Schmid (2005) form portfolios from strategies with formation periods of J = 3, 6 and 12 months and holding periods of K = 3, 6 and 12 months respectively. The NAV of these portfolios are divided into 1/K cohorts according to their holding period (K). A strategy with a three-month holding period will thus be divided into three cohorts. The idea behind the cohorts is creating a portfolio with sub-portfolios each staggered by one month, similar to Jegadeesh & Titman (1993).

Let us consider the K=3 strategy. For a strategy with a 3-month holding period, the share that has been in the portfolio for three months already will be sold and replaced by the current top-ranked share in terms of momentum. The share with the lowest momentum ranking will be sold short against the same

amount as the new long position and both are kept in the portfolio for the following three months after which both are closed out. Consequently three investment cohorts are created, each holding one long and one short position. In the K = 3 case this would result in three long and three short positions (3 zero cost strategies staggered by one month; 6 strategies in total) being held in a portfolio at any time (See Figure 12).
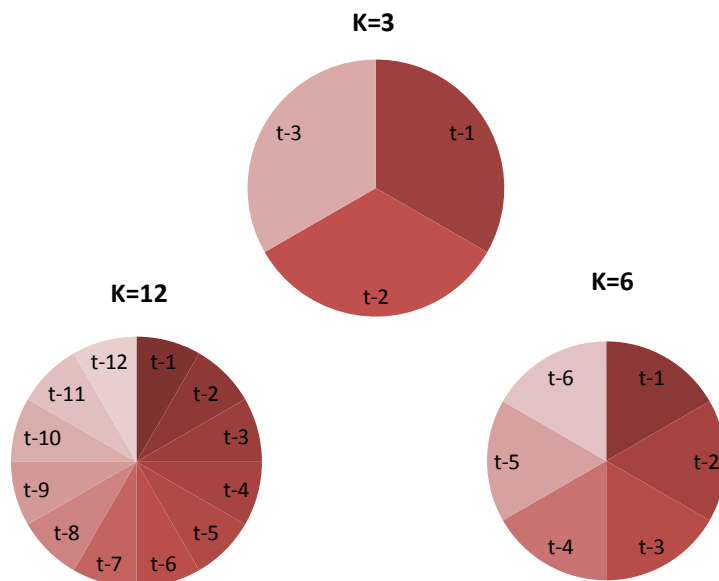
The K = 6 strategy results in 12 positions and the K = 12 strategy into a portfolio with 24 positions at all times.

Rey and Schmid (2005) use a sample of 17 to 26 stocks during the period from January 1994 to December 2004. Their portfolios generate annual returns between 9% and 44%, depending on the strategy used. The most successful strategy is the J=6, K=3 strategy which outperforms the benchmark 81.82% of the time. The momentum returns seem to be stable over the eleven-year evaluation period and are not explained by a few years of exceptional performance.

3.3   STUDIES ON DEVELOPING MARKETS

Rouwenhorst (1999) conducts a similar study to Rouwenhorst (1998), but uses a sample of 1705 shares from 20 emerging countries during 1975-1997 and a J=6, K=6 strategy. He ranks the shares according to past performance and allocates the top third to the "winner" portfolio and the bottom third to the "loser" portfolio. Even while countries such as Brazil and Zimbabwe have insignificantly positive returns and Indonesia even has negative momentum returns over the period, monthly cross-sectional average returns amongst all countries amount to 0.58% and prove to be statistically significant.

Hameed & Kusnandi (2002) investigate the profitability of momentum strategies in Asian markets, namely Hong Kong, Malaysia, Singapore, South Korea, Taiwan and Thailand over the period 1979-1994. Their methodology is similar to Rouwenhorst (1998). All momentum portfolios yield profitable returns, while the J=12, K=6 strategy on Taiwanese stocks yields the highest monthly returns of 0.6% and Malaysia the lowest with 0.19%. Not all of the returns are statistically significant. While controlling for the size and country effects, cross-sectional returns across all Asian markets were 0.19% and proved to be statistically insignificant.

The studies on developing markets (which exclude South Africa) highlight the fact that momentum strategies are not profitable on Asian markets.

3.4   SOUTH AFRICAN STUDIES

Momentum research on South African markets is very limited. Only three relevant studies were published to date.

Fraser and Page (2000) analyse momentum strategies on industrial shares of the JSE during the period of 1973 to 1997. They use a similar approach to Jegadeesh and Titman (1993), but use quintile (5 equally weighted portfolios) rather than decile portfolios. The only test a K=1, J=1 strategy and find it to be profitable, producing average returns of 1.5% per month.

Van Rensburg (2001) also uses a method similar to Jegadeesh and Titman (1993), but forms three equally-weighted portfolios instead of forming decile portfolios. He tests strategies with K=1 and J=1, 3,

6 and 12 and finds the 3, 6, and 12-month strategies to produce monthly returns between 0.85% and 1.52%.

Boshoff (2009) uses a sample of 1686 JSE shares between January 1980 and October 2007. He uses the Conrad and Kaul (1998) method to form portfolios and finds that momentum strategies cannot earn statistically significant abnormal returns, on average, over the analysis period. He also finds that adding a liquidity constraint significantly improves the results and that only one of his strategies yields statistically significant positive returns if no liquidity constraints are added.

The findings of the South African studies are contradictory and were not conducted up to the standard of the other US and international studies cited. Furthermore, all of these studies focus on the existence of the momentum effect rather than the profitability of momentum strategies.

3.5 CONCLUSIONS

This chapter gave an overview over the most authoritative literature relating to the field of research stipulated for this dissertation.

The momentum effect is found across multiple international markets and is persistent throughout different time periods. Only very limited research has been conducted on South African markets and none of the studies conducted to date focused on the profitability of momentum investing.

Very little literature exists of feasible momentum strategies that are practically implementable and are designed to reduce trading costs. Rey and Schmid (2005) is the only available study that focuses on measuring the performance of feasible momentum strategies and find such strategies to be very profitable. This fact highlights the relevance of this study to both academia and practicing investors.

Chapter 4:   Practical Momentum Investing

"In theory, there is no difference between theory and practice. But, in practice, there is."

- Jan van de Snepscheut

This chapter discusses the momentum-based investment strategy that was developed by Tom De Lange[6]. The chapter is divided into two major sections. In the first section, De Lange's trading system[7] will be discussed in some detail. The major workings of his investment approach and the rationale behind it will be described.

In the second part, the methodologies followed by the previous academic studies on the momentum effect will be evaluated and contrasted with the practical implementation of De Lange (2009) to highlight the differences in practical feasibility of the different momentum investing strategies.

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[6] De Lange has been an active fund manager from 2005 and is focused on technical analysis.

[7] The information regarding De Lange's approach was gathered in a series of informal meetings and telephone calls and will hereafter be referenced as De Lange (2009). For queries on the approach contact Tom De Lange via email at tom@vegacapital.co.za

This section will discuss the practical long-only momentum strategy used by De Lange (2009).

4.1.1   Methodology

De Lange (2009) developed a unique trading system based on technical momentum indicators that are closely related to price momentum (The indicators used will be discussed in detail in Section 6.3).   A long-only strategy is the heart of this system, although De Lange (2009) manages some long/short hedge funds that typically involve gearing. For reasons that will be discussed in the next chapter, it was chosen to focus on the long-only strategy. Therefore only this strategy will be discussed here.

De Lange (2009) exploits the momentum effect in a rather innovative manner. He bases his investment decisions solely on quantitative figures to avoid being influenced by greed and fear (Shefrin, 2007). The simplified workings of the trading system will now be discussed by breaking up the iterations pertaining to one updating interval into several steps.   In order to aid the explanation, the flow of information through a typical iteration is illustrated by the data flow diagram (DFD)[8] in Figure 13. The following discussion related to Figure 13:

Process 1: Calculate Indicator Values
At the end of every 3 months (quarterly) indicator values are calculated for all shares in the selection sample using the shares' historical closing price series over the specified formation period. This step is similar to all other academic studies discussed in the previous chapter, except that technical momentum indicators are used instead of merely price appreciation.

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[8] Should the reader not be acquainted with data flow diagrams he/she can refer to Appendix A for a brief description

Process 2: Rank Stocks

The indicator values from Process 1 are used to rank all stocks in the selection universe in ascending order according to their specific indicator values (price momentum). Each stock is assigned to a specific percentile ranking. This step is identical to other academic studies. For example, Jegadeesh and Titman (1993) rank all stocks in ascending order to form decile portfolios.

Process 3: Sell Stocks below Cut-off Ranking

This step is somewhat different to what is done in other academic studies. Whereas studies such as Jegadeesh and Titman (1993) close out all (long and short) positions of all stocks that have reached the end of their predefined holding period, De Lange (2009) only sells off stocks that fall through a certain percentile ranking threshold.

Process 4: Buy High Momentum Stocks

The highest ranking momentum stocks are bought from the proceeds from the sale of the stocks in process 3. In this step Jegadeesh & Titman (1993) would buy equal proportions of the stocks contained in the top decile in terms of momentum ranking and sell a portfolio comprised of the stocks in the lowest decile equal in value as the long portfolio short, creating a zero cost strategy. Note again that the strategy discussed here is a long-only strategy, so shares will only be bought and not sold short. Therefore an initial cash position needs to be introduced and the net asset value (NAV) of the portfolio needs to be tracked.

This concludes the description of the basic working of the De Lange (2009) portfolio formation procedure. Next some practical considerations pertaining to this momentum strategy will be discussed.
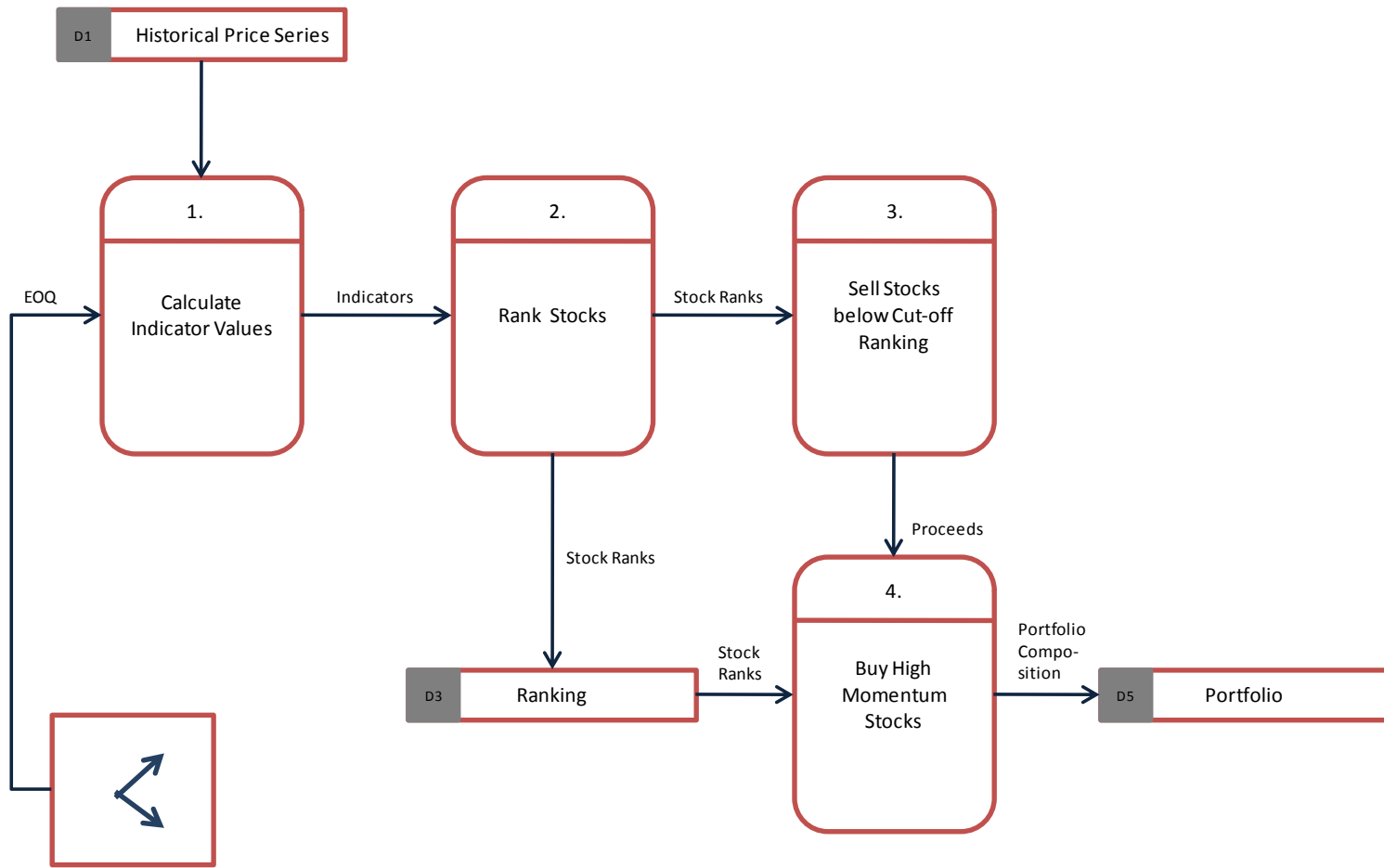
Figure 13: Momentum Trading System (De Lange, 2009)

4.1.2 Portfolio Characteristics and Rebalancing Procedure

As mentioned before, strategies followed by academic researchers such as Jegadeesh & Titman (1993) close all positions out at the end of a specified holding period. As De Lange (2009) only closes out positions in shares that fall below a cut-off ranking, his portfolios have to be rebalanced from time to time.

De Lange's portfolios contain between 10 and 15 shares. A specific number of shares between 10 and 15 is chosen and this number remains fixed for each portfolio. As all shares in the portfolio will perform differently over the quarterly horizon, certain shares in the portfolio will become overweight relative to others, increasing overall portfolio risk and lowering the benefits of portfolio diversification (See Section 2.2.1). If a share's weight becomes significantly more than 10% of the total portfolio NAV, De Lange (2009) suggests the portfolio to be rebalanced within the context of the situation in order to save trading costs. Some guidance to this process is given in the following paragraph.

The sell signal for a security is given when the respective momentum rating drops below the specified ranking percentile, e.g. 25%. By definition high momentum stocks are the ones with the highest past performance and low momentum stocks are the ones with the lowest past performance. Accordingly, the stocks sold are often those which showed little or even negative returns and are therefore relatively low in value relative to the shares remaining in the portfolio. The proceeds from selling loser stocks are used to purchase new positions, which should preferably be of the same size as the other stocks in the portfolio. However, the stocks remaining in the portfolio are per definition highly priced "winners" and the amount of money required to make up the new position in the new stocks will almost never match the amount obtained from the selling the "loser" stocks. The initial position size is defined by the number of shares in the portfolio. A 10-share portfolio will have 10 positions of 10% (in terms of NAV) in 10 different stocks. The replacement position size will have to be somewhat smaller, usually around 8%.

De Lange (2009) resolves this issue by purchasing a constant, but lower percentage of the NAV for the new positions. For example, consider a 10-stock portfolio with initial stock positions of 10% per share. If in this 10-stock portfolio 4 stocks fall below the threshold indicator ranking, these 4 stocks will be

replaced by 4 stocks that each have a position size of 8% of the portfolios' total NAV. If the total value of the intended new stock positions exceeds the proceeds from selling the loser stocks, the outstanding amount is financed by selling a part of the highest overweight stock position, reducing it to it its initial size, and then selling off part of the second-biggest position and so forth until the positions balance out. This saves on trading costs because the overweight positions are rebalanced naturally. In order to mechanize the investment decisions, the replacement position size is predefined as a percentage of the total net asset value (NAV) of the portfolio. All stocks below the 25th percentile are sold off and are each replaced by a position of 8% (in a 10 stock portfolio) and 6.67% (in a 15 stock portfolio).

The above considerations should keep the portfolio within reasonable bounds, but there are always exceptions. Sometimes, especially in strong bull-runs, positions become overweight and need to be rebalanced leaving vast amounts of cash in the portfolio. In such cases the replacement positions can be made bigger (e.g. 10% instead of 8% for a 10 stock portfolio). If some cash remains after this measure, all positions can be topped up by an equal amount until all cash is invested. The cash position will be discussed in more detail in the following paragraph.

4.1.3   Cash Position

Initially a cash amount is deposited into the portfolio. This amount is used to purchase the first set of shares according to their respective momentum ranking. It is difficult to maintain a zero cash balance, as some shares have very high prices and consequently a cash balance will remain as no exact multiple of the share can be found. However this cash balance is kept below 5% of the portfolios NAV at all times.

4.1.4   Updating Frequency

De Lange (2009) updates his portfolios on a quarterly basis. Theoretically, quarterly updates should reduce trading and therefore trading costs and taxes; however, De Lange (2009) finds that the returns and the trading frequency are not significantly affected if the portfolios are updated in monthly or quarterly intervals.

This concludes the discussion of the methodology used by De Lange (2009). The author could not locate any literature on similar strategies, but some of De Lange's own research findings will be displayed below.

4.1.5   Research by De Lange

De Lange conducted some back tests for various momentum-based fund strategies during the period from 2000 to 2006. His results are summarized in Table 1 below.

Table 1: Vega Capital Fund Strategy Back Test Results (Courtesy of Vega Capital)

Back Test Results

Strategy	Low Risk	Medium Risk	High Risk	Long only	JSE
Design Gearing Long/Short	90% / 35%	150% / 50%	200% / 80%	105% / 0%	100%
Actual Gearing	99% / 33%	148% / 52%	194% / 75%	107% / 0%	100%
Total Return, per annum	42.8%	58.1%	82.2%	41.2%	18.8%
Relative Volatility	83%	113%	147%	113%	100%
Relative Downside Risk	68%	102%	116%	96%	100%
Alpha, % per month	+2.41%	+3.00%	+3.93%	+2.00%	0.0%
Beta	0.54	0.67	0.97	0.87	1.0

The back-tested performance of De Lange's funds is phenomenal and, according to De Lange (2009) confirm some of his actual portfolios over the same interval. The first three columns in Table 1 represent various long/short geared hedge fund strategies and the last column represents the standard long-only Vega Equity strategy that is similar to the strategy that forms the basis of the simulations run in this study. All strategies yield significant outperformance in absolute terms and in terms of market model alpha. The long-only strategy's alpha (2%) is much higher than the alphas found with academic conventional strategies, while the beta figure is also very low at 0.87. The long/short strategies displayed in Table 1 all involve gearing and are therefore not comparable to the zero-cost strategies used by previous studies.

This concludes the discussion of the working and the performance of De Lange's momentum investing strategy. Next, De Lange's strategy and the strategies used by previous studies will be compared in terms of practical feasibility.

4.2   COMPARISON OF METHODOLOGIES IN TERMS OF PRACTICABILITY

The aim of this study is to investigate the performance of practical momentum investing strategies. This section will evaluate the long-only strategy proposed by De Lange (2009) along with previous academic studies in terms of their feasibility when actually implemented. Several factors such as implied holding periods and portfolio turnover, the number of shares and rebalancing strategies, will be discussed.

4.2.1   Systematic Risk and Number of Shares in Portfolio

The number of shares in De Lange's portfolios is fixed to between 10 to 15 shares. This allows the portfolio to be reasonably diversified in terms of unsystematic risk (See Section 2.2) and limits excessive trading. In terms of portfolio management theory and in the light of practical implementation, the number of shares contained in portfolios of Conrad and Kaul (1998), Jegadeesh and Titman (1993) and even Rey and Schmid (2005) seem rather inadequate. Rey and Schmid hold between 3 and 12 long positions. A portfolio with only three shares is definitely not sufficiently diversified and will be subject to excessive levels of firm-specific risk (See Section 2.2.4). Jegadeesh and Titman (1993) hold long positions in an entire decile (one tenth) of the stocks in terms of value of the sample population. Depending on the size of the sample, this can be a considerable amount of shares and results in a greater amount of trading effort and trading costs. The Conrad and Kaul (1998) portfolio selection procedure is completely inadequate for practical applications as it requires a position in every single share of the selection universe specified by a certain weighting formula (See Section 3.1).

4.2.2   Other Practical Implementation Issues

Another complication that would occur when implementing the strategies followed by Jegadeesh and Titman (1993) and Conrad and Kaul (1998) is that they implicitly assume that shares are infinitesimally divisible. It is unlikely that 10 deciles equal in value can be formed as some shares are traded at relatively high prices.

4.2.3 Trading Frequency and Portfolio Turnover

The standard academic studies employ strategies that explicitly define holding periods. Researchers such as Jegadeesh and Titman (1993) use holding periods of 3 to 12 months, which translates into portfolio turnovers equal or in excess of 100% per annum. Such high levels of portfolio turnover are very undesirable in terms of transaction costs and from a taxation perspective.[9]

De Lange (2009) merely sells stocks that fall below a certain indicator percentile ranking threshold (See Section 4.1). If, in a certain ranking period, there are no shares that fall below the threshold ranking, no shares will be sold at all. This is the single, most significant difference between the De Lange (2009) and the Rey and Schmid (2005) procedures. The strategies used by Rey and Schmid (2005) and all other previous momentum studies for that matter are limited by the fact that they adhere to predefined fixed formation holding periods that require extensive portfolio turnover. Even if Rey and Schmid (2005) enter and exit only one long and one short position per holding period (which they argue should reduce trading costs), the holding periods are always less or equal to one year, resulting in higher than desirable portfolio turnover rates. The holding periods implied by the De Lange (2009) methodology are variable and solely dependent on when the exit signal is triggered for an individual share. This could result in more or less portfolio turnover than the standard academic strategies and will need to be confirmed. According to De Lange (2009) his long-only strategies produce portfolio turnover rates that are significantly less than 100% per year.

Another issue relating to the practical implementation of the academic momentum trading rule-based strategies occurs because of the fact that all stock positions are closed out at the end of every holding period per default. Consequently, in the same period, stocks may be sold simply because they reached the end of their pre-defined holding period and be re-bought because they are still ranked highest in terms of momentum. This would result in completely unnecessary trading costs.

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[9] A more detailed discussion of impact of portfolio turnover and taxation on momentum profits will follow in Chapter 5.

4.2 CONCLUSIONS

Momentums investing strategies such as those suggested by Jegadeesh & Titman (1993) and Conrad & Kaul (1998) have little practical value because of inadequate numbers of shares in the portfolios, issues with implementing the method such as the assumption that shares are infinitely divisible and high portfolio turnovers.

The approaches of Jegadeesh and Titman (1993), Rey and Schmid (2005) and De Lange (2009) are summarized and contrasted in terms of their practical feasibility in Table 2 below. The study by Conrad and Kaul (1998) is not represented in this table because of its apparent impracticalities (it requires holding a portion of every stock of the selection universe).

The next chapter will outline some general considerations that need to be kept in mind when conducting a study such as the one proposed.

Table 2: Summary and Comparison of Momentum Strategies in Terms of Feasibility

Aspect	Jegadeesh & Titman (1993)	Rey & Schmid (2005)	De Lange (2009)
Ranking Criteria	Price Momentum	Price Momentum	Technical Momentum Indicators
Formation Period	3, 6, 9 or 12 months	3, 6, or 12 months	45 weeks
Holding Period	3, 6, 9 or 12 months	3, 6, or 12 months	Variable
Strategy Type	Long/short (zero cost)	Long/short (zero cost)	Long only (initial cash position)
Long Position	Top momentum decile	Top momentum decile	Top momentum shares
Short Position	Bottom momentum decile	Bottom momentum decile	n.a..
Exit Signal	Pre-defined holding period of 3, 6, 9 or 12 months	Pre-defined holding period of 3, 6 or 12 months	< Cut-off ranking percentile
No. of Shares in Portfolio	Top and bottom decile of sample	Between 3-12 long and 3-12 short positions	10-15 long positions
Portion of portfolio closed out and replaced over updating interval	All share positions at the end of their holding period (1/K of NAV)	All share positions at the end of their holding period (1/K of NAV)	Variable – Sold when shares fall below cut-off ranking
Portfolio turnover (p.a.)	> 1	>= 1	Variable – aim is <= 1
Rebalancing Frequency	n.a.	n.a.	Variable – if share weight is > 15% bring down to 10%
Application	Academia >>	>>	>> Practice

Chapter 5:   Explanations of the Momentum Effect

" Fool you are, to say you learn by your experience.

I prefer to profit by others' mistakes and avoid the price of my own"

–   Otto von Bismarck

Even though momentum profits are well documented, the sources of these anomalous returns remain a mystery. Researchers have taken various attempts to explain the sources of momentum.

This chapter discusses general issues that have evolved from studies on market anomalies that could render the results of such studies questionable. It is often argued by proponents of the EMH that the results of studies documenting abnormal returns emanating from trading rule based strategies might be subject to several statistical biases. These biases need to be avoided if a meaningful test is to be constructed.

Another issue faced by momentum researchers is the possibility that the momentum effect might be explainable by another well-documented anomaly. It is desirable to circumvent the abovementioned issues by designing an experiment that is robust to these factors.

Furthermore, momentum returns might be explainable simply by risk or perhaps by market inefficiencies manifested in the irrational behaviour of market participants. However, the primary goal is

not to find explanations for the momentum effect, but to investigate the profitability of feasible momentum investing strategies. Therefore the majority of this chapter will be concerned with an in-depth discussion of the possible effects of liquidity and transaction costs on momentum profits. These factors have a direct impact on the profitability of momentum strategies which represents the focus of this dissertation.

5.1 STATISTICAL ISSUES WITH TESTS FOR ABNORMAL RETURNS

The following biases are described in the CFA Level I Curriculum (Kaplan Schweser, 2008):

5.1.1 Data Mining Bias

Data mining results when researchers repeatedly use the same data until they discover a trading rule that "works". Trading rules found in this manner are prone to be tailored to the specific data set, and it is doubtful whether such trading rules can be used to generate profits in the future.

Some early studies conducted in the field of momentum investing argued that the profits derived by momentum strategies may be due to data mining. It is fairly obvious from the out of sample tests and the international studies discussed in the previous chapter that data mining cannot be used as an explanation for momentum profits.

The best way to avoid data mining bias is to test a profitable trading rule on a data set different from the one used to develop the rule (i.e. use out of sample data).

5.1.2 Survivorship Bias

Survivorship bias is often present in mutual fund performance reporting. Funds that have previously underperformed are often discontinued or rolled over into better-performing funds. Only surviving mutual funds are reported. A sample of mutual funds with a 10-year track record or price/dividend data will typically have an upward performance bias as only "survivors" are included in the sample.

In the context of the intended experiment the price series need to be adjusted for delisted stocks, share splits and dividends.

5.1.3 Small Sample Bias

Choosing the appropriate sample size is imperative for the success of a statistical experiment. A small sample might not adequately represent the characteristics of the underlying population from which it is drawn.

In terms of choosing the sample for the study, one must be wary to use a sample that properly reflects the characteristics of the market it is drawn from. One way of circumventing this problem is to use a sample containing all stocks of a specific segment of the market and drawing conclusions only about this specific segment of the market.

5.1.4 Time Period Bias

One type of small sample bias can occur when we use either a too short or a too long time period for analysis. What is true over a short time period is not necessarily true over longer periods and vice versa. If the time period for analysis is too short, there exists a risk that the effects captured only hold for that specific short period and that they do not have explanatory power over future results. On the other hand, if the period is chosen too long, the fundamental economic behaviour underlying the results may have changed, equally resulting in time period bias. A period of five years is generally regarded to be a reasonable period to establish the performance of an investment strategy.

In our case, a time period dating back 10 years from now seems to be reasonable to capture fundamental economic relationships underlying stock returns and generate enough data points to conduct statistical tests. It is however difficult to be completely certain as to whether markets have significantly changed or not over the past ten years. The choice of the time period also depends a great deal on whether the market under scrutiny has undergone significant changes.

5.1.5 Non-synchronous Trading

When back-testing infrequently traded stocks there is often a mismatch between closing price data and the actual prices that the stocks are traded at because prices might be recorded earlier in the day.

Prices of frequently traded large-cap stocks tend to more closely match the closing prices recorded in the price series. Thus a test based on large-cap samples can be expected to be more reliable.

5.2 RISK- BASED EXPLANATIONS

Several studies investigate the possibility that risk is the true driver behind momentum returns. The discussion around risk explaining momentum returns can be sub-categorized into two main divisions, namely studies that express risk in terms of standard models such as the CAPM and studies that relate to risk factors that depend on the state of the economy.

5.2.1 Systematic Risk in terms of Standard CAPM

Several studies investigate the riskiness of momentum strategies of standard CAPM, most of which find that beta cannot sufficiently explain the abnormal returns derived from momentum strategies (e.g. Jegadeesh and Titman, 1993; Rouwenhorst, 1998; Liu et al., 1999; Ryan & Obermeyer, 2004 and Rey & Schmid, 2004). The only study with results to the contrary is Conrad and Kaul (1998) who find that stocks with high realized returns are generally the ones with high expected returns in terms of the standard CAPM. In other words, they claim that momentum strategies pick more risky stocks, so higher returns are expected in any case. However, Jegadeesh and Titman (2001) reject the results of Conrad and Kaul (1998) on the grounds that they find reversals in the price of momentum stocks in the post-holding period. Hence, they argue, the stocks could not have been effectively priced and that the results of Conrad and Kaul (1998) were subject to errors.

In conclusion, there is ample evidence that momentum returns cannot be explained by the standard CAPM and are therefore not due systematic risk captured by CAPM beta.

5.2.2 Macroeconomic/ Strategy Risk

Proponents of the EMH often argue that an investment strategy based on exploiting market anomalies might bear risks that are inherent in such strategies. Examples of such risks could be that a trading-rule based investment strategy could be generating abnormal returns only in certain phases of the business cycle or that it might yield negative returns for a few consecutive periods. The anomalous returns might

not persist in future or might be significantly reduced by new investors pursuing similar or identical strategies (Kaplan Schweser, 2008).

The following studies relate to the macroeconomic risk of momentum returns.

Conrad and Kaul (1998) find that only the 9-month holding period strategy is profitable during the period 1926-1946 (the period of the great depression and World War 2).

Schiereck et al. (2002) use the macro-economic state of the economy as a proxy for systematic risk. They set out certain criteria according to which they classify the state of the economy as either "good", "neutral" and "bad". These criteria include the level of interest rates, unemployment rates, the growth rate of industrial production, the interest rate term structure and overall share market performance. They compare momentum strategy returns between the economic states and find that momentum profits are not affected by the state of the economy. As their set of lagged macroeconomic variables cannot explain their momentum strategy returns, Schiereck et al. (1999) conclude that momentum returns are not a result of systematic risk.

Chordia and Shivakumar (2002) find that AMEX momentum returns can be explained by a set of lagged macroeconomic variables (T-Bill yield, dividend yield and credit default spread). In other words, Chordia and Shivakumar (2002) find that macroeconomic variables can be used to predict the returns of momentum strategies. They also find that their momentum strategies yield positive returns only in expansionary periods and are negative (though not statistically significantly so) in recessionary periods.

Huang (2006) uses the Jegadeesh and Titman (1993) procedure in a study on momentum returns on a sample of 17 international country indices. He employs industrial production as a the sole measure for the economic states classified by Chordia and Shivakumar (2002) and concludes that momentum profits are generally more pronounced in "up" markets rather than "down" markets, deducing that momentum profits are driven by macroeconomic risk.

Rey and Schmid (2004) confirm the findings of Chordia and Shivakumar (2002) on their sample of Swiss blue chips. They find that their strategies' returns are positively correlated with the volatility of the Swiss

Market index (SMI). However, they find their long/short strategies to be more profitable in volatile down markets than in stable up markets. This aspect of the Rey and Schmid (2004) study differs from the results of Chordia and Shivakumar (2002), who claim that momentum strategies are only profitable in "up" markets.

According to the literature quoted above, there is a good possibility that momentum returns can be explained by macroeconomic risk. It is therefore necessary to compare the performance of the momentum strategies between different macroeconomic states.

5.3   IMPACT OF REPORTED MARKET ANOMALIES

Anomalies are defined as: "Security price relationships that appear to contradict a well-regarded hypothesis; in this case, the Efficient Market Hypothesis." (Kaplan Schweser, 2008).

The following market anomalies are documented in the 2008 Level 1 CFA Curriculum and are used fairly often to explain abnormal returns; that is, they are used to depict situations where abnormal returns can be earned in otherwise efficient markets. Ultimately, the influences of these documented anomalies should be removed when conducting an experiment on abnormal returns to ensure that they do not possess explanatory power over the results of the study. When they cannot be adequately avoided we must take cognisance of their possible influence on the results.

Each anomaly will be discussed briefly and is placed in context with relevant momentum studies in order to evaluate its possible impact on the results of this study. Note that the BV/MV effect, P/E ratios and the small firm effect are factors that are priced by the Fama & French Three Factor Model.

5.3.1   The Fama & French Three Factor Model

Many researchers argue that some apparent mispricings in stock markets can be explained by risk factors not effectively captured by the Capital Asset Pricing Model (CAPM).

The biggest criticism of studies that document anomalous returns based on firm characteristics is that the model used to compute returns may be flawed. It is argued that the CAPM may be ignoring certain risk components (Kaplan Schweser, 2008).

Being aware of apparent mispricings Fama and French (1993) developed a three-factor model that compensates the returns estimates for price-earnings, book-value to market-value and small firm effects. A host of researchers have, depending on the objectives of their studies, adopted this updated model to estimate returns. The viability of using the Fama and French (1993) model to measure momentum returns will be evaluated by discussing each of its three factors in the context of momentum strategies.

5.3.2   Book Value/ Market Value (BV/MV)

Fama and French (1993) find that book-to-market values are a strong predictor of future returns. They find that high BV/MV stocks yielded abnormal returns, even after adjusting for beta whereas low BV/MV stocks generally underperformed. When adjusting for firm size and BV/MV effects Fama and French (1993) found that beta has only limited explanatory power, challenging the validity of the standard CAPM.

However, all momentum studies find that the model devised by Fama and French (1993) has limited or no explanatory power over momentum profits (e.g. Fama & French, 1996; Ryan & Obermeyer, 2004; Rey & Schmid, 2005). Therefore momentum does not seem to be driven by BV/MV effects and we can divert our attention from this factor.

5.3.3   Price-Earnings Ratio (P/E)

The P/E ratio is a stock's market price divided by earnings per share. It was found that, in general, portfolios with low P/E ratios exhibit superior returns, while high P/E stocks significantly underperform the market. This phenomenon persists even after controlling for beta (Bodie, Kane, & Marcus, 2008).

Fama and French (1996) find that their Three Factor Model cannot satisfactorily explain momentum profits and a recent study conducted on European stock markets indicates that stocks selected by

momentum criteria and those selected by low P/E or high P/E criteria are not correlated (Bird & Whitaker, 2004). Grinblatt and Moskowitz (2002) find that the momentum effect is more pronounced amongst growth stocks than value stocks.

Hence we can be reasonably assured that momentum profits are not driven by P/E effects.

5.3.4 Small Firm Effect

The small firm anomaly was first discovered by Banz (1981) who found that abnormal returns could be generated simply by investing in small-cap stocks. A possible explanation for this phenomenon is that standard risk models such as the capital asset-pricing model (CAPM) fail to capture all risk components that are inherent in investing in small firm stocks.

Hong et al. (1999) show that small firms with low analyst coverage exhibit more momentum than their larger counterparts. Grinblatt and Moskowitz (2002) confirm that momentum increases for firms with few institutional owners. However Rouwenhorst (1998) finds that the momentum effect cannot be explained by the small firm effect, but is more prominent amongst small firms. To the contrary, Ryan and Obermeyer (2004) find that the average firm size of the stocks in their winner portfolios was larger than the firm size of the stocks contained in their loser portfolios.

Although there is no conclusive evidence for the small firm effect driving momentum returns, the small firm effect can be ruled out by following a similar approach to Rey & Schmid (2005) who use a sample of the stocks contained in a replicated large-cap index.

This concludes the separate discussion of each of the three anomalies that are priced by the Fama & French Three Factor Model. It is fairly obvious, also from other literature, that the P/E and BV/MV effects cannot explain the momentum effect (e.g. Grundy & Martin, 2001; Rey & Schmid, 2004). Therefore using the Fama French Three Factor Model as a proxy for risk does not seem viable. When using a sample of large and/or mid caps, the small firm effect can be ruled out and therefore all three of the Fama & French (1993) factors. Three other relevant market anomalies not explicitly covered by any standard risk model will be explained next.

5.3.5 The Neglected Firms Effect

Firms that have only a small number of analysts following them tend to produce abnormally high returns. These excess returns appear to be caused by the lack of institutional interest in the firms, which causes that less information is available about those firms, making them riskier investments. Contrary to the small firm anomaly, the neglected firm effect applies to all sizes of firms (Bodie, Kane, & Marcus, 2008).

However, studies investigating the impact of trading volume on momentum profits find that momentum returns are more prominent amongst high turnover stocks (Glaser & Weber, 2003).

The neglected firm effect does not seem to have explanatory power over momentum returns; however, it can be removed by restricting the sample to the most liquid and most prominent stocks such as those contained in a large-cap index.

5.3.6 Earnings Surprises to Predict Returns

Ball and Brown (1968) were the first to discover that even a while after earnings announcements, cumulative earnings continued to drift upwards for "good news" and downwards for "bad news". This is contrary to the expected behaviour of efficient markets. Foster et al. (1984) found that when investing in stocks with earnings surprises, investors can reap average abnormal returns of 25% in the 60 days following the earnings announcement. In other words, markets do not adjust as fast to quarterly earnings surprises as would be expected by the EMH. Consequently, earnings surprises could be used to identify stocks that will produce abnormal returns.

Jegadeesh and Titman (1993) find that earnings surprises can explain a part, but not all of the momentum profits. Chan et al. (1996) document that price momentum is more persistent than earnings momentum and therefore conclude that earnings surprises cannot be the driver behind momentum returns.

5.3.7   Calendar Studies

It is found that stocks generally have exceptionally high returns in January. This phenomenon is very prominent among small capitalization stocks. In other words, Investors can reap profits by buying stocks during December and selling them off during the first week in January. This is also a direct challenge to the EMH and to the CAPM. De Bondt and Thaler (1987) and Ritter (1988) hypothesize that tax-loss selling at the year-end might be a possible driver behind the January effect.

Literature is contradictory on this matter. Grinblatt and Moskowitz (2002) find that January and December are the most profitable months on average for their simulated momentum strategies on a US sample, whereas Rey and Schmid (2004) find no such evidence on their sample of Swiss blue chips.

 The impact of the January effect needs to be assessed by determining whether exceptionally high returns occur in the month January relative to the other months.

5.4   BEHAVIORAL EXPLANATIONS

The lack of conclusive evidence that momentum returns can be explained by risk factors has led researchers to pursue behavioural explanations for the momentum effect who seek to find evidence that markets are in fact inefficient and that irrational investors drive prices to non-effective levels. Although it is beyond the scope of this dissertation to find behavioural explanations for momentum results, the main concepts relating to this field will be briefly explained.

Behavioural theories imply that the consequence of irrational investors participating in financial markets is that rational investors who are aware of the behavioural biases of their irrational counterparts can exploit this behaviour generating higher returns at lower levels of risk (Shefrin, 2007). The academic school of thought associated with such phenomena is referred to as behavioural finance. A host of behavioural models have been generated, attempting to explain momentum returns, some with reasonable success. Behavioural finance deals with a variety of psychological phenomena found in financial markets.

The "underreaction" bias, the "overreaction and subsequent price reversals" bias, the "anchor-and-adjust" bias and the "representativeness" biases have been used in attempts to explain the momentum effect. The underreaction and the overreaction with subsequent reversal are the most common behavioural models used to explain the momentum effect. For example, Jegadeesh and Titman (1993) attribute the momentum effect to investor underreaction to the announcement of firm-specific information. Daniel, Hirshleifer and Subramanyam (1998) find that momentum returns are driven by investor overreaction to the release of firm-specific information and subsequent reversion to efficient levels.

Not dwelling on behavioural finance too long, the focus will return to factors affecting the profitability of feasible momentum strategies, how such factors can compromise the accuracy of momentums studies and which measures can be employed to prevent a loss of accuracy in the proposed study. The remainder of this chapter will discuss the impact of market microstructure effects on momentum studies.

5.5   MARKET MICROSTRUCTURE EFFECTS

This section of the chapter is the most voluminous one and it will discuss issues related to market microstructure effects pertaining to momentum studies. This is an important domain for this dissertation as market microstructure effects are closely related to the profitability of momentum strategies and incorrectly accounting for such factors could severely skew the results of the study. First general issues relating to the liquidity of momentum stocks will be discussed, followed by a short description of the components of transaction costs, and finally a discussion of studies relating to unconditional trading costs and the sub-components of conditional trading costs.

5.5.1   Liquidity

The illiquidity of shares is a primary concern in low market capitalisation and emerging markets (Rouwenhorst K. G., 1999). Liquidity problems with momentum strategies arise when the positions need to be liquidated and be replaced by new positions. When testing momentum strategies it is important to consider the liquidity of the selection universe, as the opportunity costs of not being able to trade quickly and at the prevailing market prices might substantially skew the results as the trades.

Jegadeesh and Titman (2001) resolve this issue by restricting their sample to shares that trade above $5 and excluding the shares constituting the bottom decile of NYSE stocks in terms of market capitalization. They find that their adjustments to restrict illiquid stocks do not have a significant effect on the results, but that the stocks chosen by their strategies were in any case only those with high market capitalization and high trading volume (i.e. liquid stocks).

De Lange (2009) applies a certain liquidity ranking to screen shares for inclusion into the selection universe. The details of this screening process remain the property of Vega Capital[10], but it involves excluding shares below a certain weighted threshold in terms of trading volume and market capitalization.

Lee and Swaminathan (2000) find that for US stocks price momentum is more prominent among large capitalization stocks than among small capitalization stocks and Glaser and Weber (2003) find that on the German stock markets momentum strategies perform better among high-turnover stocks. Consequently, it seems unnecessary to make any adjustments for illiquidity or thin trading in the case of testing momentum strategies.

However, **Lesmond et al. (2000)** and **Moskowitz and Grinblatt (2004)** find that momentum strategies following the Jegadeesh and Titman (1993) procedure tend to pick illiquid and volatile stocks for their loser portfolios (short positions). This fact complicates matters for momentum strategies employing long/short strategies. A solution to this problem will be proposed in the discussion of the transaction costs relating to long and short positions.

The remainder of this section deals with the impact of transaction costs (trading costs) on momentum profits and consequently on momentum studies.

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5.5.2 Explicit vs. Implicit Trading Costs

Total transaction costs can be subdivided into explicit and implicit trading costs (See Figure 14 below). Taxes and brokerage involved with trading are referred to as explicit trading costs. Implicit costs refer to bid-ask spreads, the impact of the trade itself on the price of the security and the opportunity cost of untimely execution of the trade.
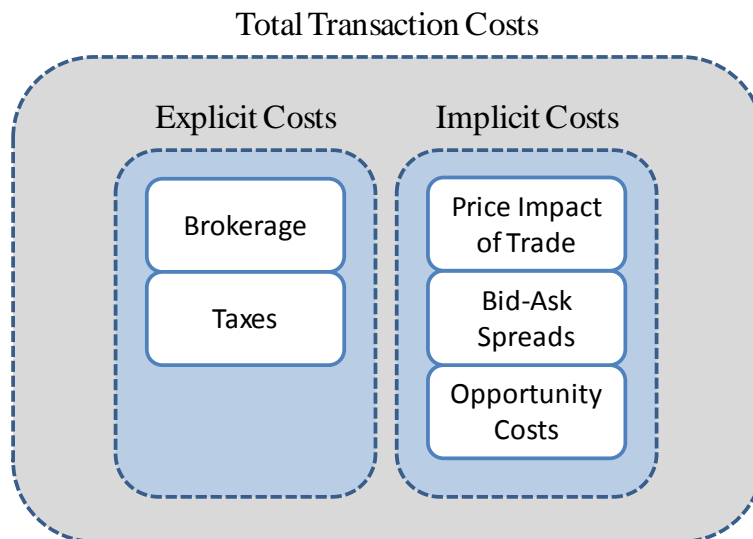
Figure 14: Components of Transaction Costs

Implicit costs such as price impacts and opportunity costs are very hard to measure, making the interpretation of such costs extremely difficult. Consequently, most momentum studies completely disregard trading costs or deduct a certain fixed percentage of the value of each trade referred to as "unconditional" trading.

5.5.3 Unconditional Trading Costs

The results of and the methodologies followed by some studies employing unconditional trading costs will be discussed briefly below in order to establish a general overview of the treatment and interpretation of transaction costs by previous momentum studies.

Jegadeesh and Titman (1993) use unconditional transaction costs of 0.5 percent. Their K=6, J=6 strategy produces returns that are reliably different from zero at 9.29% per year.

Grundy and Martin (2001) find that the returns of their J=6, K=6 strategy becomes statistically insignificant at the 5% level of significance for round-trip[11] transaction costs of 1.5%. At round trip transaction costs of 1.77% these profits are driven to zero.

Ryan and Obermeyer (2004) report the annualized returns generated by their J=6, K=6 zero-cost strategy at different levels of transaction costs. These (annualized) returns are summarized in Table 4 below.

Table 3: Unconditional Transaction Costs vs. Strategy Returns (Ryan and Obermeyer, 2004)

Transaction Costs	1%	0.5%	0.3%	0.1%
Winner minus loser returns (%)	4.21	8.53	10.3	10.54

Rey and Schmid (2005) argue that the momentum profits generated by their strategies applied to Swiss blue chips are robust to transaction costs. They compute the level of trading costs at which the returns of their strategies become statistically insignificant at a 10% level of significance. They also establish the level of trading costs where the respective strategy returns are driven to zero.

Table 4: Level of Trading Costs driving Strategy Returns to Zero (Rey and Schmid, 2005)

Strategy	J=6, K=3	J=6, K=6	J=6, K=12
Level of trading costs (%) causing returns to drop below statistical significance.	1,38	1,22	1,56
Level of trading costs (%) at which returns are driven to zero.	1,94	2,06	2,01

De Lange (2009) uses unconditional one-way trading costs of 0.5% for his back tests. He derives this amount as follows: He uses the average bid-ask spread on the JSE top 40 and adds this percentage to the 0.25% brokerage charged per transaction by Vega Capital unit trusts (De Lange, 2009). The reason De Lange (2009) used the JSE top 40 spreads is that he only includes the most liquid shares in his selection universe. The author reconstructed the calculation on September 9, 2009 calculating the bid-

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[11] Round-trip costs refer to selling a stock position and replacing it with (a) long position(s) equal in value.

ask spreads from the JSE Top 40 prices quoted by Standard Bank Online Trading[12] and adding the 0.25% brokerage:

Table 5: JSE Trading Cost Estimation on September 9, 2000

Trading Cost Component	Costs [%] per Trade
Average JSE Top40 Spread	0.17
Vega Unit Trust brokerage	0.25
Total	0.42

The same calculation on November 18, 2009 yielded:

Table 6: JSE Trading Cost Estimation on November 18, 2009

Trading Cost Component	Costs [%] per Trade
Average JSE Top40 Spread	0.12
Vega Unit Trust brokerage	0.25
Total	0.37

Following from the calculations above, allowing for 0.5% - 0.6% unconditional average transaction costs can be regarded to be conservative from a South African perspective when the selection sample is restricted to liquid stocks only.

This concludes the discussion on unconditional trading costs. The next section will deal with conditional trading costs and will discuss every driving force of transaction costs in context of momentum studies.

5.5.4   Conditional Trading Costs

Transaction costs that are dependent on specific situations or strategies are referred to as *conditional trading costs*. Studies on conditional transaction costs investigate the sources and the drivers of transaction costs. This section discusses impact of several factors that influence the level of transaction costs possibly encountered when following momentum investment strategies.

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[12] Source: https://securities.standardbank.co.za/ost/

Unconditional transaction costs are driven by a variety of factors, each of which will be addressed briefly. An overview over these factors is given in Figure 14 below. Many of these factors are interrelated and several are related to the liquidity of a stock. If the liquidity of a stock is influenced by a trade in any way, implicit trading costs will most likely be affected.
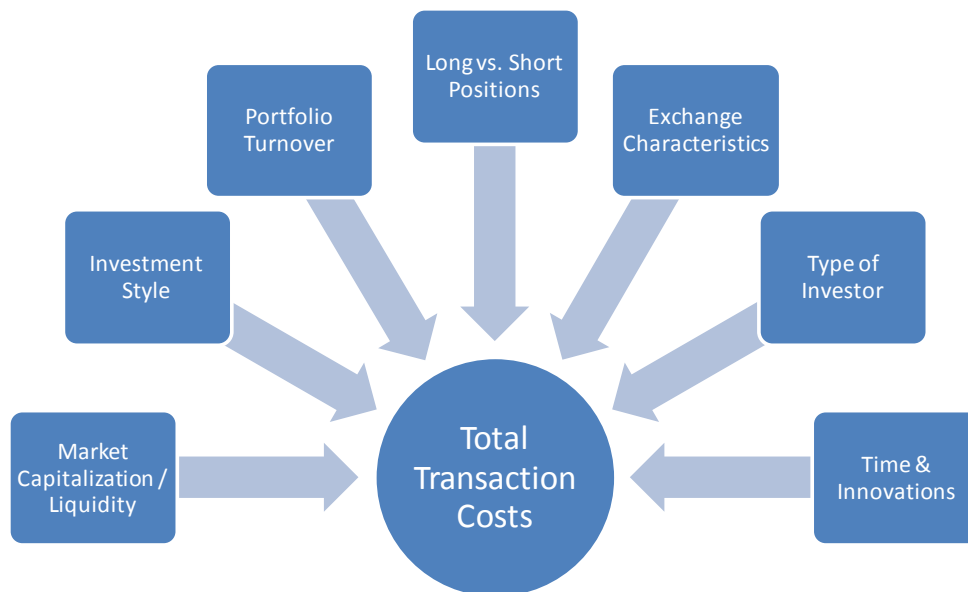
Figure 15: Determinants of Transaction Costs

A short discussion of each of these factors itself and its relation to momentum investing follows below.

MARKET CAPITALIZATION

The market capitalization of a stock is often regarded as a direct proxy for the liquidity of a stock. As the large cap stocks are usually traded at high volumes it is unlikely that an individual trade affects the liquidity and therefore the price of the stock. Bid-ask spreads are generally lower for large-cap shares and they also tend to trade more efficiently.

Keim & Madhavan (1998) set out the relationship between trading costs and market capitalization (see Figure 16 below). Trading costs increase exponentially for smaller stocks, while average total one-way transaction costs for technical traders drop to about 0.6% for large-cap stocks on US markets. Although

indicated in Figure 16, note that the differentiation of trading costs between value, index and technical strategies will be discussed later in this section.
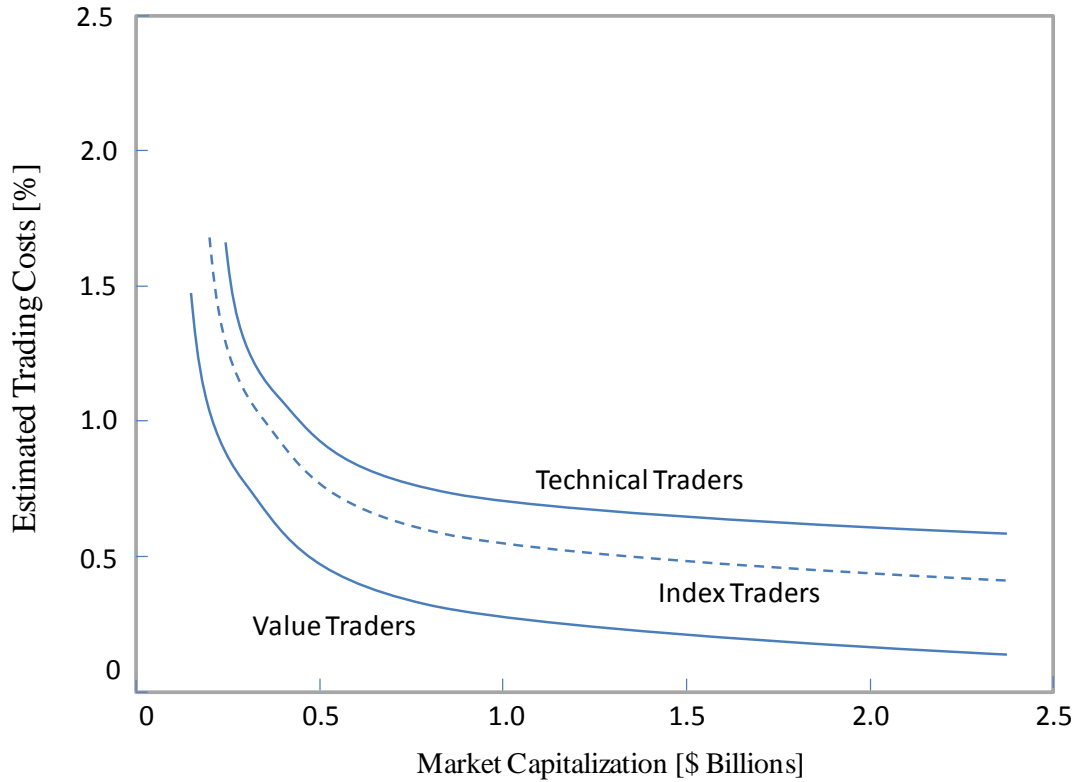
Figure 16: Trade Costs as a Function of Market Cap and Investment Style (Source: Keim, 2003)

The study by Keim was conducted in 2003. The latest available estimates for total (implicit and explicit) trading costs available for US large-caps at the date of print of this document are displayed in Figure 17 below. Apart from giving an indication of the latest large-cap trading costs on US markets, Figure 17 also illustrates how trading costs vary through market cycle stages and through the passage of time.

US Large Cap Trading Costs (bpe)
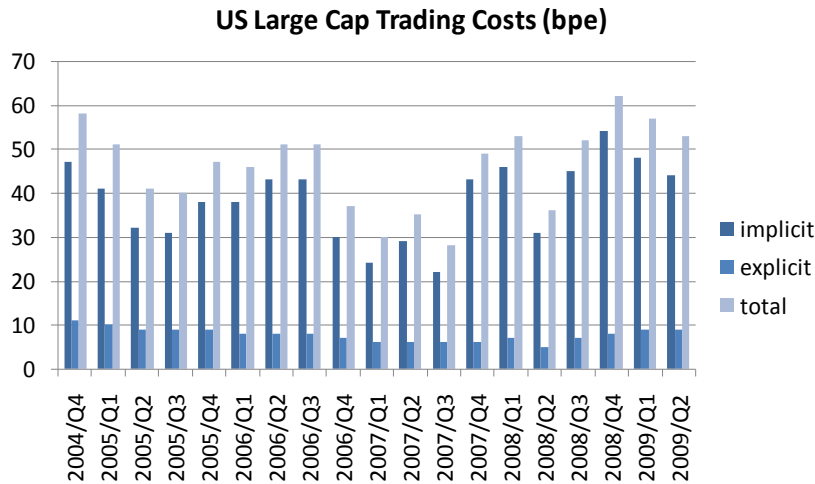
Figure 17: One-Way US Equity Trading Costs in Basis Points (adapted from ITG, 2009)

The maximum total trading costs for US large-caps over the period between Q4, 2004 and Q2, 2009 were recorded in Q4, 2008 and amount to just above 60 basis points (0.6%) per trade. For the remainder of the period the total trading costs actually stay well-below 60 basis points.

INVESTMENT STYLE

Keim (2003) conducts an in-depth analysis of conditional trading costs related to different investment styles. He argues that total trading costs differ for momentum, value and index strategies. He derives trading costs as a function of the market cycle stage and investment style.

He estimates the trading costs of momentum, value and index strategies from the trades of 33 active fund managers in the US and in 36 other countries in both developed and emerging countries over the period from 1997 to 2000. He notes that momentum buys occur predominantly in rising markets and that momentum sells occur mostly in declining markets. This is contrary to the timing of buys and sells of value and index strategies. Value buys generally occur when prices decline or in "down" markets' and value sells are usually executed when the market is "up". Index buys and sells are unrelated to the prevailing market conditions. As most market participants buy when the market rises and sell when the market is falling, the costs associated with momentum trades are expected to be higher than the unconditional average as the general demand for liquidity in those times is higher (See Figure 16).

Furthermore it is of utmost importance for momentum traders (who generally trade over short-term to medium–term horizons) that the trades occur in a timely manner. If a trade takes too long to clear, much of the underlying price movement might not be captured and opportunity costs will rise. This is in contrast to value or index strategies which are not critically dependent on fast execution since they generally take on long-term horizons.

Although the interpretation of the opportunity costs is somewhat ambiguous, Keim (2003) derives a model to quantify these costs and concludes that the implicit trading costs for momentum strategies are much higher than those associated with value or index strategies. According to his results, monthly total trading costs (explicit and implicit) amount to 1.13% to 1.31% on average for momentum strategies, which will dissipate the abnormal returns generated by most academic momentum strategies (Please refer to Chapter 3).

PORTFOLIO TURNOVER

It is intuitive that investment strategies exhibiting high portfolio turnover will have higher total trading costs. This can be a very limiting factor for momentum strategies, as standard academic momentum strategies rely on frequent trading. For example, Jegadeesh and Titman (1993) find that the average turnover of their K=6, J=6 strategy is 84.8% semi-annually. Lesmond et al. (2004) find that the trading frequency required to execute standard momentum strategies prohibits momentum profits.

Keim (2003) sets forth a table that displays the profitability of a typical academic momentum strategy in terms of monthly portfolio turnover and the corresponding trading costs. A copy of the abovementioned table is displayed below (See Table 7). The table maps momentum profits in terms of trading costs per trade and monthly portfolio turnover. Keim (2003) uses the average monthly profits of *1.11%* derived by Moskowitz and Grinblatt (2002) and subtracts trading costs as a function of portfolio turnover.

The monthly portfolio turnover[13] implied by the Grinblatt and Moskowitz (2002) strategy is 110% and the average total transaction costs for this representative momentum strategy are estimated to lie between 1.7% to 3.4% of trade value (Keim D. , 2003). Using these criteria as inputs and scanning through Table 7, a momentum strategy such as the one used by Grinblatt and Moskowitz (2002) yields profits that are already deep in the loss region of the matrix in Table 7.

In conclusion, it is absolutely vital for momentum strategies to focus on lowering portfolio turnover.

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[13] Keim (2003) interprets turnover as follows: When 50 percent of the value of the holdings in the portfolio is sold at a certain time and is immediately replaced by a new position equal in value, portfolio turnover amounts to 100 percent.

The sensitivity of momentum profits to trade costs and portfolio turnover.

The table reports profits to momentum trading after adjustment for transaction costs. The values in the table are based on monthly momentum profits reported in Grinblatt and Moskowitz (2002) of 1.11% that are unadjusted for trading costs. Each cell in the table is defined as monthly profit (i.e., 111 basis points) minus (monthly turnover in percent)*(trade costs in basis points). Monthly turnover represents roundtrip monthly turnover - for example, if during the month a portfolio manager sells 50% of the value of the positions in her portfolio, then her total trading volume during the month will be 100% of the value of her portfolio: 50% for the securities she sold and 50% for the assets bought to replace the sold positions. Trade costs (at the top of the columns) are one-way costs. Profits are in italics, losses are in bold. For example, the strategy reported in Grinblatt and Moskowitz reports an unadjusted monthly profit of 111 basis points and a monthly turnover of 103%. If the trade costs associated with that strategy were 1.0% on average, the strategy would yield an average monthly profit of 8 basis points.

| Monthly Turnover	Trade Costs (Price Impact + Commissions) in basis points																																				
	40	45	50	55	60	65	70	75	80	85	90	95	100	105	110	115	120	125	130	135	140	145	150	155	160	165	170	175	180	185	190	195	200	205	210	215	220
30	99	98	96	95	93	92	90	89	87	86	84	83	81	80	78	77	75	74	72	71	69	68	66	65	63	62	60	59	57	56	54	53	51	50	48	47	45
35	97	95	94	92	90	88	87	85	83	81	80	78	76	74	73	71	69	67	66	64	62	60	59	57	55	53	52	50	48	46	45	43	41	39	38	36	34
40	95	93	91	89	87	85	83	81	79	77	75	73	71	69	67	65	63	61	59	57	55	53	51	49	47	45	43	41	39	37	35	33	31	29	27	25	23
45	93	91	89	86	84	82	80	77	75	73	71	68	66	64	62	59	57	55	53	50	48	46	44	41	39	37	35	32	30	28	26	23	21	19	17	14	12
50	91	89	86	84	81	79	76	74	71	69	66	64	61	59	56	54	51	49	46	44	41	39	36	34	31	29	26	24	21	19	16	14	11	9	6	4	1
55	89	86	84	81	78	75	73	70	67	64	62	59	56	53	51	48	45	42	40	37	34	31	29	26	23	20	18	15	12	9	7	4	1	-2	-5	-7	-10
60	87	84	81	78	75	72	69	66	63	60	57	54	51	48	45	42	39	36	33	30	27	24	21	18	15	12	9	6	3	0	-3	-6	-9	-12	-15	-18	-21
65	85	82	79	75	72	69	66	62	59	56	53	49	46	43	40	36	33	30	27	23	20	17	14	10	7	4	1	-3	-6	-9	-13	-16	-19	-22	-26	-29	-32
70	83	80	76	73	69	66	62	59	55	52	48	45	41	38	34	31	27	24	20	17	13	10	6	3	-1	-5	-8	-12	-15	-19	-22	-26	-29	-33	-36	-40	-43
75	81	77	74	70	66	62	59	55	51	47	44	40	36	32	29	25	21	17	14	10	6	2	-2	-5	-9	-13	-17	-20	-24	-28	-32	-35	-39	-43	-47	-50	-54
80	79	75	71	67	63	59	55	51	47	43	39	35	31	27	23	19	15	11	7	3	-1	-5	-9	-13	-17	-21	-25	-29	-33	-37	-41	-45	-49	-53	-57	-61	-65
85	77	73	69	64	60	56	52	47	43	39	35	30	26	22	18	13	9	5	1	-4	-8	-12	-17	-21	-25	-29	-34	-38	-42	-46	-51	-55	-59	-63	-68	-72	-76
90	75	71	66	62	57	53	48	44	39	35	30	26	21	17	12	8	3	-2	-6	-11	-15	-20	-24	-29	-33	-38	-42	-47	-51	-56	-60	-65	-69	-74	-78	-83	-87
95	73	68	64	59	54	49	45	40	35	30	26	21	16	11	6	2	-3	-8	-13	-17	-22	-27	-32	-36	-41	-46	-51	-55	-60	-65	-70	-74	-79	-84	-89	-93	-98
103	70	65	60	54	49	44	39	34	29	23	18	13	8	3	-2	-7	-13	-18	-23	-28	-33	-38	-44	-49	-54	-59	-64	-69	-74	-80	-85	-90	-95	-100	-105	-110	-116
105	69	64	59	53	48	43	38	32	27	22	17	11	6	1	-5	-10	-15	-20	-26	-31	-36	-41	-47	-52	-57	-62	-68	-73	-78	-83	-89	-94	-99	-104	-110	-115	-120
110	67	62	56	51	45	40	34	29	23	18	12	7	1	-5	-10	-16	-21	-27	-32	-38	-43	-49	-54	-60	-65	-71	-76	-82	-87	-93	-98	-104	-109	-115	-120	-126	-131
115	65	59	54	48	42	36	31	25	19	13	8	2	-4	-10	-16	-21	-27	-33	-39	-44	-50	-56	-62	-67	-73	-79	-85	-90	-96	-102	-108	-113	-119	-125	-131	-136	-142
120	63	57	51	45	39	33	27	21	15	9	3	-3	-9	-15	-21	-27	-33	-39	-45	-51	-57	-63	-69	-75	-81	-87	-93	-99	-105	-111	-117	-123	-129	-135	-141	-147	-153
125	61	55	49	42	36	30	24	17	11	5	-2	-8	-14	-20	-27	-33	-39	-45	-52	-58	-64	-70	-77	-83	-89	-95	-102	-108	-114	-120	-127	-133	-139	-145	-152	-158	-164
130	59	53	46	40	33	27	20	14	7	1	-6	-13	-19	-26	-32	-39	-45	-52	-58	-65	-71	-78	-84	-91	-97	-104	-110	-117	-123	-130	-136	-143	-149	-156	-162	-169	-175
135	57	50	44	37	30	23	17	10	3	-4	-11	-17	-24	-31	-38	-44	-51	-58	-65	-71	-78	-85	-92	-98	-105	-112	-119	-125	-132	-139	-146	-152	-159	-166	-173	-179	-186
140	55	48	41	34	27	20	13	6	-1	-8	-15	-22	-29	-36	-43	-50	-57	-64	-71	-78	-85	-92	-99	-106	-113	-120	-127	-134	-141	-148	-155	-162	-169	-176	-183	-190	-197
145	53	46	39	31	24	17	10	2	-5	-12	-20	-27	-34	-41	-49	-56	-63	-70	-78	-85	-92	-99	-107	-114	-121	-128	-136	-143	-150	-157	-165	-172	-179	-186	-194	-201	-208
150	51	44	36	29	21	14	6	-2	-9	-17	-24	-32	-39	-47	-54	-62	-69	-77	-84	-92	-99	-107	-114	-122	-129	-137	-144	-152	-159	-167	-174	-182	-189	-197	-204	-212	-219
155	49	41	34	26	18	10	3	-5	-13	-21	-29	-36	-44	-52	-60	-67	-75	-83	-91	-98	-106	-114	-122	-129	-137	-145	-153	-160	-168	-176	-184	-191	-199	-207	-215	-222	-230
160	47	39	31	23	15	7	-1	-9	-17	-25	-33	-41	-49	-57	-65	-73	-81	-89	-97	-105	-113	-121	-129	-137	-145	-153	-161	-169	-177	-185	-193	-201	-209	-217	-225	-233	-241
165	45	37	29	20	12	4	-4	-13	-21	-29	-38	-46	-54	-62	-71	-79	-87	-95	-104	-112	-120	-128	-137	-145	-153	-161	-170	-178	-186	-194	-203	-211	-219	-227	-236	-244	-252
170	43	35	26	18	9	1	-8	-17	-25	-34	-42	-51	-59	-68	-76	-85	-93	-102	-110	-119	-127	-136	-144	-153	-161	-170	-178	-187	-195	-204	-212	-221	-229	-238	-246	-255	-263
175	41	32	24	15	6	-3	-12	-20	-29	-38	-47	-55	-64	-73	-82	-90	-99	-108	-117	-125	-134	-143	-152	-160	-169	-178	-187	-195	-204	-213	-222	-230	-239	-248	-257	-265	-274
180	39	30	21	12	3	-6	-15	-24	-33	-42	-51	-60	-69	-78	-87	-96	-105	-114	-123	-132	-141	-150	-159	-168	-177	-186	-195	-204	-213	-222	-231	-240	-249	-258	-267	-276	-285
185	37	28	19	9	0	-9	-19	-28	-37	-46	-56	-65	-74	-83	-93	-102	-111	-120	-130	-139	-148	-157	-167	-176	-185	-194	-204	-213	-222	-231	-241	-250	-259	-268	-278	-287	-296
190	35	26	16	6	-3	-13	-22	-32	-41	-51	-60	-70	-79	-89	-98	-108	-117	-127	-136	-146	-155	-165	-174	-184	-193	-203	-212	-222	-231	-241	-250	-260	-269	-279	-288	-298	-307
195	33	23	14	4	-6	-16	-26	-35	-45	-55	-65	-74	-84	-94	-104	-113	-123	-133	-143	-152	-162	-172	-182	-191	-201	-211	-221	-230	-240	-250	-260	-269	-279	-289	-299	-308	-318
200	31	21	11	1	-9	-19	-29	-39	-49	-59	-69	-79	-89	-99	-109	-119	-129	-139	-149	-159	-169	-179	-189	-199	-209	-219	-229	-239	-249	-259	-269	-279	-289	-299	-309	-319	-329

LONG VS. SHORT POSITIONS

As discussed previously under the impact of liquidity on momentum returns, it was found that standard academic momentum strategies tend to pick volatile short positions. In essence, this finding implies that short positions are more costly than long positions. Total costs of such positions are difficult to assess as opportunity costs can be expected to be involved when entering and exiting such positions.

In order to maintain the accuracy of momentum strategies and to save on trading costs it might be advisable to focus on the long side of momentum investing strategies. Moskowitz and Grinblatt (2004), for example, restrict their analysis to long positions only to avoid positions in small and illiquid stocks.

EXCHANGE CHARACTERISTICS

Keim & Madhavan (1998) find that the type of the exchange on which the trades occur also has a profound impact on the both explicit and implicit trading costs. On average trades conducted on the NYSE were cheaper than those on the NASDAQ. The NYSE operates as a specialist auction market where immediacy is supplied by the public limit order. Bid-ask spreads are very low on the NYSE (Keim & Madhavan, 1998).

US Equity Trading Costs Q3 2000 (bpe)
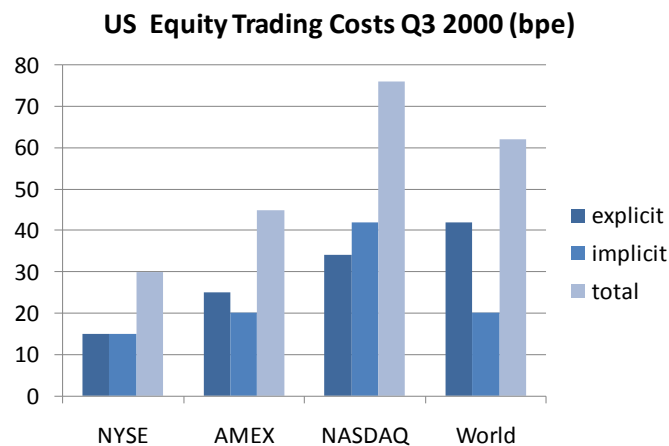
Figure 18: One-Way US Equity Trading Costs Q3, 2000 (Adapted from Domowitz, 2001)

Consequently, the impact of trading costs can be significantly reduced by choosing to conduct all trading activity via specified exchanges such as the NYSE and the AMEX on US markets.

Domowitz, Glen and Madhavan (2001) find that average US explicit trading costs exhibit a declining trend. They also remark that, in general, implicit costs decrease at a much faster rate than explicit costs, leading to rapidly decreasing total trading costs. Domowitz et al. (2001) reason that this decline might be due to the increased presence of institutional investors resulting in more pressure on suppliers of trading services because institutions tend to be able to negotiate lower commissions. Innovations such as the low-cost Electronic Crossing Networks used by institutional traders might also have played a significant role. Furthermore soft dollar practices payments by which brokers return a portion of the stated commission to their clients have become increasing popular, reducing the actual quoted trading costs.

These developments may speak in favour of momentum strategies in future and reduce the impact of transaction costs on momentum studies using recent samples.

5.6   TAXATION

Taxation is a subject area that the author deems very important in the context of investigating the profitability of momentum investing strategies. However, the author was not able to source any meaningful study relating to the impact of taxation on momentum returns.

In most tax regimes around the world, long-term investments are favoured over short term trading. Short-term investment returns are taxed at the investor's marginal income tax rate, while longer-term investments are generally taxed at the investor's capital gains tax rate which is usually significantly lower.

US federal tax legislation differentiates between short-term capital gains and long-term capital gains. Profits that are derived from selling assets that have been in the investor's possession for less than one year are taxed as short-term capital gains at the income tax rate which is typically around 25% or even more. Profits on Investments that are held for one year or more are classified as long-term capital gains and are taxed at the investor's capital gains tax rate. If the investor is in the 25% income tax bracket or

higher, the investor will pay the maximum capital gains tax of 15%. Investors in lower income tax brackets may pay as little as 5% (Stock Market Investors, 2009).

Although the specific tax rates will vary from country to country and between the different types of investors such as institutions, corporate investors and individual investors, all investors will likely be faced by the differences in tax treatment between long-term and short-term profits. As discussed above, the differences in tax rates between the two types of classification are substantial and cannot be ignored.

These tax implications (at least 10% per year in US markets) are so profound that maintaining portfolios with turnover rates[14] greater than 1 per year is simply not viable from an after-tax perspective as it is highly unlikely that the difference in tax rates can be recovered by a trading strategy focusing on shorter horizons.

A sensible parameter to evaluate an investment strategy's practical feasibility is thus to assess the portfolio turnover rate. Should the portfolio turnover rate be in excess of 100 percent it is unlikely that the portfolio is feasible from a tax or transaction cost perspective.

5.7   CONCLUSIONS

This chapter discussed factors that could influence studies on the profitability of momentum strategies and how these factors can be mitigated. The most important findings and their implications for the selection of the stock sample for the study and guidelines for the methodology to be used are summarized below.

The price series to be used for the simulations should:

- Be out of sample to prevent data mining bias;

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[14] The author uses the SEC definition for portfolio turnover (refer to Glossary)

- Date back not more than 10 years to capture the prevailing economic relationships;
- Include delisted securities to prevent survivorship bias;
- Exclude illiquid stocks to avoid market microstructure-related issues such as the difficulties with estimating opportunity costs for imperfect execution of trades;
- Exclude small-cap stocks to avoid the small firm effect from having explanatory power over the results;
- Preferably be comprised of stocks that receive sufficient analyst scrutiny such as those contained in large-cap indices

The following guidelines were established for the empirical testing procedure:

- The January returns of momentum strategies should be compared to the returns in other months in order to assess whether the January effect can explain momentum returns.
- The performance of momentum strategies should be assessed between different macroeconomic states and in different periods. Momentum profits seem to be not explainable by systematic risk as defined by standard risk models such as the CAPM and the Fama & French Three Factor model, but there is ample evidence of momentum strategies being subject to macroeconomic risk.
- Portfolio turnover should be computed. It is important for momentum strategies to limit portfolio turnover. Apart from trading costs being higher for momentum strategies than for value or index strategies, taxation has a profound impact on trading intensive strategies such as momentum investing. US Portfolios with turnover rates in excess 100% per year are taxed at the individual investor's marginal tax rate as opposed to the capital gains tax rate that is charged for portfolios that have turnover rates below 100% per year.
- The strategy should focus on a long-only strategy since momentum strategies tend to pick volatile and illiquid stocks for their short positions.

The next chapter will discuss the methodology used to conduct the empirical tests. The methodology is based on the guidance of this chapter.

Chapter 6: Research Design and Methodology

"New ideas require new structures."

– Leroy Hood

The author decided to test a long-only trading system similar to the one used by De Lange (2009) on the JSE and to conduct an out of sample test on the S&P 500. This chapter will discuss the empirical testing methodology used to establish whether such an investment approach can be used to generate abnormal returns. The tests have a slightly different focus compared to previous studies. While risk-adjusted returns will be measured, some practical measures such as portfolio turnover will also be included in the analysis in order to assess the practicability of the trading system.

6.1 RESEARCH HYPOTHESES

The aim of this study is to determine whether feasible momentum investing strategies similar to those used by De Lange (2009) are able to consistently outperform benchmark returns. Emanating from the research objectives stated in Chapter 1 and the discussion leading up to this chapter, the following specific hypotheses can be formulated:

The null hypothesis for both the baseline and the out of sample test holds that feasible momentum strategies cannot, on average, generate abnormal returns.

$$H_0: \quad \alpha_{Momentum} = 0$$

The null hypothesis will be rejected if the alpha is statistically significant.

Algebraically, for the baseline test and the out of sample test, respectively:

$$H_1: \quad \alpha_{JSE} \geq 0$$

$$H_2: \quad \alpha_{S\&P500} \geq 0$$

Both the baseline test and the out of sample test are comprised of three different portfolio simulations, one for every indicator used. Therefore each hypothesis test involves three separate sub-hypotheses in terms of the indicators used.

The selection of the data set will be discussed next.

6.2   DATA COLLECTION AND PREPROCESSING

The tests were conducted on two data samples, namely JSE large- and mid-caps and the stocks constituting a replicated S&P500 index. Both samples span across the same time period from January 2000 to September 2009 and will be described in this section.

The reason for choosing a sample period of the past ten years for both samples is to ensure that the fundamental economic relationships are more or less consistent with the situation pertaining in contemporary markets.

6.2.1   JSE Test Data

The baseline sample includes all listed and delisted closing price series of mid- and large-cap stocks on the JSE between January 2000 and September 2009.

- A period of around 60 months (5 years) can generate enough data points for tests for statistical significance using monthly returns. Using a sample period of 10 years sub-divided into two equal 5-year periods allows an evaluation of whether momentum returns are robust across different time periods and market states.

- Small-cap stocks are excluded to prevent small firm bias and liquidity-related issues from influencing the results. The benchmark chosen is the JSE All Share index, as market model estimation requires the use of a market wide index.

The relevant database was provided by Vega Capital, who in turn sourced their data from I-Net Bridge[15]. The data is fully adjusted for stock splits, reverse splits, stock dividends, special dividends and spin-offs. In other words, all dilutive effects are removed from the data so that the price series reflects an accurate pure capital return, which represents the source of momentum returns. The data is not adjusted for ordinary or normal cash dividends, meaning that the ordinary value weighted index can be used as a benchmark instead of a total return index.

Although the samples were carefully chosen to avoid most factors that could compromise the results, the JSE baseline sample may still have several problems:

- The availability of historical price series for delisted JSE stocks is limited. Accurate and complete price series of delisted securities are hardly available.

- Liquidity issues may affect the results of mid-cap JSE stocks even though small-caps are excluded.

- The results might be influenced by risk factors uniquely associated with developing markets.

- The JSE is overweight in mining companies; making it an inadequate benchmark as investing in such a benchmark would require the portfolio to be excessively risky.

The US out of sample data was specifically chosen to avoid the problems associated with the JSE baseline test and to enable an isolated analysis of the momentum effect.

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[15] http://www.inetbridge.co.za/

The out of sample test was conducted on the constituents of the S&P 500 over the same period as the JSE test. Following the reasoning of Ryan and Obermeyer (2004) and Rey and Schmid (2005), the out of sample tests were conducted on a replicated large-cap index over a period of 10 years.

The S&P500 index contains the 500 largest US-based stocks in terms of market capitalization and turnover from leading US industries. To be included in the S&P500 index stocks need to fulfil several requirements. They must, amongst other criteria, have a market capitalization in excess of $3 billion and a public float of at least 50% and the ratio of annual dollar value traded to market capitalization must be higher than 0.3. Due to their large market capitalization and their high liquidity, S&P 500 stocks exhibit some of the lowest transaction costs globally.

The S&P 500 is widely regarded as the best gauge of US equity and the overall US market as it covers about 75% of all equity. It is designed to be easily replicable and cost efficient and it is relatively diversified across industries, as illustrated in Figure 19 below. The S&P500 thus represents a very good benchmark as opposed to the JSE All Share.
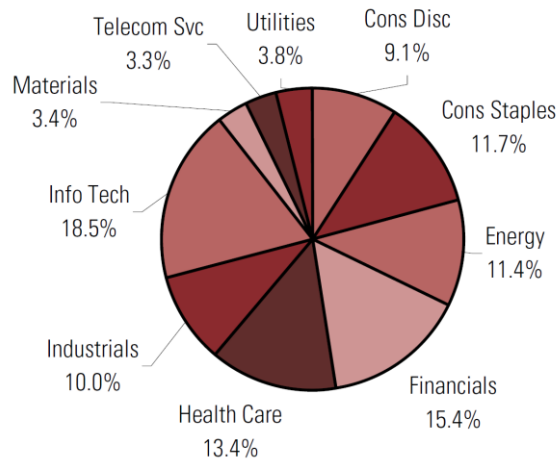

Figure 19: S&P 500 Sector Breakdown (Source: Standard & Poor's, 2009)

Further issues and criteria that led to the choice of the replicated S&P 500 constituents sample:

- By using a replicated large-cap index as a sample, the small firm effect and market microstructure effects that might compromise the integrity of the results can be eliminated.
- Implicit trading costs, even if incorrectly estimated, would be small and therefore not significantly influence the results.
- S&P 500 historical price data is readily available at reasonable cost.
- Delisted share price series are available at reasonable cost.
- A comprehensive list of S&P 500 index listings and de-listings necessary to create a database of the stocks contained in a replicated index is available from Standard and Poor's (See Appendix C:).

The historical price data series were purchased from Premiumdata[16], an Australian data vendor. The data is fully adjusted for stock splits, reverse splits, stock dividends, special dividends and spin-offs. The data is also adjusted for inter-exchange movements. For example, a share that used to trade on the NYSE and now trades over the counter on the NASAQ will still have its complete historical price series. Most delisted companies' historical price series is included. The data is not adjusted for cash dividends, so the standard index (not the total return index) will be used as the benchmark price series.

This concludes the discussion of the data samples used. The remainder of this chapter will focus on the methodology used in this study.

6.3 METHODOLOGY

The emphasis of this study lies in assessing the performance feasible momentum strategies. Therefore the scope is confined to testing only one set of parameters for three different indicators on two sets of data rather than using different ranking periods, resulting in a total of three strategies to be tested on each data set.

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[16] http://www.premiumdata.net/

Portfolios are formed using the De Lange (2009) methodology with the MOM, RSMOM and MACDX indicators on the South African and US markets. It should be noted that long-only strategies will be tested as opposed to the long/short strategies tested in typical momentum studies such as Jegadeesh and Titman (1993).

The rationale behind using a long-only strategy is that implicit transaction costs related to volatile short momentum positions are likely to be high and are difficult to measure. Therefore, confining the study to testing merely long strategies will eliminate the possibility that the results are biased by inaccurately accounting for transaction costs.

6.3.1 Tests

As mentioned above, the empirical testing procedure will encompass two main parts, namely the baseline test on JSE mid- and large-caps and the out of sample test on the constituents of the replicated S&P500 index. First the baseline test is conducted on the JSE in order to assess whether the strategies adapted from De Lange (2009) are, in fact, profitable over the sampling period. Following the baseline test, an exact replica of the baseline test is performed out of sample, on the S&P500.

In order to assess whether the strategies are robust over different periods of time and across market states the 10-year sample will be split in two equal parts. The impact of the January effect will be evaluated by comparing the momentum strategy January returns to annual aggregate returns.

6.3.2 Indicators

For ranking purposes, the standard price momentum with a formation period of 12 months will be used additionally to De Lange's MACDX and RSMOM indicators. A short description and the calculation of all indicators to be used are given below.

MOMENTUM (MOM)

The momentum indicator (hereafter referred to as "MOM") is the basic measure of price momentum used in most academic momentum studies (For example Jegadeesh & Titman (1993), Conrad & Kaul

(1998) etc. The MOM indicator computes the percentage price change of a security over a certain period of time, referred to as the formation period. Mathematically:

$$MOM_t = \frac{(Price_t - Price_{t-j})}{Price_{t-j}} * 100$$

Where:

$Price_t$ = Price of the security at time t

$Price_{t-j}$ = Price of the security j periods ago

Jegadeesh and Titman (1993) use strategies with 3, 6, 9 and 12 month formation periods for their study. The formation period in months corresponds to "*j*" in the MOM formula above. The reason for using the J=12 indicator is that it was the best-performing indicator in the Jegadeesh and Titman (1993) study on a sample of US stocks. Should the optimized technical indicators add significant value to the security selection process, it can be expected that the portfolios formed by these indicators will perform better than the expected best-performing pure momentum indicator on US samples.

MACDX

The Moving Average Convergence-Divergence (MACD) indicator was developed by Gerald Appel, the publisher of *Systems and Forecasts* and is well-regarded amongst technical analysts. The MACDX indicator used by De Lange (2009) is simply a normalized version of the MACD indicator.

The MACD indicator is calculated by subtracting a long-term (slow) exponential moving average from a short-term (fast) exponential moving average of previous closing prices.

$$MACD_t = SMA_t - LMA_t$$

Where:

- SMA_t = Short Term Exponential Moving Average at time t
- LMA_t = Long Term Exponential Moving Average at time t

The MACDX (MACD Index) indicator is the MACD divided by the long-term moving average:

$$MACDX_t = (SMA_t - LMA_t)/LMA_t$$

This refinement of the MACD serves to standardize the MACD measure, which in its raw form is an absolute measure and thus not suitable for comparison between different stocks, hindering the ranking process. The parameters used for the MACDX indicator are as follows:

- The fast moving average usually ranges from 6 to 19 units (hours, days, weeks etc.) Following the guidance of De Lange (2009), a 15-week fast moving average will be used.
- The slow moving average is normally two or three times as long as the fast moving average. For example, if the short moving average is 12 units, the long moving average is between 24 and 36 units. De Lange (2009) suggests a 45-week slow moving average.

RSMOM

The third indicator to be used in this study is the RSMOM (Relative Strength Momentum) indicator. Again the various components that comprise the indicator will be discussed.

First, the relative strength (RS) measure is calculated by dividing the closing price of the security by the index value.

$$RS_t = \frac{Cl_t}{Index\ Value_t}$$

Where:

- RS_t = The relative strength of a stock at time t
- $Index\ Value_t$ = The price of the corresponding benchmark index at time t

The RSMOM indicator is simply the momentum of the of the RS measure, smoothed by a 45-week exponential moving average.

$$RSMOM = \frac{(RSs_t - RSs_{t-15})}{RSs_{t-15}} * 100$$

Where:

- RSs_t = The 45-week exponential moving average of the RS figure at time t

- RSs_{t-15} = The 45-week exponential moving average of the RS figure at time t-15

The MACDX and the RSMOM indicators are both closely related to ordinary price momentum (which is in essence expressed by the MOM indicator discussed above), but are both expected to be more reliable than standard price momentum as they use moving averages to smooth out the returns used as signals.

6.3.3 Rebalancing Criteria

The sell-off threshold is set at the 45th percentile (i.e. securities in the portfolio will be sold off if their momentum rating drops below the 45th percentile ranking in terms of indicator ranking of all securities in the sample. Furthermore no share is allowed to constitute more than 10 percent of the portfolio when bought and the portfolio will be rebalanced if a share constitutes more than 15% of the portfolio. The same rules regarding position sizes as discussed in Section 4.1.4 will be employed.

6.3.4 Transaction Costs

Unconditional trading costs of 0.6% will be used in both the baseline test and the out of sample test due to the ambiguity of the interpretation of implicit trading costs. This figure is considered to be conservative for both the baseline test according to De Lange (2009) and the sample of S&P500 constituents according to Keim (2003).

Referring to Figure 16 in Section 5.5.4 showing total transaction costs as a function of the investment style and market capitalization and to Table 8 below, transaction costs can be expected to be lower than 0.6% as the median market capitalization for S&P 500 companies is almost $8-billion and momentum strategies on large-caps are already expected to have trading costs as low as 0.6% and decrease more for larger capitalization.

Table 8: S&P 500 Stock Characteristics (Source: Standard & Poor's, 2009)

Index Portfolio Characteristics		
Number of Companies		500
Adjusted Market Cap ($ Billion)		9,336.51
Company Size By Market Cap (Adjusted $ Billion):		
	Average	18.67
	Largest	329.73
	Smallest	0.81
	Median	7.98
% Weight Largest Company		3.53%
Top 10 Holdings (% Market Cap Share)		19.74%

6.3.5 Number of Shares in Portfolio

The number of securities in every simulated portfolio is set to strictly 15 to eliminate most firm-specific risk without holding an excessive amount of securities in the portfolio (See Section 2.2.4).

6.3.6 Updating Frequency

As suggested by De Lange (2009), the portfolios will be updated quarterly. If a stock delists between two analysis periods, the stock is sold and the proceeds are kept as a cash balance until the next analysis period.

6.3.7 Taxation

The study views taxation effects from the perspective of fund managers who manage individual portfolios for clients. The effect of taxation will be measured in a qualitative rather than in a quantitative manner. Portfolio turnover will be calculated for each of the tested strategies. If it is more than 100% per annum, then the strategy will be rendered impractical due to tax implications. Note that while the 100% turnover rule applies only to the US sample. The South African investor is subjected to a much more vague tax legislation based on the intent stated at inception by the investor to hold the securities in his/her portfolio for more than three years. However, for South African portfolios with turnover rates in excess of 100% it is very unlikely that the investor will be able to substantiate the intent of maintaining a holding period of more than three years. Due to the reasoning above the 100% portfolio

turnover rule will be applied to evaluate both, US and South African portfolio performance in terms of taxation.

6.4 MEASUREMENT OF KEY VARIABLES

The key input variables to the analysis are the monthly benchmark and portfolio returns series over the analysis period. Monthly portfolio returns are measured as the percentage change of the NAV of the portfolio

Monthly returns are calculated as follows:

$$r_t = \frac{NAV_1 - NAV_0}{NAV_0}$$

Where:

NAV_1 = Market value of the portfolio at the end of the evaluation period (current market value)

NAV_0 = Market value at the beginning of the evaluation period (market value one month ago)

Benchmark returns are computed by the same simple calculation. Note that cash dividends are excluded from the analysis; consequently no cash flows except the initial cash deposit have to be considered.

6.4.1 Market Model Parameter Estimation

Abnormal returns are measured by ex-post alpha and systematic risk is assessed in terms of historical beta. The market model parameters are estimated by regressing monthly portfolio returns against market index returns using ordinary least squares as described in Section 2.2.7. As this study is concerned with measuring ex-post returns and entails no forward-looking application and is not concerned with illiquid stocks, betas are not adjusted for instability or thin trading.

A basic t-test is used to determine whether alpha is statistically significant at the 5 percent level of significance for each strategy on both samples. As mentioned before, the market model regression relies on the assumption that the error terms are not correlated and that they are normally distributed with an expected value of zero. As this cannot simply be assumed the following steps were followed to establish statistically reliable model parameters.

A regression analysis was conducted according to the guidelines of the CFA Institute (Kaplan Schweser, 2009):

1. Run trend analysis and compute the residuals. Test for serial correlation using the Durbin Watson test.

    - If no serial correlation is detected, the standard market model OLS is used.

    - If serial correlation is detected another model is fitted (e.g. AR)

2. If the returns series exhibit serial correlation, the series are re-examined for stationarity before applying an AR model.

    - If the series (portfolio returns and benchmark returns) are cointegrated the linear model is used.

    - If the data is not cointegrated or stationary, first differencing is applied to convert the data to stationary data.

3. After the series is covariance stationary, an autoregressive model with one lagged value of the variable (i.e. and AR (1) model) is applied and again tested for serial correlation and seasonality.

    - If no serial correlation remains the model is used.

    - If serial correlation is still present, more lagged values of the beta variable are introduced until all serial correlation is removed.

4. After an appropriate model has been specified, the residuals are tested for autoregressive conditional hetereoskedacity (ARCH). The square of the residuals are regressed on the squared lagged values of the residuals.

    - If the coefficient is not significantly different from zero, the model is used.

    - If the coefficient is significantly different from zero ARCH is present and is corrected by using generalized least squares.

The regressions were conducted using the program E-views. For sample outputs refer to Appendix D.

6.4.2   Additional Performance and Risk Measures

Supplementary performance and risk measures used will be discussed briefly.

THE INFORMATION RATIO

The information will be used to evaluate the strategies' performance in terms of active return per unit of active risk. The information ratio over certain period is defined as the average active return divided by active risk.

$$Information\ Ratio = \frac{Active\ Return}{Active\ Risk}$$

Active return (also known as outperformance or tracking error) is computed by subtracting benchmark returns from the returns of an actively managed portfolio.

$$active\ return = R_P - R_B$$

Active risk (also known as tracking risk) is defined as the standard deviation of active return.

$$active\ risk = s_{(R_P - R_B)}$$

The information ratio penalizes portfolios that have a high standard deviation of active returns (active risk) relative to portfolios that outperform the benchmark in a more predictable and less volatile manner. It can thus be stated that the higher the information ratio the better the portfolio's performance.

KURTOSIS AND SKEWNESS

Additional risk measures employed include kurtosis and skewness of the portfolio. Returns distributions with significant negative skew and excess kurtosis are deemed more risky as a distribution of returns exhibiting such characteristics has "fat tails" that are skewed to the negative side, indicating that extremely negative returns are likely to be incurred.

PORTFOLIO TURNOVER

In addition to the academic performance measures, portfolio turnover will be computed for the various strategies tested to determine the strategies' viability in term of tax treatment.

In accordance with the US Security Exchange Commission (SEC) definition[17], portfolio turnover is calculated by dividing the lesser of purchases or sales of portfolio securities by the monthly average total value of the portfolio during the reporting period.

6.5 LIMITATIONS

The data used in this study ignored dividend information and the strategy returns will be measured against a capital gains benchmark instead of a total returns benchmark. Previous studies such as Rey and Schmid (2005) have found that excluding dividends from the analysis causes only minor differences in the results. This and the fact the momentum strategies under scrutiny focus on price appreciation rather than total returns and issues related to data availability led the author to the choice of a set data that is adjusted for cash dividends. However, the reader needs to consider the possible effects of such simplifying adjustments. First, the dividend yield between momentum stocks and the index chosen might differ, possibly compromising a realistic representation of the results. Secondly, the price drop of the stock price on the ex-dividend date might influence the trading-rule based stock selection process. As mentioned before, previous studies have found that dividends do not significantly impact the results of momentum strategies. De Lange (2009) confirms these findings with his own research and practical experience. De Lange (2009) also finds that the average price drop in momentum stocks instilled by dividends is relatively small compared to the average price of stocks leaving the strategies relatively unaffected by the dividend characteristics of stocks.

As mentioned before, the approach to taxation is not accurate for the South African case. Although there tax classification is directly dependent on portfolio turnover in the US, South African tax legislation is somewhat vague in this respect. Currently, to be classified as a trader one must prove the intent of holding securities for less than three years and vice versa for being an investor.

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[17] http://www.sec.gov/rules/ic/2008/ic-28442.pdf

Due to the lack of proper research published on transaction costs in South Africa, the author took a rather intuitive approach to for determining the level of unconditional transaction costs which may be subject to error.

6.6   EXPECTED OUTCOMES

The author hopes to confirm the findings of De Lange (2009) that abnormal returns can be derived by employing a feasible long-only momentum strategy on a sample of JSE stocks. Since the presence of the momentum effect has been widely documented on US equity markets by various studies (e.g. Jegadeesh and Titman, 1993; Grundy and Martin, 2001), a momentum-based strategy is expected to be profitable on US markets. It would be interesting to see how the technical indicators perform relative to standard price momentum. The author expects the strategies based on technical indicators to outperform the strategies employing standard price momentum.

6.7   CONCLUSIONS

This chapter discussed the data and the methodology to be used to execute the proposed hypothesis tests and to investigate the research questions. The following chapter is concerned with presenting the research results.

Chapter 7:   Analysis and Findings

"A careful analysis of the process of observation in atomic physics has shown that the subatomic particles have no meaning as isolated entities, but can only be understood as interconnections between the preparation of an experiment and the subsequent measurement."

- *Erwin Schrodinger*

This chapter is organized around presenting the findings with regards to the hypotheses and the research questions. The results are displayed either in tabulated format or graphically and are categorized according to the sample from which they were derived.

7.1   PRESENTATION OF RESULTS OVER COMPLETE PERIOD (2000-2009)

This section is concerned with analyzing the performance and risk of the JSE and S&P 500 strategies over the complete period from period from January 2000 to September 2009.

Various performance and risk measures that pertain to the three different strategies (MOM, RSMOM and MACDX) applied to the two samples (JSE large- and mid-caps and the constituent stocks of the S&P500) are displayed in Table 9 below. Performance measures are displayed under *Panel A* and include geometric mean monthly returns, arithmetic mean monthly returns, monthly market model alpha and finally, information ratios. Risk measures including market model beta as a proxy for systematic risk and volatility (standard deviation) as a measure of total risk are displayed under *Panel B*. The combined interpretation of skewness and the kurtosis of the distribution of monthly strategy returns give an indication towards the likelihood of extremely negative or positive returns for that strategy.

The results presented in Table 8 will now be discussed.

7.1.1 Performance Measures

All strategies outperform their respective benchmark on an absolute basis (all strategies have positive average active returns) and also on a risk-adjusted basis (all strategies have positive alphas).

The best-performing strategy is the plain momentum strategy applied on the JSE (JSE MOM) with a significant monthly market model alpha of 1%. This is a surprising finding as one would expect the strategies based on technical indicators such as MACDC and RSMOM which were optimized on the JSE, to yield superior returns. However, the MACDX strategy performs best on the US sample. The worst-performing strategies are RSMOM on the JSE sample with an alpha of 0.77 and MOM with an alpha of 0.3 on the JSE and S&P500 samples, respectively. Overall the JSE strategies yield statistically significant alphas, whereas the alphas on the S&P 500 are positive but not statistically significantly so at the 5% level of significance.

The information ratio (IR) is highest overall for the JSE MOM strategy with a value of 0.23.The IRs of the MACDX and RSMOM strategies on this sample are of the same order of magnitude with values of 0.2 and 0.17, respectively. The S&P500 portfolios exhibit information ratios that are orders smaller and range from 0.06 to 0.17, indicating that the reward for taking on active risk is less on the sample of US large-caps.

7.1.2 Risk Measures

The market model betas of the JSE strategies are slightly above the market average of 1, indicating that these portfolios are slightly more risky than the index in terms of systematic risk. The betas relating to the SP&500 sample revolve closely around 1, with MACDX and MOM strategy betas being slightly below 1 and RSMOM being slightly above 1, indicating systematic risk levels that are more or less comparable to the benchmark itself.

Table 9: Risk and Performance Measures for all Strategies and Samples from 2000-2009

Sample	INDEX	JSE			INDEX	S&P 500		
Strategy	JSE ALSI	MACDX	RSMOM	MOM	S&P 500	MACDX	RSMOM	MOM
Panel A: Performance Measures								
Geometric mean return (monthly, %)	1.01	1.77	1.60	1.86	-0.30	-0.30	0.13	-0.11
Arithmetic mean return (monthly, %)	1.09	2.07	1.90	2.15	-0.14	0.83	0.45	0.17
Market model alpha (monthly, %)*	–	**0.92**	**0.77**	**1.00**	–	0.96	0.60	0.30
Alpha p-values (dec.)	–	*0.035*	*0.004*	*0.016*	–	*0.08*	*0.23*	*0.54*
Mean outperformance (monthly, %)	–	0.98	0.81	1.06	–	0.97	0.59	0.31
Information ratio	–	0.20	0.17	0.23	–	0.17	0.11	0.06
Panel B: Risk Measures								
Beta	–	1.05	1.04	1.06	–	0.98	1.04	0.92
Volatitilty (montly, %)	5.89	7.70	7.64	7.57	5.67	8.04	7.96	7.35
Skewness **	0.10	-0.47	**-0.63**	-0.25	0.11	-0.26	-0.24	-0.32
Kurtosis ***	0.03	**1.02**	**2.65**	**0.93**	2.74	**2.76**	**1.02**	**1.39**

* Alphas that are statistically significant at the 5% level of significance appear in bold font

** Skewness levels exceeding an absolute level of 0.5 are considered to be significant and appear in bold font

*** Kurtosis levels exceeding an absolule value of 1 are considered to be significant and appear in bold font

It is apparent that the momentum strategies are generally more volatile than their benchmarks. The JSE ALSI and the S&P500 have average annual standard deviations of 5.89 percent and 5.67 percent, respectively, while the momentum strategies have standard deviations ranging from 7.35 percent to 8.04 percent.

The monthly JSE ALSI benchmark returns exhibit reasonable measures of kurtosis and skewness and therefore follow a relatively standard bell-shaped normal distribution. The S&P 500 returns, while exhibiting a reasonable level of skewness do exhibit positive excess kurtosis of 2.74, indicating a benchmark distribution with "fat tails".

All momentum strategies have slightly negative skews, indicating that there is a greater than normal chance for extremely negative returns. However, the negative skew is only significant for the JSE RSMOM strategy while the skew levels of the other strategies exhibit reasonable levels of negative skew. Every one of the six momentum strategies tested also exhibits excess kurtosis and therefore has a fat-tailed returns distribution. This finding, combined with the finding that all momentum strategies exhibit some negative skew, leads to the conclusion that the momentum strategies are prone to have large outlying negative returns.

7.1.3   Portfolio Turnover

In order to assess whether the momentum strategies under scrutiny are viable from a tax perspective, the annual portfolio turnover was computed for each strategy (Refer to Table 12 below). The reason for not including an aggregate measure of portfolio turnover in Table 9 below is that it could be misleading, because the aggregate could be below the 100 percent threshold while some years may exhibit turnovers in excess of 100%, which would have lead to a re-classification to short-term capital gains by tax authorities.

The annual portfolio turnover of every momentum portfolio is below 100%, indicating that the strategies are in fact feasible in terms of the tax implications discussed in Section 5.6. The worst-performing strategy in terms of portfolio turnover is S&P500 RSMOM strategy. Although the aggregate annual strategy portfolio turnover is 44 percent, the 2001 figure amounts to 99 percent, almost

exceeding the classification threshold. Note that the 2009 portfolio turnover was not computed as the samples only reached up to September 2009, which would have biased the results which are expressed in annual terms.

Table 10: Strategy Annual Portfolio Turnover per Strategy

Sample	JSE			S&P 500		
Year	MACDX	RSMOM	MOM	MACDX	RSMOM	MOM
2000	0.07	0.19	0.17	0.00	0.70	0.02
2001	0.33	0.29	0.32	0.83	0.99	0.62
2002	0.14	0.24	0.22	0.24	0.38	0.40
2003	0.74	0.57	0.87	0.26	0.44	0.36
2004	0.07	0.34	0.16	0.42	0.30	0.26
2005	0.32	0.32	0.20	0.35	0.15	0.48
2006	0.57	0.50	0.35	0.31	0.35	0.28
2007	0.13	0.05	0.12	0.23	0.34	0.27
2008	0.45	0.30	0.24	0.45	0.30	0.57
Average*	0.31	0.31	0.30	0.34	0.44	0.36

*A*verage annual portfolio turnover turnover*

This concludes the discussion of the tests that pertain to the three samples over the complete period from 2002 to 2009. Next, the effects of seasonality and macroeconomic states will be discussed by analysing Table 12.

7.2   PRESENTATION OF RESULTS OVER 5-YEAR SUB-SAMPLES

In the previous section the performance of the momentum strategies was analysed over a near 10-year horizon. In order to assess whether the robustness of the strategies' performance is consistent between different time periods the 10-year sample period was sub-divided into two equal near 5-year periods of 58 months each. The first sub-period spans from January 2000 to the end of September 2004 and the second from October 2004 to September 2009.

Referring to the results presented in Table 12, all strategies are strikingly more profitable over the first sub-period (hereafter referred to as S1). All strategies exhibit positive alphas and information ratios over S1. This period encompasses the collapse of the dot-com bubble in 2001 and the beginning of a long bull-run that lasted until the beginning of the sub-prime crisis (see Table 11 below). Although the South African stock market took some hardship during the dot-com bubble, the South African economy

experienced a period of uninterrupted growth from 1999 to September 2008 and therefore throughout the JSE sample period of S1.

Dot-Com bubble	March – Nov 2001	One of the longest growth periods of the American economy came to an end with the collapse of the dot-com bubble and the 9/11 terrorist attacks. Despite the length of the preceding period of growth (nearly 10 years) this recession was brief and shallow.
Subprime Crisis	Dec 2007-present	The sub-prime mortgage crisis was the trigger for the collapse of the US housing bubble and a global financial crisis. Major sufferers were the financial and automobile industries.

The second sub-period (hereafter referred to as S2) is characterised by the major bull-run from 2003 to 2007 and the bursting of the sub-prime bubble at the end of 2007/ the beginning of 2008. Apart from the aggregate arithmetic and geometric returns being lower for S2, alphas and information ratios also differ significantly between S1 and S2, indicating that the momentum strategies perform badly in "down" markets. The JSE MACDX and RSMOM strategies even *underperform* the market having aggregate alphas of -0.25 percent and -0.33 percent over S2. Nevertheless the JSE MOM strategy and all S&P 500 strategies are able to generate positive alphas.

An interesting observation is that the betas (systematic risk) and standard deviations (total risk) increase from S1 to S2 for the JSE sample but decrease from S1 to S2 on the S&P 500 sample.

All strategy returns exhibit significant positive skew during S1 and significant negative skew during S2. All strategies except the RSMOM strategies exhibit positive levels of kurtosis. While the S&P 500 MACDX strategy has the most favourable kurtosis and skewness characteristics during S1, it also has the worst kurtosis and skewness characteristics during S2. Therefore it has great upside potential during S1, but also great downside potential during S2.

In conclusion, the profitability of the long-only momentum strategies differs widely between periods, suggesting high levels of macroeconomic and strategy risk.

Table 12: Comparison of Strategy Performance between Sub-Periods

Sample	JSE						SP500					
Strategy	MACDX		RSMOM		MOM		MACDX		RSMOM		MOM	
Sub-Period*	S1	S2	S1	S2	S1	S2	S1	S2	S1	S2	S1	S2
Panel A: Performance Measures												
Geo. return (monthly, %)	2.49	1.02	2.24	0.95	2.22	1.50	-0.32	-0.28	0.38	-0.28	-0.24	0.03
Arithm. return (monthly, %)	2.07	1.02	2.46	1.32	2.50	1.78	1.45	0.18	0.74	0.15	0.11	0.23
Alpha (monthly, %)**	**1.98**	-0.25	**1.73**	-0.33	1.70	0.23	1.67	0.25	0.97	0.23	0.32	0.29
Alpha p-values (dec.)	*0.003*	*0.785*	*0.004*	*0.743*	*0.016*	*0.506*	*0.08*	*0.61*	*0.26*	*0.63*	*0.68*	*0.55*
Outperf. (monthly, %)	1.97	-0.05	1.67	-0.08	1.71	0.39	1.64	0.27	0.93	0.24	0.30	0.31
Information ratio	0.42	-0.06	0.42	-0.07	0.35	0.06	0.25	0.05	0.16	0.05	0.05	0.07
Panel B: Risk Measures												
Beta	0.98	1.14	0.92	1.18	1.01	1.11	1.15	0.86	1.17	0.95	1.13	0.78
Volatitilty (monthly, %)	7.46	7.93	6.82	8.43	7.74	7.45	8.89	7.07	8.89	7.30	8.40	6.15
Skewness***	**0.62**	**-0.83**	**0.91**	**-0.98**	**0.82**	**-0.84**	**1.86**	**-1.13**	**1.22**	**-0.84**	**1.06**	**-0.95**
Kurtosis****	0.23	**1.54**	-0.18	**3.54**	0.46	**1.47**	**2.44**	**2.79**	-0.25	**3.37**	**1.02**	**1.50**

* S1 refers to the period from January 2000 to September 2004 and S2 refers to the period from October 2004 to September 2009
** Alphas that are statistically significant at the 5% level of significance appear in bold font
*** Skewness levels exceeding an absolute level of 0.5 are considered to be significant and appear in bold font
**** Kurtosis levels exceeding an absolule value of 1 are considered to be significant and appear in bold font

The performance of the momentum strategies over the entire sample periods is graphically represented in Figure 20 and Figure 21 for the JSE sample and Figure 22 and Figure 23 for the S&P 500 sample. The figures confirm the findings regarding the performance of the strategies during different macro-economic states discussed previously. Note that periods in which economy growth stagnates or is negative are indicated by light shading in the graphs.

As illustrated in Figure 20 for the JSE sample and in Figure 22 for the S&P 500 sample, the momentum strategies tend to outperform the benchmark in "up" markets and underperform the benchmark in "down" markets. For example, the JSE MACDX portfolio value appreciates by a phenomenal 1200 percent between January 2000 and May 2007 and plummets by an excruciating 57 percent between May 2009 and September 2009.
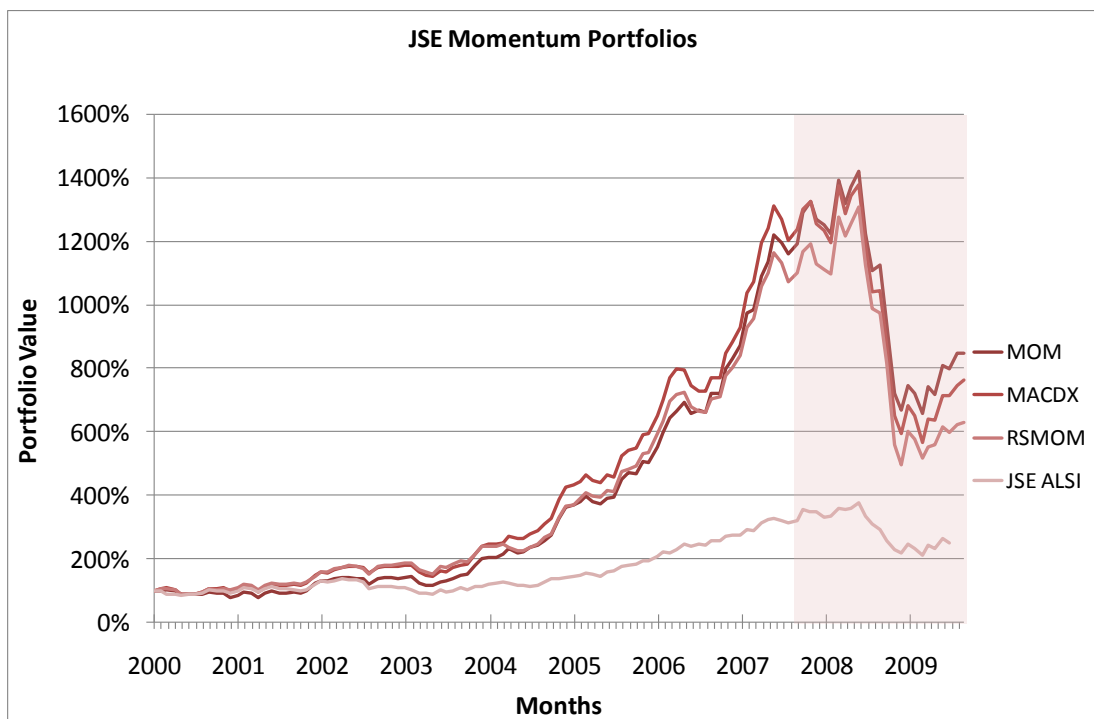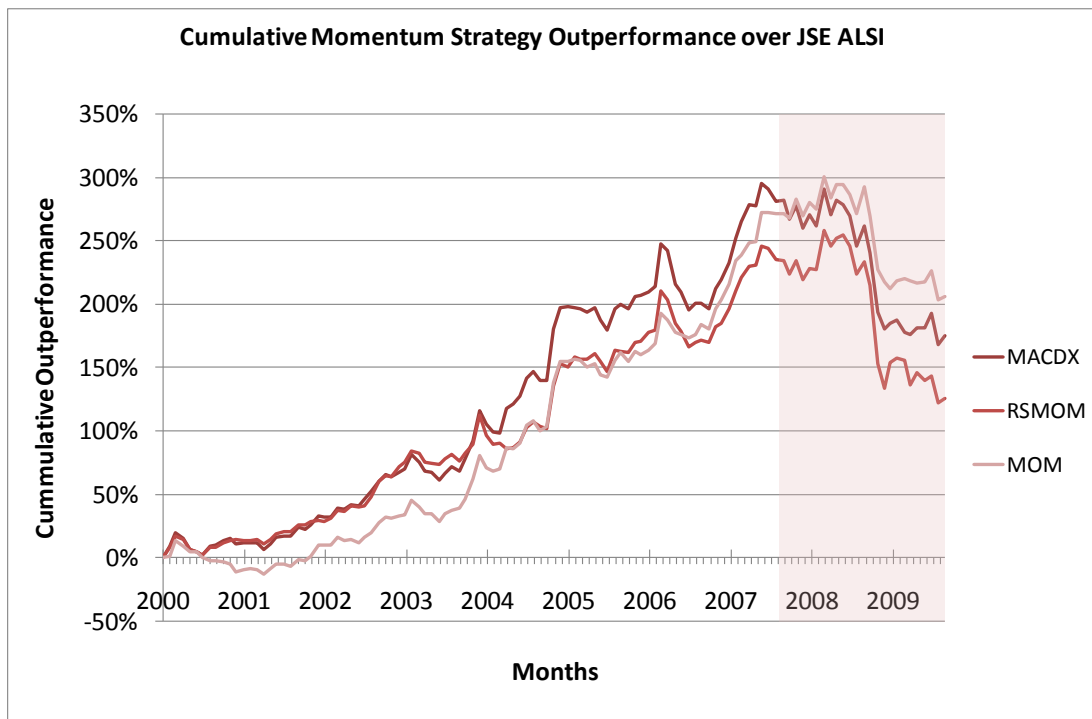

Figure 20: Absolute JSE Momentum Strategy Performance

A more meaningful insight about the performance of the JSE momentum strategies can be gained from analysing Figure 21 for the JSE sample, showing the cumulative outperformance of each strategy over the benchmark. Until March 2000 all strategies outperform the benchmark, however, in the aftermath of the bursting US dot-com bubble between March 2000 and mid-2001, the MACDX and RSMOM strategies perform significantly better than the MOM strategy, which actually underperforms the market. From there on all three strategies continue to outperform the JSE ALSI, with the MACDX yielding the best results until 2006. In mid-2006, the MACDX and the RSMOM strategies take a near 40 percent dip relative to the benchmark while the MOM strategy only loses 10% of its cumulative outperformance over the benchmark.


Figure 21: Relative JSE Momentum Strategy Performance

During the financial crisis of 2008/2009, the same pattern occurs. The MACDX and RSMOM portfolios plummet, shedding 40 percent and 30 percent of their relative outperformance relative to the benchmark, respectively, while the MOM strategy only falls by 14 percent. Overall, the JSE MACDX strategy performs best of all in up markets and worst of all in down markets. The MOM strategy,

because of its limited downside, performed best overall, but underperformed the JSE MACDX and JSE RSMOM strategy for most of the interval 2000-2001.

The momentum strategies behave similarly on the S&P 500, however, the performance between the strategies differs more significantly. The US market is characterised by two severe bear runs, the dot com bubble and its aftermath from March 2000 to September 2003 and the sub-prime/financial crisis from December 2007 till the publishing date of this dissertation.
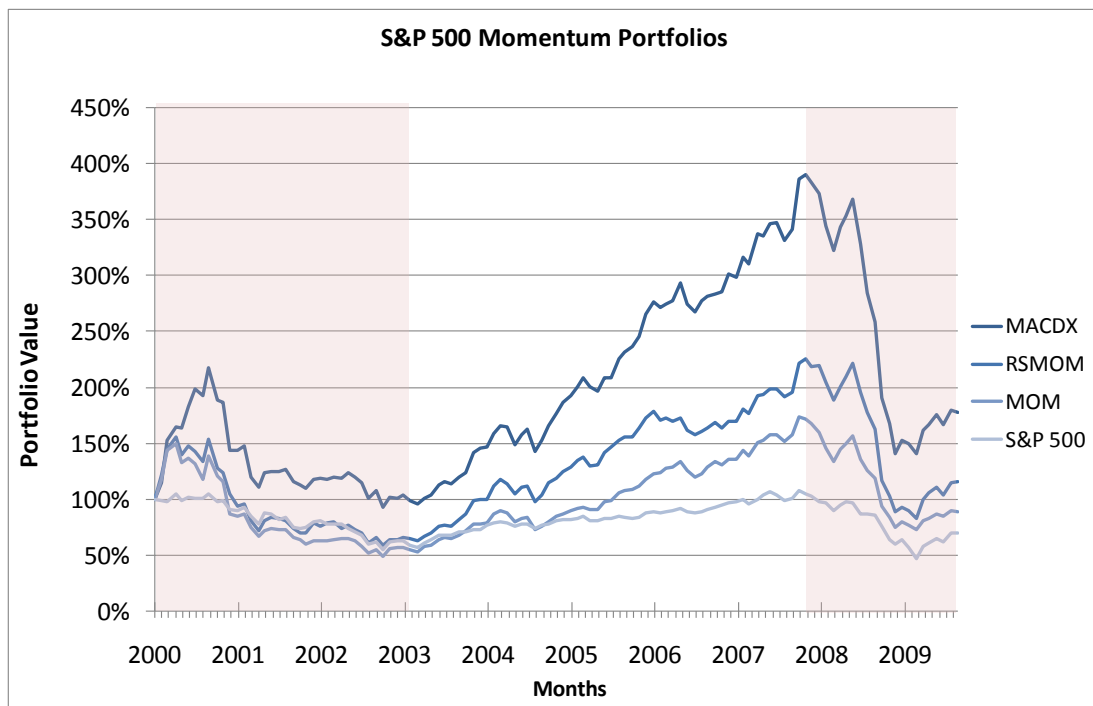
Figure 22: Absolute S&P 500 Momentum Strategy Performance

The MACDX strategy gains heavily on a few rocketing software and semiconductor stocks from March to September 2000, justifying the extreme outperformance of the strategy (See Figure 23 below). The same stocks plummet again until sold in beginning 2001 causing relative underperformance. The MACDX strategy is able to maintain positive levels of outperformance at all times, whereas the other strategies' underperformance from March 2000 to mid 2001 causes their previous accumulated outperformance to be dissipated.

All strategies yield significant outperformance in the bull-run from 2002 to 2008. Two important aspects should be noted when comparing the performance between the S&P500 and the JSE samples. First, the outperformance (active returns) of the JSE strategies over the JSE ALSI, on average, is much greater than the outperformance of the S&P500 strategies over the S&P500, suggesting either a difference in the effectiveness of the strategies between US and South African markets or a difference in effectiveness of the strategies between large- and mid-cap samples and the largest large-caps. Second, the difference in performance between the strategies is more pronounced on the S&P 500 sample than on the JSE sample. The S&P MACDX performs far better than the S&P RSMOM strategy and the S&P RSMOM strategy, in turn, outperforms the S&P MOM strategy by far (See Figure 23).
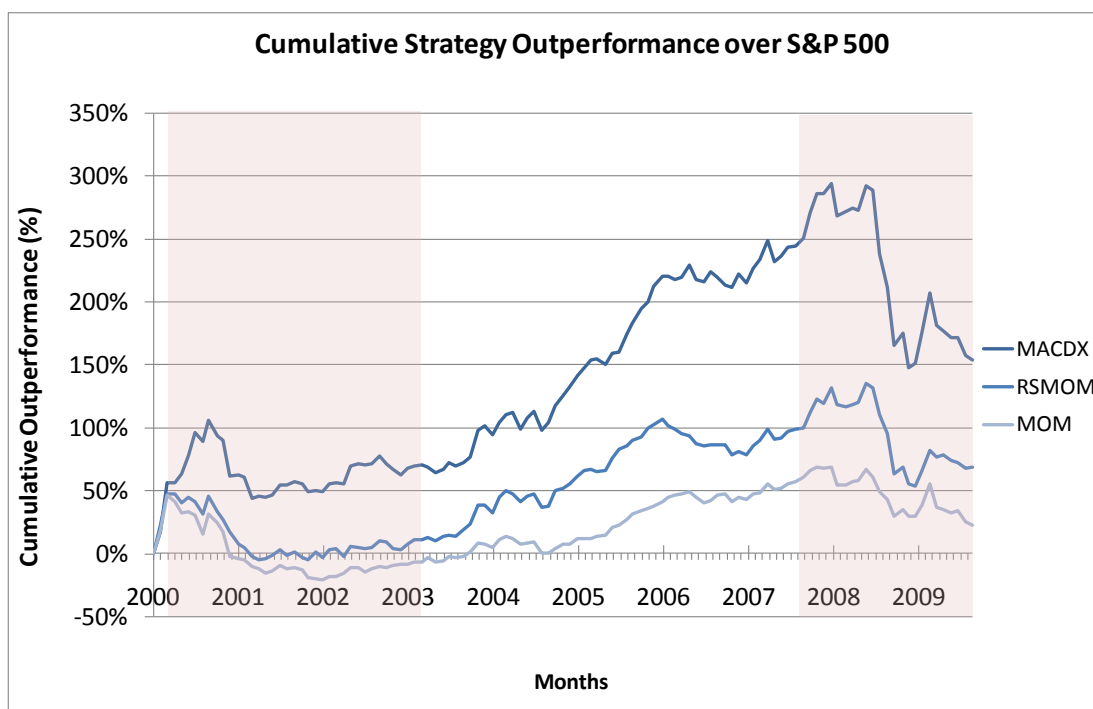
**Figure 23: Relative S&P 500 Momentum Strategy Performance**

When comparing Figure 21 to Figure 23 it is obvious that the JSE strategies' performance is much closer to each other.

This concludes the discussion of the performance of the momentum strategies on the JSE and on the constituents of the S&P500. Next the possible influence of the January effect on momentum returns will be discussed.

7.4 JANUARY EFFECT AND SEASONALITY

As mentioned in the previous chapter, it is necessary to evaluate the possible influences of the January effect on the results obtained. Should momentum returns be explainable by the January effect one would expect the momentum strategies to have extremely high returns in January, on average.

In order to assess the impact of the January effect on the JSE and the S&P500 samples, the average calendar month returns of each strategy are plotted alongside index returns in Figure 24 and Figure 25, respectively.
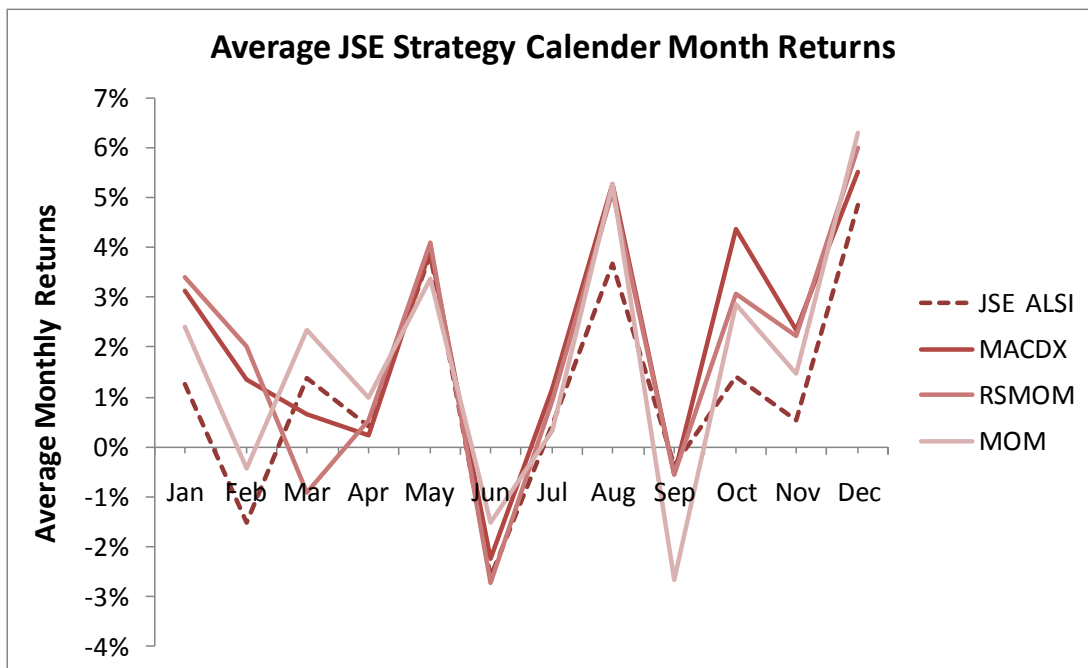
Figure 24: Average Calendar Month Returns for JSE Strategies

Clearly there is no convincing evidence for the January anomaly on the JSE sample as the outperformance over the index is much greater in October and the highest returns in absolute terms actually occur in December.

The evidence on the S&P500 presented in Figure 25 is somewhat different. All three momentum strategies significantly outperform the benchmark in January, more than in any other month. Thus there is a possibility that tax-loss selling may have some explanatory power with regard to the results.

Furthermore, both samples exhibit significant evidence for the seasonality of returns. The old Wall Street saying "Sell in May and go away" seems to be applicable for both the JSE and the S&P 500 stocks as there is a significant drop in performance in June. May, August and October generally yield high positive returns, while February, June and September are associated with negative returns.
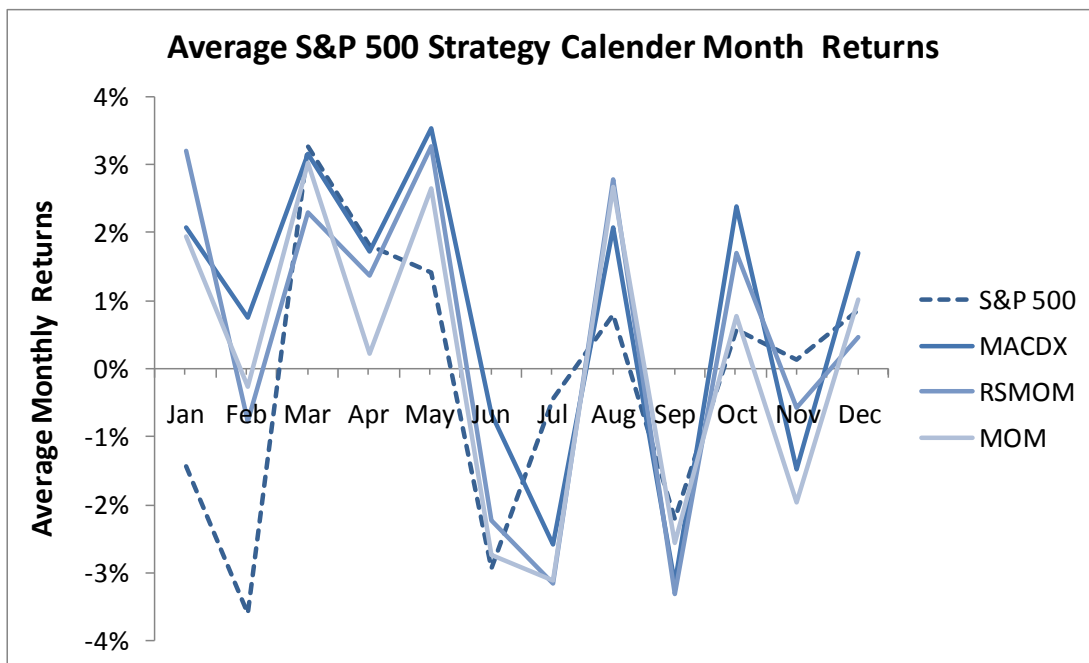

Figure 25: Average Calendar Month Returns for S&P 500 Strategies

In conclusion, there is ample evidence for seasonality of momentum returns on both samples and some evidence for the January effect explaining some of the momentum returns on the S&P 500 sample.

7.5 CONCLUSION

In this chapter the empirical results pertaining to the hypothesis test and the research questions were presented. The null hypothesis that the long-only momentum strategy proposed cannot, on average outperform the market-wide index could be rejected at a 5 percent level of significance for the sample

of JSE large and mid-caps. Although positive alphas were recorded for the strategies simulated on the S&P500, the null hypothesis could not be rejected at the 5 percent level of significance and the January effect may have some explanatory power with regard to the results. Nevertheless, the strategies generated positive active returns on both samples on average, which remains a remarkable result.

It was found that the momentum strategies underperform their passive benchmarks in "down" markets and outperform their benchmarks in "up" markets and exhibit clear signs of seasonality. Hence the momentum strategies are subject to macroeconomic risk and strategy risk. The January effect seems to be possible driver behind the momentum returns for the S&P500 sample but not for the JSE sample.

The following chapter concludes this study and is aimed at tying together the results, findings and conclusions of all other chapters and re-iterate the complete line of argument.

Chapter 8: Conclusions and Recommendations

"You get recessions, you have stock market declines. If you don't understand that's going to happen, then you're not ready, you won't do well in the markets."

- Peter Lynch

This chapter gives an overview over the study discusses the findings in the context of previous literature and suggests further future research.

8.1 MAIN FINDINGS

By reviewing previous academic studies on momentum investing, the author found that most academic studies employ methodologies that are unlikely to be used in practice because of impractical numbers of shares in the portfolios, inefficient rebalancing procedures, and most prominently, annual portfolio turnovers in excess of 100 percent. Such high turnover rates could result in the profits that are derived from momentum strategies, to be subjected to short-term capital gains taxation (or taxation at the investor's marginal income tax rate, depending on the tax jurisdiction of the investor's country of residence) rather than the long-term capital gains tax rate. This would render momentum portfolios ineffective as the profound difference in taxation is unlikely to be recovered by investment performance. The strategies investigated and tested by this study, are applied in practice and are aimed at keeping transaction costs and portfolio turnover to a minimum.

Efficient market literature suggests that momentum returns could be explainable by statistical biases, by inaccurate experiments and by means of other anomalies or risk factors. Amongst other considerations, small-cap stocks were excluded from the study to avoid the small firm effect from influencing the results and to avoid inaccuracies due to the difficulties in estimating indirect transaction costs pertaining to illiquid small-cap stocks. Furthermore it was decided to test a long-only strategy to avoid the difficulties with estimating the indirect transaction costs pertaining to illiquid short momentum positions documented by previous studies.

All feasible long-only momentum strategies were found to be profitable over the period from January 2001 to September 2009, on the JSE large- and mid-cap sample, as well as on the sample of the replicated S&P500 constituents. All momentum strategies also proved to be feasible in terms of portfolio turnover, which was found to be below 100 percent in every year for each strategy. The null hypothesis that feasible momentum strategies cannot produce statistically significant abnormal returns could be rejected for all JSE strategies at the 5 percent level of significance. Although the S&P500 sample also yields positive market model alphas, the null hypothesis cannot be rejected at the 5 percent level of significance.

A different picture manifests itself when the sample 116-month sample is split into two 58-month sub-samples. In terms of abnormal returns, information ratios and active returns, all momentum strategies perform significantly better over the first sub-period from January 2000 to September 2004 than over the second sub-period from October 2004 to September 2009. This led to the conclusion that momentum strategies similar to the ones tested are subject to strategy risk. Furthermore, the momentum strategies produced high abnormal returns in "up" markets or periods of economic expansion, and low or negative abnormal returns in "down" markets or periods of economic hardship, suggesting that the strategies are subject to macroeconomic risk.

All momentum strategies exhibit seasonality in their returns and the January effect seems to be partly responsible for the abnormal returns derived on the S&P500 sample.

8.2 ANOMALIES OR SURPRISING RESULTS

It was expected that the portfolios selected on the basis of the technical indicators that were developed and optimized by De Lange (2009) on South African markets would outperform standard price momentum. However, standard price momentum yields the best results over the period from 2000 to 2009 on the sample of JSE large- and mid-caps. On the other hand, on the sample of replicated S&P 500 constituents, both technical indicators perform far better than standard price momentum.

8.3 LARGER RELEVANCE

This dissertation establishes a bridge between the academic field of momentum effect research and the practical application of such strategies to manage actual portfolios.

While most academic studies use hypothetical trading rule-based momentum strategies to prove the existence of the momentum effect or develop models to find explanations for the momentum effect, very little research exists that investigates the profitability of practically feasible momentum strategies.

For instance, previous academic studies ignore the relationship between portfolio turnover and the tax treatment; they hold excessively large or extremely small numbers of shares in the simulated momentum portfolios, and often assume that shares are infinitely divisible. All these factors can have a profound impact on the performance of momentum strategies, causing most academic research to be far removed from the practice of active portfolio management.

This study tests an investment strategy that is as a matter of fact practicable and therefore gives a much better understanding as to whether abnormal returns can be derived from momentum strategies.
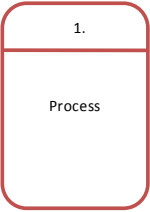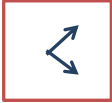
8.4 RECOMMENDATIONS FOR FUTURE RESEARCH

While conducting some supplemental tests, the author noticed that portfolios with 10 shares performed worse than portfolios with 15 shares. Contrary to the findings of De Lange (2009) the author found that the S&P 500 MACDX strategy performed orders better when monthly updating was used rather than quarterly updating. The impact of changing such portfolio parameters should be further researched.

Rey and Schmid (2005) find that their long/short momentum strategy performs best in volatile "down" markets, whereas the long-only strategy tested in this dissertation performed significantly worse in "down" markets. It should be investigated how the addition of short position affects portfolio performance overall and especially in times of economic hardship. However such a study will have to investigate implicit transaction costs encountered with short momentum positions in much more detail than could be done in this study.

Appendix A: Data Flow Diagram Elements

The IDEF® data flow diagram consists of three types of elements: data stores, processes and time triggers.

IDEF Symbol	Description
D1 Data Store	Data stores are represented by horizontal rectangular boxes with caption and index number, e.g. "Data Store" (D1). Data stores are static
1. Process	Processes are indicated by vertical rectangular boxes with rounded corners and sequence index number, e.g. "Process" (1.). Processes perform calculations on data fed from data stores and can change the format of data and input data into other data stores.
	Time triggers: Square box with clock hands triggering a process at certain predetermined time intervals, e.g. at the end of every quarter of a year (EOQ).

Appendix B: Working Process of Software

The software used for the simulation process consists of three parts, namely a MS Access database, a program called Ariel and a separate Excel macro-enabled worksheet. Ariel is a program developed and used by De Lange (2009) in day-to-day fund management and for back testing. Its stock ranking and indicator building functionality is very similar to Equis' Metastock®, a commercially available technical analysis package that was initially intended to be used for ranking stocks for this study. Ariel differs from Metastock® and most other commercially available programs in that it contains portfolio tracking functionality.

The software functionality needed for this study:

- Historical Price Series Database
- Share Scanner
- Share Ranking Functionality
- Portfolio Tracker

Historical Price Series Database:

An MS Access database containing the historical closing price series of the JSE large- and mid-cap stocks and the replicated constituents of the S&P 500 was created. The S&P 500 constituents' price series were truncated according to the exact periods they were listed in the index.

Share Scanner:

The scanning functionality is contained within Ariel and is used to calculate the indicator values for all shares in the selection sample at a specific point in time.

Share Ranking Functionality:

The indicator values are copied to the macro-enabled Excel sheet and ranked according to their indicator values. All shares falling below the cut-off ranking percentile are displayed and are subsequently sold and replaced with the highest ranking stocks.

Portfolio tracker

It is necessary in this study to keep track of the positions that are not closed out and are carried over to the next period. Cash and equity positions can be entered and withdrawn and trading costs are subtracted as a percentage of each trade. The program computes the daily closing balance of the overall portfolio. For back testing, the date is simply changed to the desired date in history. The program updates all portfolio holdings when the date is shifted one period ahead. Functionality such as the portfolio manager requires extensive programming or purchasing expensive institutional software. The author believes that this might be a reason for the rather simplistic approach to portfolio formation formed in previous studies.

Appendix C: Historical S&P 500 Constituents

An excerpt of the table used to reconstruct the historical constituents of the S&P 500 index is displayed in below.

Table 13: Historical Constituents of S&P 500

Date	Additions Company	Ticker	Deletions Company	Ticker
03/01/00	NCR Corp.	NCR	NONE	
05/01/00	Young & Rubicam	YNR	General Instrument	GIC
28/01/00	Biogen Inc.	BGEN	Foster Wheeler	FWC
28/01/00	Conexant Systems	CNXT	Consolidated Natural Gas	CNG
28/01/00	Harley-Davidson	HDI	Fleetwood Enterprises	FLE
15/03/00	Sabre Holdings Corporation	TSG	Service Corp. International	SRV
31/03/00	Linear Technology	LLTC	Monsanto Company	MTC
31/03/00	Veritas Software	VRTS	Pep Boys	PBY
31/03/00	Pharmacia Corp.	PHA	Pharmacia & Upjohn Inc.	PNU
17/04/00	Altera Corp.	ALTR	Atlantic Richfield	ARC
04/05/00	Siebel Systems Inc.	SEBL	CBS Corp.	CBS
04/05/00	Sapient Corp.	SAPE	Reynolds Metals	RLM
09/05/00	Maxim Integrated Products	MXIM	Jostens Inc.	JOS
31/05/00	American Power Conversion	APCC	Mirage Resorts	MIR
02/06/00	Agilent Technologies	A	NACCO Industries	NC
07/06/00	Starbucks Corp.	SBUX	Shared Medical Systems	SMS
12/06/00	Convergys Corp.	CVG	Times Mirror	TMC
15/06/00	MedImmune	MEDI	Central & South West	CSR
15/06/00	NONE		MediaOne Group Inc.	UMG
16/06/00	Charter One Financial	CF	NONE	
16/06/00	Novellus Systems	NVLS	Champion International	CHA
20/06/00	Sanmina Corp.	SANM	Warner-Lambert	WLA
20/06/00	Tiffany & Co.	TIF	Silicon Graphics	SGI
28/06/00	Mercury Interactive	MERQ	Milacron Inc.	MZ
28/06/00	Visteon Corp.	VC	IKON Office Solutions	IKN
30/06/00	Broadcom Corporation	BRCM	GTE Corp.	GTE
05/07/00	Qwest Communication Int'l	Q	US West	USW
12/07/00	Stilwell Financial	SV	Kansas City Southern Industries	KSU
14/07/00	CIT Group Inc.	CIT	Union Pacific Resources	UPR
26/07/00	JDS Uniphase Corp.	JDSU	Rite Aid Corp.	RAD
27/07/00	Palm Inc.	PALM	3Com Corp.	COMS
18/08/00	KeySpan Corp.	KSE	New Century Energies	NCE

Appendix D: Regression Estimation Examples

The regression results for the MACDX indicator on both the JSE and S&P500 strategies are displayed below.

Dependent Variable: JSEMACDX
Method: Least Squares
Date: 11/26/09   Time: 15:10
Sample (adjusted): 1 116
Included observations: 116 after adjustments

	Coefficient	Std. Error	t-Statistic	Prob.
C	0.919113	0.431282	2.131117	0.0352
JSE	1.053486	0.072262	14.57874	0.0000

R-squared	0.650885	Mean dependent var	2.066321
Adjusted R-squared	0.647822	S.D. dependent var	7.695862
S.E. of regression	4.567077	Akaike info criterion	5.892715
Sum squared resid	2377.833	Schwarz criterion	5.940190
Log likelihood	-339.7775	Hannan-Quinn criter.	5.911987
F-statistic	212.5396	Durbin-Watson stat	1.805426
Prob(F-statistic)	0.000000		

Residuals and squared residuals are identified as white noise. This is the best regression model.

Dependent Variable: SPMACDX
Method: Least Squares
Date: 11/26/09   Time: 14:48
Sample: 1 116
Included observations: 116

	Coefficient	Std. Error	t-Statistic	Prob.
C	0.964311	0.543383	1.774645	0.0786
SP500	0.978109	0.096252	10.16194	0.0000

R-squared	0.475295	Mean dependent var	0.826694
Adjusted R-squared	0.470693	S.D. dependent var	8.041663
S.E. of regression	5.850593	Akaike info criterion	6.388054
Sum squared resid	3902.156	Schwarz criterion	6.435530
Log likelihood	-368.5071	Hannan-Quinn criter.	6.407327
F-statistic	103.2650	Durbin-Watson stat	1.528465
Prob(F-statistic)	0.000000		

Identify ARMA(1,1) model on residuals

Dependent Variable: SPMACDX
Method: Least Squares
Date: 11/26/09   Time: 14:49
Sample (adjusted): 2 116
Included observations: 115 after adjustments
Convergence achieved after 13 iterations
MA Backcast: 1

	Coefficient	Std. Error	t-Statistic	Prob.
C	0.336591	0.518542	0.649110	0.5176
SP500	0.965291	0.085502	11.28964	0.0000
AR(1)	0.643895	0.107494	5.990032	0.0000
MA(1)	-0.626947	0.132673	-4.725505	0.0000

R-squared	0.598496	Mean dependent var	0.700772
Adjusted R-squared	0.587645	S.D. dependent var	7.961164
S.E. of regression	5.112253	Akaike info criterion	6.135321
Sum squared resid	2900.999	Schwarz criterion	6.230797
Log likelihood	-348.7809	Hannan-Quinn criter.	6.174074
F-statistic	55.15356	Durbin-Watson stat	1.882323
Prob(F-statistic)	0.000000		

Inverted AR Roots	.64
Inverted MA Roots	.63

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