Fusion investing:

An esoteric approach to portfolio formation

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DECLARATION

I, Yudhvir Seetharam, declare that this research report is my own unaided work. It is submitted in partial fulfilment of the requirements for the degree of Master of Commerce in Finance at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination at this or any other university.

Yudhvir Seetharam

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Definitions of Terms and Abbreviations

Adaptive Market Hypothesis: A new version of the Efficient Market Hypothesis where efficiency is seen as cyclical – dependent upon the interaction of market participants at any point in time.

AMH: Adaptive Market Hypothesis

Attribution Theory: A theory in social psychology that strives to determine how individuals explain causes of behaviour and events (Heider, 1958).

Autocorrelation (or serial correlation): The dependency of one observation at a point in time to another observation at another point in time. If autocorrelation is present in a data series, particular forms of statistical analysis cannot be conducted without first correcting or accounting for autocorrelation.

Bayes Theorem: A theorem in statistics that links the degree of belief in an outcome before and after accounting for evidence (Bayes and Price, 1763).

Behavioural Portfolio Theory: A theory which states that investors create a portfolio that meets a broad range of goals. The portfolio can be thought of as a pyramid, where each layer represents a different goal.

Bernstein's Theorem: Any real-valued function on the line $[0, \infty)$ that is strictly monotone is a mixture of exponential functions. Non-negative functions which have a strictly monotone derivative are referred to as Bernstein functions (Bernstein, 1928).

CDF: Cumulative distribution function

Contrarian investing: *See **value investing***

EMH: Efficient Market Hypothesis

Esoteric: Intended for or understood by a particular group of individuals.

Fama and French three factor model: A micro-economic model that attempts to explain share returns via three factors: a value factor (HML), a size factor (SMB) and a share's beta.

Free Cash Flow Hypothesis: A hypothesis that stipulates the tendency of management to spend excess cash flow on negative net present value projects as opposed to a payout to shareholders.

Fusion investing: A style of investing that combines fundamental, technical and behavioural analysis with no regard to traditional asset classes.

Fusion fund returns: Returns of the fusion fund, calculated as monthly fluctuations in the price of the fusion portfolio.

Fusion strategy returns: Returns of the fusion strategy, calculated as 12 month buy-and-hold returns, averaged over 12 months.

Gaussian distribution: Also referred to as a normal distribution, this is a continuous distribution which has a "bell-shaped" probability density function. It was first introduced by Gauss (1857).

Information Theory: A theory developed by Shannon (1948) to quantify information.

Informational Theory of Investment: A newly developed theory of investment based on the premise of information theory. Under this setting, information is regarded as a reduction of entropy. When combined with a learning algorithm, this theory is helpful in analysis of market patterns.

J=6, K=6 momentum strategy: Under this notation, the first number corresponds to the number of periods of historical data used to calculate past returns. The second number corresponds to the number of periods the share is held in the portfolio.

JSE: Johannesburg Securities Exchange Ltd.

January effect: The January effect refers to the tendency of shares to generate above-average returns in the month of January. It was first documented in Wachtel (1942).

Mental accounting: A process consisting of coding, categorisation and evaluation of economic outcomes.

MPT: Modern Portfolio Theory

PMPT: Post-Modern Portfolio Theory

Prospect Theory: A descriptive theory by Kahneman and Tversky (1979) which tries to reconcile real world actions and behaviour of investors with that of utility theory.

SD: Stochastic Dominance

Rational expectations: A presumption of the Efficient Market Hypothesis where agents' predictions of the future value of economically relevant variables are not systematically wrong - the errors are random (Muth, 1992).

Value investing: Also known as contrarian investing, value investing is based on correctly identifying shares that are inexpensive relative to a price multiple and purchasing these shares to generate profitable returns in the long term.

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ABSTRACT

This study contributes to the debate on active and passive portfolio management by providing an alternate means of constructing an active portfolio. This "fusion strategy" has underpinnings in the realm of behavioural finance, namely the value-growth phenomenon and the momentum effect. The fusion strategy developed in this study was compared against two passive benchmarks and four active benchmarks. All returns are calculated net of transaction costs, initially set to 1% per month per share. Statistical testing, done via stochastic dominance, yielded inconclusive results in the majority of cases. The exception however, was that Fund B stochastically dominated the fusion strategy at second order. This implies that a risk-averse investor would prefer to invest in Fund B. By the use of Sharpe and Treynor ratios, the results were also inconclusive. However, the Sortino ratio shows that the fusion strategy outperforms all benchmarks chosen, except Fund A. The performance of the fusion strategy was also not induced by either a sector rotation strategy, the existence of the January effect or by the level of transaction costs.

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1 Introduction

Finance theory unequivocally states that in efficient markets, a portfolio manager who utilises active strategies cannot outperform his counterpart who utilises passive strategies, after transaction costs. Many academics and practitioners have investigated this claim and whilst there is consensus amongst groups of individuals, there is no ruling on the claim itself. In this study, focus is given as to whether pricing anomalies found in the literature can be exploited simultaneously. This study contributes to the debate on active and passive portfolio management by providing an alternative means of constructing an active portfolio. The strategy is referred to as a fusion strategy and has underpinnings in the realm of behavioural finance, namely the value-growth phenomenon and the momentum effect.

"Fusion investing is a relatively new approach that attempts to integrate traditional and behavioural paradigms to create more robust investment models" (Lee, 2003, p. 1). The term, fusion investing, was first presented by Lee (2003). The concept of incorporating behavioural finance into share valuation was new at this stage of the financial markets profession. Although the author did not formalise the idea, this presentation was simply to raise awareness of incorporating behavioural finance into share valuation.

The first study to suggest the use of a sentiment indicator in the valuation of a share was conducted by Shiller (1984). The author considered a universe where there are two types of traders – information traders (known as the "smart money") and noise traders (the ordinary investor). The model presented by the author shows that price is a weighted average of fundamental value and noise trader demand. In the presence of transaction costs, price will not necessarily equal fundamental value. As fundamental analysis provides a component of the share price, information traders (rational investors) need to consider trends. This is similar in notion to the Keynesian idea that the financial market is a "beauty contest" (Keynes, 1938).

Bird (2007) provided the first formal introduction to fusion investing. Using his prior studies as examples, Bird (2007) expanded upon the idea of fusion investing. He suggested that three different approaches to exploiting pricing differences be investigated: the value approach, fundamental approach (accounting-based analysis) and momentum approach. The earliest (and perhaps only known literature) on the evaluation of a fusion strategy is that of Bird and

Casavecchia (2007b). The study focuses on European markets during the period 1989 to 2004. The authors find that both enhancements (momentum and fundamentals), independently and in combination, improve the timing ability of the manager in selecting value and growth stocks and that the momentum enhancement subsumes the fundamental enhancement in better identifying value shares.

The premise of investing on the existence of anomalies in the market or in particular asset classes has become known as style investing and is popular amongst actively managed funds. In the financial market environment, investors (or portfolio managers) classify assets into broad categories such as large-cap shares, government bonds, venture capital, *inter alia* and thereafter decide how much of capital to invest in each class (R. Bernstein, 1995).

> Some investment styles have a record of producing respectable long-term results. Even the most successful styles and strategies, however, sometimes experience extended dry spells. Indeed, styles that pay off in one economic environment frequently fail in another one. Obviously, any technique that can predict the performance of various styles would be of considerable practical value. (Arnott, Kelso, Kiscadden and Macedo, 1989, p. 28)

The authors explore the possibility of selection styles in portfolio formation. However, they state that implementation of a particular style, whilst generating high returns, will also generate high turnover and transaction costs. For example, the use of style momentum investing[1] is in and of itself a driver of high returns and high transaction costs. Barberis and Shleifer (2003) state that the popularity of assets depends on their performance. Thus, investors would flock to those assets that provide better returns, thereby driving up prices in a self-fulfilling prophecy. This shows the impact of investor sentiment in financial markets (Seetharam, 2010). Chen and De Bondt (2004) suggest that astute investors should incorporate style characteristics into their asset allocation strategies. The authors show that investors that follow styles based on size, book-to-market ratios or dividend yields could earn superior returns over the period 1977 to 2000. It is unclear however, what the explanations are for the cross-sectional differences in returns, or whether they are rational (irrational) in nature.

[1] Style momentum is a form of sector rotation that buys those shares that had the best past returns and sells short those shares that had the worst past returns (Chen & De Bondt, 2004).

van Rensburg and Robertson (2003a) investigate the cross-sectional explanatory power of various style characteristics on the Johannesburg Securities Exchange Ltd. (JSE). Six candidate factors are found to be significant out of a total of 24 effects investigated. In the construction of a multifactor model, size and price-to-earnings ratios are found to have the most explanatory power. This supports the work of van Rensburg (2001) in testing a multifactor pricing model on South African shares. Whilst the factors (and ensuing model) had no theoretical explanation at the time of publishing, the authors acknowledge that the above mentioned factors are anomalies on the JSE. Thus, an investment strategy should (hypothetically) be able to exploit these anomalies profitably.

1.1 Research problem and objectives

From the perspective of an active fund manager, three questions need to be asked (as per Bird, 2007):

1. Is the market you operate in efficient? If not, why is it inefficient?
2. Would these inefficiencies persist in the future?
3. How does your investment strategy exploit these inefficiencies?

The focus of this study is on the last point listed above. Given that literature (both local and international) has documented the existence and non-existence of the value-growth[2] and momentum[3] anomalies in South Africa, an attempt is made to design a strategy that utilises these pricing inefficiencies, assuming the above inefficiencies to be present in the South African market yet not necessarily throughout the entire sample period[4]. Further, literature has shown that a combination of a value strategy or fundamental strategy with a momentum strategy seems a viable means of achieving above average returns (see Bird & Casavecchia 2007a; 2007b). Thus, this research aims to encapsulate the idea by Lee (2003) and Bird and Casavecchia (2007b) by designing an investment strategy that exploits the value, fundamental and momentum anomalies. Although the screening methods are chosen based on prior studies, no published study has utilised these screens in the sequence outlined below. This study therefore offers an interpretation of fusion investing.

[2] Fama and French (1993), Basiewicz and Auret (2010), *inter alia.*

[3] Jegadeesh and Titman (1993), Fraser and Page (2000), *inter alia.*

[4] This point is clarified in Section 2.1.2.

Consider Figure 1 below. Each shaded circle represents a sample space. From the population of all shares, those considered value shares are selected. From that sample, those that are fundamentally sound and exhibit winning momentum characteristics are chosen. The first two screens are evaluated on an annual basis whereas the final screen is evaluated monthly. As firms release financial statements annually, any significant information contained in this release would cause the firm's share price, as well as related data, to change in the long term. The inclusion of a monthly momentum screen should be effective in capturing short term fluctuations present between releases of financial statements.

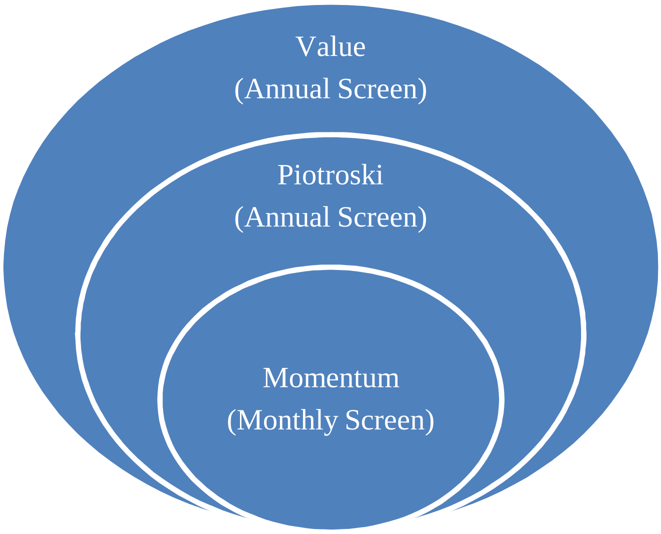

Figure 1 – Venn diagram of the fusion strategy

Thus, any share that passes all of the above criteria is considered inexpensive (the value screen), financially sound (the Piotroski screen) and has positive prior performance (the momentum screen).

This study draws on differing areas of the literature to present a comprehensive opinion on the fusion strategy. Apart from implications for efficient markets, the psychological evidence surrounding the above financial anomalies as well as the practical implications for the fusion strategy are investigated. For instance, based on the work of Chordia and Shivakumar (2002), this study informally analyses the performance of the fusion strategy over business cycles as the above cited literature show that size, value, and momentum factors track business cycles.

1.2 Summary of findings

The fusion strategy developed in this study was compared against two passive benchmarks and four active benchmarks. An additional comparison was conducted with the fusion strategy and an (artificial) equally weighted ALSI. All returns are calculated net of transaction costs, initially set to 1% per month. Statistical testing, done via stochastic dominance, yielded inconclusive results in the majority of cases. The exception however, was that Fund B stochastically dominated the fusion strategy at second order. This implies that a risk-averse investor would prefer to invest in Fund B and that Fund B has a greater probability of achieving higher returns than the fusion strategy. However, it is interesting to note that the above results, whilst true statistically, do not provide a complete picture. By the use of risk-adjusted portfolio performance measures, specifically the Sharpe and Treynor ratios, the fusion strategy yields mixed results. However, the Sortino ratio shows that the fusion strategy outperforms most of the benchmarks it was compared against. The performance of the fusion strategy was also not induced by either a sector rotation strategy or the existence of the January effect. Sensitivity to the level of transaction costs was also investigated. The level of transaction costs that results in a break-even return for the fusion strategy was found to be at least 6.50% per month. This amount is economically significant. Thus, notwithstanding the significant influence of transaction costs, the results are promising.

As this study is pioneering in South Africa, various avenues for research can be explored. Empirically, one can alter the fusion strategy to more accurately determine which optimal combination of screening criteria as well as screening delineation points (such as a median split instead of quartiles), provides the best performance. Theoretically, one can explore the nature of the “fusion investor”, with particular emphasis to his utility function and interaction with the rest of the market.

This study will proceed as follows. An overview of the literature surrounding this field and its direct relations will be examined in Chapter 2. Thereafter, Chapter 3 outlines the fusion strategy and appropriate statistical methodology for analysis of its returns. Chapter 4 presents and discusses the results along with particular sensitivity tests and biases that were present in this study. Lastly, Chapter 5 provides an excursus into the caveats and avenues for future research of this study, ending with a conclusion. Appendix A provides mathematical derivations for select components of the statistical methodology, Appendix B provides additional graphs of stochastic dominance tests and Appendix C details the results of the fusion strategy against an (artificial) equally weighted passive benchmark.

2 Literature Review

The chapter begins with a summary of active and passive management of portfolios. This discussion will inherently include background into the Efficient Markets Hypothesis (EMH) and the role of transaction costs. Thereafter, the literature surrounding modern portfolio theory (with specific focus to the most recent developments) will be analysed. Finally, an extensive analysis of the fusion strategy's components will be conducted, followed by the statistical method used to examine the returns and ending with explanations offered from behavioural finance.

2.1 Active and passive portfolio management

A simple question lies at the heart of both finance academia and practice – can a portfolio manager achieve superior returns than the market, after costs? A plethora of studies have been conducted, and yet there has been no clear consensus of whether active or passive portfolio management is more beneficial in terms of returns. Underlying the question is the theory surrounding the EMH. Whilst it is not the purpose of this review to provide an extensive discourse on EMH literature, a brief discussion is instructive.

Kendall (1953) analysed a sample of firms from the United Kingdom and found that no autocorrelation was apparent in share prices. This implied that prices behaved in a random manner, with equally likely probabilities of increasing, decreasing or remaining the same. Roberts (1959) enhanced this implication by analysing shares in the United States. Using these two findings, Fama (1965) presented the Efficient Markets Hypothesis. Since its publication, the EMH has generated much debate amongst academics and practitioners alike. To date, whilst there may be a consensus in some circles, there is no definitive proof of whether the EMH holds.

2.1.1 The forms of market efficiency

The EMH requires that agents have rational expectations (that is, on average, the population of agents are correct, even when no single agent is) and that these agents update their expectations whenever new information arises. The EMH requires that investors' reactions follow a Gaussian distribution so that no abnormal profits can be realised. Each of the forms of efficiency, as described by Fama (1965) requires a differing set of requirements to hold true.

The weak form of market efficiency states that future prices cannot be predicted by analysing past prices. In the long run, investment strategies will not earn excess returns after costs. More specifically, strategies focused on technical analysis will not be able to consistently produce excess returns whereas strategies focused on fundamental analysis may still provide excess returns. Statistically, share prices do not exhibit serial correlation – they follow a random walk.

The semi-strong form of market efficiency provides that share prices adjust quickly to public information. Neither a fundamental- nor a technical analysis-based strategy will earn excess returns. However, those that have access to private information may be able to obtain superior returns.

Lastly, under strong form efficiency, share prices fully reflect both public and private information. Thus, no sustainable superior returns, after costs, can be achieved in the long run.

There is a vast amount of literature surrounding tests for market efficiency.[5] This study indirectly offers a test of the semi-strong and weak forms of efficiency as it utilises financial statement analysis in its methodology.

2.1.2 An alternative view of efficiency

The EMH asserts that financial markets are informationally efficient. That is, one cannot consistently achieve returns in excess of average market returns on a risk-adjusted basis, given the information publicly available at the time the investment is made. Tests of the EMH have yielded both positive and negative results. Inevitably, once a particular result is found, it becomes prone to criticism, sometimes rightfully so. For example, Malkiel (2005) states irrevocably that a passive index fund has significantly beaten an active fund over a 30 year horizon. From this the author concludes that the EMH holds. Malkiel (2005) however fails to mention that transaction costs have not been taken into account – an important factor in deciding which strategy is superior.

Roberts (1959) is one of the early academics to suggest enhancing technical analysis with the aid of fundamental analysis. At a time pre-dating the publication of both the EMH and the Capital Asset Pricing Model (CAPM) of Sharpe (1964), the suggestions of Roberts (1959)

[5] The interested reader is referred to Sewell (2011) for an extensive discussion.

show that irrespective of whether one perceives the market to be efficient, one can still economise time in the search for greater returns.

Lo (2004 and 2005) describes a new form of market theory – the Adaptive Market Hypothesis (AMH). This approach utilises concepts from finance and the principles of evolution. It is simply stated as follows: "Prices reflect as much information as dictated by the combination of environmental conditions and the number and nature of 'species' in the economy" (Lo, 2005, p. 19). Species refer to market participants (asset managers, hedge funds, traders, *inter alia*). Thus, the efficiency of the market at any point in time is related to the factors of evolution and competition present.

It presents a simple, philosophical and pleasantly intuitive view of market efficiency. Market efficiency can be seen as cyclical. There are times of inefficiency and efficiency. For a market to become efficient, it must first be inefficient and *vice versa*. The influence of market participants (through trading or financial product innovation) influences this efficiency, sometimes in a disruptive way. To date, no formal methodology has been published on testing the AMH. However, authors have nonetheless proposed and tested methods (for example, Todea, Ulici & Silaghi, 2009; *inter alia*). It is with this viewpoint (in support of the AMH), that this study draws upon. In relation to the objectives set forth in Chapter 1, it was assumed that the market in which the fusion strategy is developed and implemented in is inefficient, with these inefficiencies possibly persisting into the future. The AMH enhances this assumption by stating that these inefficiencies are cyclical in nature. Thus, one would expect the fusion strategy to have periods of both superior and inferior performance.

2.1.3 The role of transaction costs

Transaction costs consist of two components – explicit costs, such as brokerage fees and taxes; and implicit costs, such as bid-ask spreads and the price impact of the trade (Boussema, Bueno & Sequier, 2001). As implicit costs are difficult to quantify, many studies instead deduct a fixed percentage of the value of each trade to account for trading costs. This value is referred to as unconditional trading costs.

Studies that have utilised unconditional, round-trip[6] trading costs range from 0.5% (Jegadeesh & Titman, 1993) to 1.5% (Grundy & Martin, 2001). Friedrich (2010) finds that a range of between 0.5% and 0.6% is considered a conservative amount for South African

[6] Round-trip trading costs refer the costs of entering and subsequently exiting a position.

shares of high liquidity. Ray and Schmid (2005) conduct stress testing on the value of trading costs to determine the point at which the returns of their momentum strategy becomes statistically insignificant at the 90% level of significance. A value of 1.22% a month achieves this goal, whilst a value of 2.06% eliminates the momentum profits (from an economic perspective). This study uses an amount of 1% per share per month for transaction costs. This is discussed further in Chapter 3.

2.2 Portfolio Theory – developments and applicability

Another line of thought parallel to the EMH is known as Modern Portfolio Theory (MPT). The fundamental building block of MPT is mean-variance optimisation developed by Markowitz (1959). Simply, mean-variance optimisation posits that investors should be compensated for additional levels of non-diversifiable risk. This optimisation is given by efficient portfolios which focus on three key variables: mean return, correlation and standard deviation. MPT relies on these statistical tools to enable the portfolio manager to select those shares which will provide the highest return at a given level of risk (and *vice versa*) in *equilibrium conditions*. Indeed, an entire field of research and practice has been born out of the analysis of a single variable of MPT, the standard deviation (most commonly given by σ), in *non-equilibrium conditions*. Nevertheless, a shortcoming of standard deviation as a measure of risk is that it measures both upside and downside risk. Further, its use relies on asset returns following a Gaussian distribution.

The salient point is that the use of standard deviation, no matter how accurate it may be, does not satisfy the needs of an investor.[7] Further, a distinction should be made between volatility and risk. According to MPT, standard deviation is synonymous with risk. However, standard deviation simply refers to the volatility of returns – a higher standard deviation implies that returns are more volatile. *Ceteris paribus*, investors prefer less volatility to more volatility. However, not all investors prefer less risk to more risk. Indeed, risk can be seen as an emotional aspect of investing. Investors perceive risk as either: the risk of loss, the risk of underperformance or the risk of failing to meet one's goals (Swisher and Kasten, 2005). A new measure, semi-variance and consequently, downside risk, measures only those returns

[7] Under the assumptions of MPT, the typical investor is assumed to be risk-averse. Kahneman and Tversky (1979) challenge this assumption, which resulted in the emergence of Prospect Theory. Under Prospect Theory (more specifically the concept of loss aversion), the investor strongly prefers to avoid losses rather than acquire gains.

that fall below the mean. This new measure is intuitively appealing and as such, Post Modern Portfolio Theory (PMPT) uses downside risk as the measure on which to compare returns against. Surprisingly, Markowitz (1959) states that "downside semi-variance" would be a more appropriate measure for building portfolios (Markowitz, 1959, p. 194).

2.2.1 Semi-deviation as a measure of risk

The use of standard deviation presents several challenges. First, its use is reliant on the underlying distribution of returns being symmetric and following a Gaussian distribution. Bekaert, Erb, Harvey and Viskanta (1998) show that asset returns, particularly in emerging markets, do not meet the above criteria. Given that standard deviation is a component of MPT, if standard deviation is considered ineffective in its use, one must then question the applicability of MPT including the use of the equilibrium measure of risk, β (beta). As a result, the use of semi-deviation has received favour amongst academics and practitioners alike. It is defined as:

$$O_B = \sqrt{E\{\min[(R - B), 0]^2\}} \qquad \{1\}$$

where *R* denotes the asset return and *B* denotes the benchmark or target return. The above formula considers those returns that fall below the benchmark only. Thus, it is a measure of downside risk.

The practicality of the above measure is twofold. It combines two statistical measures, variance and skewness, into a single statistic, making it a useful inclusion in one-factor models. Second, semi-deviation is applicable when the underlying distribution is either symmetric or asymmetric.

Empirical studies such as Sortino and van der Meer (1991) and Estrada (2001), *inter alia*, have tested the use of semi-deviation as a measure of risk. In cross-sectional returns and cross- sectional industry tests, the statistic was found to be an appropriate measure of risk.

The performance of portfolio managers under MPT was measured by ratios that unitise returns per level of risk. Examples include the Sharpe ratio (Sharpe, 1966), the Treynor ratio (Treynor, 1965), the Information ratio (Sortino and Price, 1994) and Jensen's alpha (Jensen, 1968). The Sharpe ratio uses the standard deviation of total portfolio returns in excess of a risk free rate to measure a manager's performance. It is simple and intuitive to use yet ignores diversification of the portfolio. The Treynor ratio creates a characteristic line to evaluate manager performance. It measures portfolio beta relative to a market index proxy. Whilst the ratio is simple and intuitive to use for a cost-benefit comparison, the values obtained are often difficult to interpret and often ignore unsystematic risk. Sortino and Price (1994) derive the Information Ratio which measures standard deviation of return in excess of a benchmark, to a style index (in other words, tracking error). It provides a direct comparison of performance to a benchmark per style of investing yet it implicitly assumes that both portfolios have the same level of systematic risk. Finally, Jensen’s alpha is one of the few measures that rely on regression techniques for estimating performance where the deviation between the returns generated by any asset pricing model and the actual asset return is captured by an intercept term, alpha. Whilst a regression approach might yield more accurate results, it relies on the presumption of the particular asset pricing model as an appropriate model of risk (this includes measuring an asset’s beta and using an appropriate market proxy instead of the elusive market portfolio itself). Modigliani and Modigliani (1997) develop a risk-adjusted performance measure. It is simple to understand, similar in vain to the Sharpe ratio yet significantly easier to interpret. However, this ratio also relies on the use of standard deviation – the use of which is questioned (as discussed previously). Goetzmann, Ingersoll and Spiegel (2007) develop a Manipulation Proof Performance Measure (MPPM). The MPPM is a (1) single valued score which is (2) independent of monetary value and (3) the uninformed investor cannot enhance estimated score. The authors outline four conditions for a measure to be considered manipulation proof. The measure should (1) result in an increase score with increased return, (2) the function should be concave, (3) it should be time inseparable and (4) it should have a power utility form. This implies that informed investors should be able to get higher scores. Goetzmann et al. (2007) show that the measure is better at detecting and ranking fund performance over many other popular performance measures. However, as the MPPM is based on von Neumann-Morgenstern utility axioms of von Neumann and Morgenstern (1944), it can be argued that it is not appropriate in light of Prospect Theory (in which investors exhibit different levels of utility towards losses and gains).

To date, PMPT utilises the Sortino ratio (Sortino and Price, 1994) only. The Sortino ratio measures excess returns per unit of *downside* risk. Given the advances in finance theory and the intuitive appeal of PMPT, this study uses the Sortino ratio as a measure to compare performance of the fusion strategy against passive and active benchmarks.

2.3 Value investing

There is a vast array of literature that documents the performance of shares selected on relative valuation multiples. The evidence points to value shares (those with low relative price multiples) outperforming growth shares (those with high relative price multiples). The most common of these multiples are the: Price to Earnings (P/E), Price to book (P/B) and Price to Cash Flow (P/CF) ratios. A typical strategy would be constructed as follows. First, data would be obtained for the relative multiple under investigation. Second, shares would be ranked from highest to lowest according to the multiple chosen. Third, the top grouping (percentile, quartile, *inter alia*) of shares would be termed the value portfolio, whilst the bottom grouping would be termed the growth portfolio.[8] Value shares ranked according to P/E, P/B and P/CF have been shown to outperform growth shares ranked accordingly (see, respectively, Basu, 1977, Fama & French, 1992 and Lakonishok, Shleifer & Vishny, 1994).

Fama and French (1993) propose that the outperformance of value shares over growth shares, in effect, a value premium, is due to the inherently riskier nature of value shares relative to growth shares. The authors note that this premium is not captured by the standard CAPM of Sharpe (1964). Others, such as Black (1993) and Kothari, Shanken and Sloan (1995) offer that the value premium is a result of data mining or data selection biases. There is, however, a third explanation offered by Lakonishok et al. (1994). The first two explanations above attempt to reconcile the value anomaly with the current paradigm of efficient markets. Lakonishok et al. (1994) instead deviate from this paradigm and suggest that the value premium is a consequence of the judgemental mistakes of investors. This is in line with the earliest philosophy of value investing by Graham and Dodd (1934) – a value strategy is successful because it is contrary to the market. The relative valuation multiples used would appear to reflect the systematic errors made by investors in their forecasting. A high (low) P/B value may indicate that the current price of the share is inflated (deflated) relative to its book value. This implies that investors irrationally attribute too large (small) a weighting to the good (poor) performance of the firm in the recent past and assume this performance would continue into the near future. If (or perhaps when) the firm fails to meet investors' expectations, the P/B multiple would correct itself to reflect this updating of information.

[8] Note that these classifications apply when the multiple has the share price as the numerator. If the share price were the denominator, the value portfolio would have the *highest* respective multiples (E/P, B/M, CF/P), whereas the growth portfolio would have the *lowest* respective multiples.

Relative valuation multiples can thus provide good proxies for mean reversion of shares and market performance.[9] Further, Rousseau and van Rensburg (2004) point out that whilst the performance of value shares is impressive in most markets; this performance is typically attributed to only a handful of shares in the value portfolio. As the value of these multiples become extreme, there is a greater probability that the share's price will adjust to correct for this, such that the multiple reverts to "acceptable levels".

In a South African context, Graham and Uliana (2001) find that post-1992, value shares outperform growth shares, whereas pre-1992, growth shares outperform value shares. Whilst they do not attempt to offer explanations for this anomaly, they do posit that economic and political conditions surrounding South Africa during this time may have impacted the results. Nevertheless, the findings of Graham and Uliana (2001) show that the value-growth phenomenon does exist in South Africa.

The weakness of a value strategy lies in determining when this reversion will occur. A possible way of enhancing a value strategy would then be to delay the purchase of the value share until it reaches its turning point. This can be achieved via a screening criterion. Recent studies have suggested two distinct approaches – enhancement of a contrarian strategy with fundamentals or with momentum.

2.4 Fundamental investing

Value shares are typically neglected by both analysts and investors and thus provide an opportunity to investigate performance with as little market noise as possible. Arbel and Strebel (1982) document the neglected firm effect – the tendency of firms that are not closely followed by analysts to provide unexpectedly high returns. It follows that if one can correctly identify a share that is both neglected and inexpensive, a remarkable profit opportunity arises. One could conduct analysis of these firms' financial statements, which would provide a reliable indicator of past performance, and the data are also readily accessible.

Prior research documents that high book to market (B/M) firms outperform low B/M firms (see Fama & French, 1992 and Lakonishok, Shleifer & Vishny, 1994). The success of this outperformance rests with a few firms that perform significantly better than most in the

[9] For the purposes of this study, it is important to note that the relative valuation multiple used does not provide any significant insight into the timing of any mean reversion (in contrast to LaPorta, Lakonishok, Shleifer & Vishny, 1997).

chosen sample. It can be deduced that if an investor is able to select *ex-ante*, those firms that he judges to be superior future outperformers, the investor is able to consistently earn above average returns. Piotroski (2000) examines whether an accounting-based fundamental analysis strategy can earn positive returns for an investor. The author investigates the use of such a heuristic in choosing between strong and weak value firms. Application of fundamental analysis to accounting statements led to a successful application of a heuristic that discriminates between good performers and poor performers. During the sample period of 1976 to 1996, returns generated from this fundamental-based approached were 23% annually, excluding transaction costs. This also lends credence to various behavioural models that were developed by Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998) and Hong and Stein (1999). The effectiveness of the fundamental analysis strategy in Piotroski (2000) appears to be greatest in a slow information dissemination environment, evidence similar in line with the momentum strategy tested by Hong, Lim and Stein (2000). In these environments, value firms are typically neglected by analysts – hence the slow absorption of information released from those firms. Lastly, the author shows that the success of the strategy is based on the ability to predict future performance and the market's inability to recognise these predictable patterns. When examining earnings announcements, returns for winner shares are 4.09% significantly higher than those for loser shares. This is comparable to the value versus glamour (growth) announcement return difference in LaPorta, Lakonishok, Shleifer and Vishny (1997).

The performance of this strategy highlights many anomalies documented in Fama (1998). The ability to discriminate, *ex ante*, between strong and weak performers suggests that the market does not efficiently incorporate past information into current prices – a violation of weak form and semi-strong form efficiency.

2.4.1 Prior fundamental analysis research

2.4.1.1 The univariate approach

LaPorta (1996) and Dechow and Sloan (1997) show that systematic errors in market expectations about long term earnings growth rates partially explain the success of a contrarian strategy (given by book-to-market values). Many investment strategies have been designed and tested based on the market's inability to fully incorporate signals of financial performance by firms.[10]

Frankel and Lee (1998) implement a fundamental analysis approach that identifies shares whose prices lag their fundamental values. These undervalued shares are identified via earnings forecasts and accounting-based valuation models (such as a residual income model). Over the three year investment period analysed, this strategy is successful at generating significantly positive returns. Generally, analysts prefer not to follow poor performing, low volume or small firms (Hayes, 1998). Thus, these firms are less likely to have forecast data, a consequence of the neglected firm effect described earlier. This poses a significant problem for using Frankel and Lee's (1998) forecast based method to select value shares. As all listed shares (irrespective of analyst following) are required to publish financial statements, it is logical to use financial statements as a basis for share analysis.

2.4.1.2 The multivariate approach

Holthausen and Larcker (1992) show that a statistical model can be used to accurately predict future excess returns. Given the complexity of these methodologies and the vast amount of data required, Lev and Thiagarajan (1993) use 12 financial signals that are popular amongst analysts. These signals are shown to be correlated with contemporaneous returns after controlling for current earnings innovations, firm size and macroeconomic conditions. Ou and Penman (1989) develop such a strategy to predict future changes in earnings. This strategy is based on various financial ratios obtainable from historic financial statements, similar to the Piotroski score used in this study. Abarbanell and Bushee (1997) test the ability of Lev and Thiagarajan's (1993) strategy to predict future changes in earnings and future revisions of analysts' forecasts thereof. They find that some of the signals suggested by Lev and Thiagarajan (1993) are economically justified in assessing future firm performance.

Piotroski (2000) provides a strategy similar in spirit to Lev and Thiagarajan (1993). Whilst some of the signals are common to both studies, many used in Piotroski (2000) do not correspond to prior research. The reasons for this deviation are threefold. First, the population under investigation in Piotroski (2000) is restricted to value firms.[11] These firms are typically smaller in size and often more financially distressed compared to growth firms. Thus, the

[10] See Piotroski (2000) for an extensive discussion.

[11] This provides some justification for the order of the fusion strategy screens outlined in this study.

signals used in the Piotroski score are chosen to specifically measure profitability and default risk trends. Second, whilst signals such as capital expenditure decisions would be reasonably good indicators of financial performance, they are of secondary importance relative to the signals chosen to capture the health of a firm. Bernard (1994) and Sloan (1996) both show that accounting returns and cash flow, each relative to the other, is of importance when assessing future performance prospects. Third, neither Lev and Thiagarajan (1993) nor Abarbanell and Bushee (1997) offer an optimal set of signals. There is thus room for the use of alternative and perhaps complementary signals to demonstrate the performance of a fundamental analysis strategy, in general. The Piotroski score is the aggregate sum of each signal, once that particular signal has been reduced to binary form. By focusing only on value firms, the Piotroski score is able to provide a reliable gauge of financial health and investment potential of a value firm. Further, Piotroski (2000) postulates that if analysts exhibit under-reaction to financial statements – analysts are inefficient in analysing and interpreting financial statements – this will lend to the success of both the Piotroski score and momentum strategies.

2.4.2 A contrarian strategy with fundamentals

Piotroski (2000; 2005) demonstrated that the use of select financial ratios provides a good measure to differentiate between good and poor performers. Both Piotroski (2000) and Scott, Stumpp and Xu (2003) find that the market's reaction is slow with respect to accounting-based information. In the case of value shares, which have typically low expectations, any deviation from said expectations would plausibly create either significant profits or losses. This explains why publicly available information can be (profitably) used to provide medium term insights to the performance of (value) shares. Mohanram (2005) finds that similar variables used by Piotroski (2000) can be used to differentiate between good and poor performers.

2.5 Momentum investing

2.5.1 Definition and early history

Momentum can be defined as the "continuation of the direction of prior stock returns" (Griffin, Ji & Martin, 2003, p. 2515). Jegadeesh and Titman (1993) examine the profitability of a relative strength trading strategy[12] (buying past winners and selling past losers) for a holding period that varies between three and twelve months. The findings show that significant profits can be made using this strategy during the sample period 1965 to 1989. The particular strategy examined in detail is the *J=6*, *K=6* strategy. The evidence is consistent with a delayed price reaction to firm-specific information and inconsistent with the lead-lag effect[13] of Lo and MacKinlay (1990). Further, the results are not due to the systematic risk of the trading strategy (Jegadeesh & Titman, 1993).

The momentum effect was thus discovered by Jegadeesh and Titman (1993) and still remains an anomaly that defies traditional finance theory. In a subsequent study, Jegadeesh and Titman (2002), the authors find that their momentum strategy continued to remain profitable. Rouwenhorst (1998) examines a momentum strategy in twelve European markets and finds its existence apparent. Chui, Titman and Wei (2000) find the effect in emerging markets and Fraser and Page (2000) find its persistence in the South African market.

2.5.2 Related empirical findings

Grinblatt, Titman and Wermers (1995) examine the performance of mutual funds in the United States. On average, those that followed a momentum strategy realised significantly better returns than those funds that did not. Indeed, the authors found that fund performance was highly correlated with a fund's ability to implement momentum strategies and to herd. Intuitively, if a fund lacks the ability to time entry and exit in and out of the market, its next best strategy would be to follow the consensus (herd). Schierek, De Bondt and Weber (1999) find that both a momentum and contrarian strategy outperforms a passive approach in Germany during the period 1961 to 1991. As the strategies require limited trading, the authors submit that trading costs do not substantially alter their results. In an attempt to offer risk-based explanations, the authors examine factors such as share beta, standard deviation and firm size. None of the examined factors satisfactorily explain the persistence of profits under either the momentum or contrarian approach. Benson, Gallagher and Teodorowski (2007) examine the role of momentum in the active asset allocation environment using data

[12] A relative strength trading strategy is similar in concept to momentum investing. The distinction lies in the terminology. Positive (negative) momentum refers to the positive (negative) *difference* between returns. In contrast, positive (negative) relative trading strength refers to the positive (negative) *ratio* of returns.

[13] The examination of shares sorted according to size, shows that the returns of larger shares lead the returns of smaller shares. Hence, the lead-lag effect.

on Australian securities. Their results show that momentum investing does exist amongst Australian mutual funds and that those funds with no market timing ability are most likely to be momentum investors.

2.5.3 Possible explanations of momentum

Many academics have attempted (unsuccessfully) to explain momentum via asset pricing models. Fama and French (1996) resign that momentum cannot be explained by their three-factor model in which winner shares tend to positively affect the size coefficient (given by *SMB* in the model) whereas loser shares tend to negatively affect the size coefficient. The extension of these effects to the long term tends to predict a reversal of returns, not a continuation (momentum). Thus, the model cannot explain the momentum anomaly. Conrad and Kaul (1998) argue that past winners have higher unconditional expected returns than past losers, thus these returns will not change over time and result in persistent profits. Jegadeesh and Titman (2002) show that the method used by Conrad and Kaul (1998) is biased and those cross-sectional differences in expected returns explain a minute proportion of momentum profits. Chordia and Shivakumar (2002) use a conditional asset pricing model with lagged macroeconomic risk factors that captures momentum in the United States reasonably well. These variables are related to the business cycle and show that momentum returns during an expansion are statistically positive whereas those during a recession are negative, albeit insignificant. Unfortunately, Griffin, Ji and Martin (2003) show that the model by Chordia and Shivakumar (2002) is not robust on a global level. The authors' findings support the notion that macroeconomic risk, a significant contributor to momentum, is largely country specific. The model by Chordia and Shivakumar (2002) generates inaccurate global momentum forecasts and is thus inadequate in explaining momentum-generated returns. Lastly, Cooper, Gutierrez and Hameed (2004) find that momentum is not primarily driven by market risk (it is idiosyncratic in nature).

Behavioural models (discussed in a Section 2.8) by Daniel, Hirshleifer and Subrahmanyam (1998) and Hong and Stein (1999) imply that momentum and subsequent reversals should be stronger following market gains than market declines (as investors exhibit increased overconfidence and lower risk aversion during market gains). Cooper et al. (2004) find that these models do not stand up to empirical testing. Thus, there has been no viable explanation of the momentum effect to date. Hvidkjaer (2006) attempts to explain the persistence of the momentum effect from the perspective of trading. The intuition surrounding the explanation in Hvidkjaer (2006) is as follows. If the predictions of behavioural models are uncorrelated across investors, trading will occur but the price effects would be minimal. However, when the models lead to the same conclusion, the prices will either move upwards (due to increased investor demand) or downwards (due to decreased investor demand). This occurs even in the absence of new fundamental information (Shleifer, 2000). The most pertinent link between cognitive biases and prices would then be the trading behaviour of investors. Hvidkjaer (2006) examines whether this trading behaviour is rational or irrational in nature by using transactions data on all NYSE/AMEX[14] shares over the period 1983 to 2002. The author finds that large traders are less susceptible to momentum effects than small traders and suggests that momentum can be partially driven by the behaviour of small traders.

2.5.4 A contrarian strategy with momentum

De Bondt and Thaler (1985; 1987) suggest that share prices tend to overreact to information. A contrarian strategy (which buys past losers and sells past winners) was shown to earn abnormal returns over a three to five year holding period. Other strategies have used shorter holding periods of either days or months. Whilst these also show abnormal returns, it is possible that these returns can be explained by short-run price fluctuations and lack of liquidity. Jegadeesh and Titman (1995) examine this anomaly and provide evidence in favour of the above interpretation. Early literature on market efficiency focused on strategies that bought past winners and sold past losers (for example, R. Levy, 1967)[15]. Grinblatt and Titman (1989; 1991) document that many mutual funds have a tendency to buy shares that have increased in price over the last quarter. The question under review is to reconcile the relative strength trading strategy with the contrarian trading strategy, as both have supportive literature. One possible reason for the discrepancy is that the contrarian strategy utilises either a short term (one week or one month) or long term (three to five years) holding period whereas the relative strength strategy utilises a holding period between three and twelve months.

Bird and Casavecchia (2007a) suggest that an improvement in momentum of a value share provides a good signal of a sustained improvement in (both fundamental and market driven)

[14] New York Stock Exchange/ American Stock Exchange

[15] R. Levy's (1967) results have come under heavy criticism from Jensen and Bennington (1970), by arguing that the different strategies were examined *before* developing a strategy that worked. They find that R. Levy's (1967) results were prone to selection bias.

performance. Anecdotally, the universe of value stocks can be seen as a lemons problem[16] where cheap shares are interspersed with inexpensive shares (those that present a good investment opportunity). An improvement in momentum for a particular value share signals that the share has received increased attention, presumably brought on by an improvement in performance. As high momentum also indicates strong sentiment (increased popularity of the share leads to increased trading, driving up the share price), any decrease would be synonymous with the share reaching the peak of its price life cycle. Fraser and Page (2000) investigate the presence of both value and momentum phenomena on the JSE. They find, independently, that both phenomena exist. The authors find that the P/B ratio is the ideal indicator to use for a value strategy and a 12 month past return is the best period to use for a momentum strategy.

2.6 Fusion investing

Bird and Casavecchia (2007b) evaluate the approaches by Bird and Whitaker (2004) and Piotroski (2000) to enhance value style portfolios. The study focuses on European markets during the period 1989 to 2004. To identify value shares, the authors use a Price to Sales ratio, as this was found to be the most effective in European markets. The earnings forecast method of Ou and Penman (1989) is used as a fundamental indicator and the specific momentum indicator used is an acceleration indicator. This price acceleration measure is analysed with the aim to synchronise the long-short strategy with market cycles. Two types of acceleration are defined in Bird and Casavecchia (2007b): short acceleration is calculated as the ratio between the three month and the six month price momentum. It is used to divide the bottom momentum quintile - those stocks that exhibit more losing characteristics. Similarly, long acceleration is calculated as the ratio between the 12-month and the 24-month price momentum. It is used to divide the top momentum quintile - those stocks that exhibit more winning characteristics. Further, they find that both enhancements (momentum and fundamentals), independently and in combination, improve the timing ability of the manager in selecting value and growth stocks and that the momentum enhancement subsumes the fundamental enhancement in better identifying value shares. Specifically, the success rate of enhancing a value style with a momentum indicator increases from 42% to 53% over a one

[16] Akerlof (1970) describes the market for lemons as the information asymmetry that exists when the seller knows more about the product than the buyer. Here, “lemon” refers to a defective product.

year holding period. Thus, Bird and Casavecchia (2007b) provide evidence of the success of the fusion strategy (without using that particular terminology) in European markets.

The sorting and ranking procedure in Bird and Casavecchia (2007b) differs from that used in this study. The authors first sort shares into value and growth groupings and thereafter simultaneously sorts these shares according to fundamentals and momentum; with each sort conducted on an annual basis. Further, the acceleration measure used by the authors is not used in this study, primarily due to data constraints.

2.7 The role of stochastic dominance in empirical finance

Decision theory is concerned with identifying values and uncertainties in a given decision that result in the optimal outcome (Wald, 1939). It is one of the core aspects of any financial or investment decision. Traditional finance theory, beginning with MPT, assumes that investors are rational at every point in time (Markowitz, 1959). Further, in this framework, the investor's utility is a function of wealth which is non-decreasing ($U'(w) \geq 0$) and exhibits diminishing marginal utility ($U''(w) < 0$) – in other words, the investor is risk-averse. However, based on the works of Friedman and Savage (1948), Markowitz (1952a) and Kahneman and Tversky (1979), prospect theory was developed as a contender to the traditional framework. Friedman and Savage (1948) provide a hypothesis which includes the traditional axioms of von Neumann and Morgenstern (1944) as well as a theoretical justification for a section of the utility function to be convex – a section which exhibits increasing marginal utility ($U''(w) > 0$). Markowitz (1952a) in an attempt to refine the work of Friedman and Savage (1948) adds that investors possess a utility function which consists of two concave and two convex segments. Using this theoretical foundation, Kahneman and Tversky (1979) find experimental evidence that supports the notion of the utility function described previously and formalise the concept of Prospect Theory. The authors conclude that investors maximise the expected value of the function for the convex segment for negative outcomes and the concave segment for positive outcomes. The evolution of utility functions is presented in Figure 2 below. The left-most function corresponds to that used in Markowitz (1959), the middle-left to that used in Friedman and Savage (1948), the middle-right to that used in Markowitz (1952a) and the right-most to that used in Kahneman and Tversky (1979).

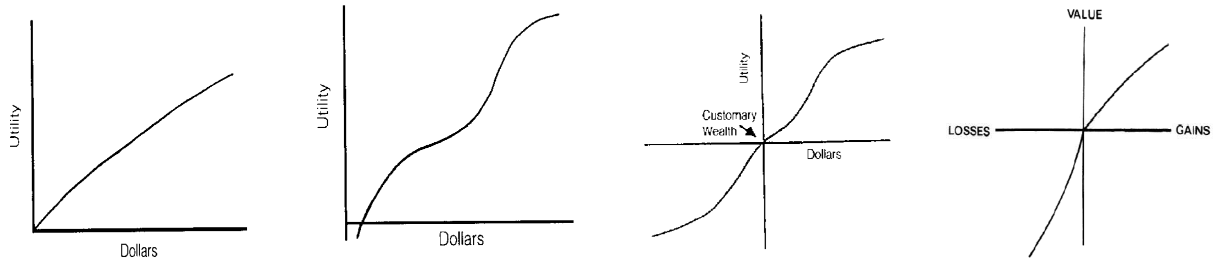

Figure 2 – Evolution of utility functions (Lopes, 1987).

Under the original methodology of Prospect Theory, investors would overweight unlikely events independently of their relative outcomes. This would lead decision makers to choose the worst of two options based on their cumulative probability distributions. Thus the theory as presented in Kahneman and Tversky (1979) gave rise to violations of first order stochastic dominance which presumes an expected utility maximiser possesses an increasing utility function – in other words, the decision maker would instead choose the better of two options based on their cumulative probability distributions. Tversky and Kahneman (1992) thus developed a variant of the original theory, referred to as Cumulative Prospect Theory. Under this variant, cumulative probabilities are transformed to weighted cumulative probabilities, shown in Figure 3 below. This leads extreme events of small probability to be appropriately weighted as opposed to equally weighting all extreme events of small probability (as per the original Prospect Theory). This ensured that first order stochastic dominance was not violated.

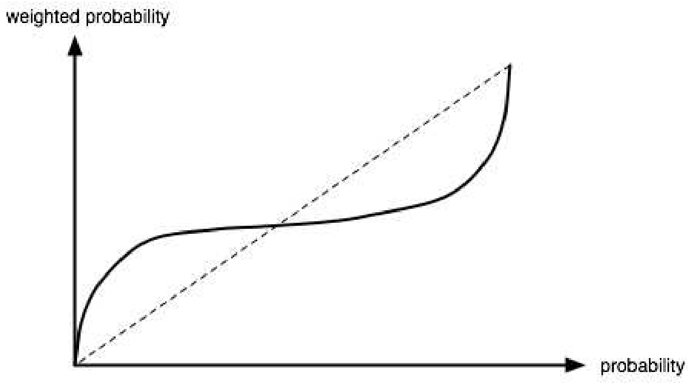

Figure 3 – A weighting function used in Cumulative Prospect Theory

The main development of SD theory was due to Hadar and Russell (1969), Hanoch and Levy (1969), Rothschild and Stiglitz (1970) and Whitmore (1970).[17] Hadar and Russell (1969) develop theorems for ordering uncertain prospects related to first and second order stochastic dominance. Hanoch and Levy (1969) present a framework for incorporating SD to portfolio selection and optimisation. Rothschild and Stiglitz (1970) view financial returns as a random variable and attempt to model portfolio selection based on this precept and SD rules. Whitmore (1970) develops criterion for third degree dominance and its inclusion in the field of utility theory. Since these developments, application of SD rules to finance, statistics and empirical data have been successful (see H. Levy, 1992).

The primary advantage of SD theory in finance over MPT is that SD theory is based on an axiomatic model of risk-averse preferences. The MPT model of mean-variance optimisation does not model the entire spectrum of risk-averse preferences. Moreover, as discussed previously, the use of standard deviation as a measure of risk is not an accurate description of an investor's attitude towards risk. Porter (1974) shows that the use of semi-variance as a measure of risk is consistent with the rules of SD theory. Thus, there exists a relationship between the use of SD rules, semi-variance as a measure of risk and concepts from behavioural finance.

2.8 Explanations from behavioural finance

The existence and persistence of momentum and value strategies go against the literature on market efficiency. Proponents of behavioural finance have associated the persistence of these market anomalies to cognitive biases of investors. Frank (2004) presents experimental evidence of over- and under- reaction on the JSE. The results show that the markets will under-react to reliable information and over-react to unreliable information.

2.8.1 A behavioural framework for investing

The classification of objects into categories based on some similarity among them is one of the foundations of human thought (Rosch & Lloyd, 1978). In the financial environment, investors (or portfolio managers) classify assets into broad categories such as large-cap shares, government bonds, venture capital, *inter alia* and thereafter decide how much of

[17] Since the development of Prospect Theory, there has been subsequent development into Prospect Stochastic Dominance (Linton, Massoumi & Whang, 2005). However, application of this technique is beyond the scope of this study.

capital to invest in each class (R. Bernstein, 1995). The process of allocating capital into such categories has become known as style investing.

Intuitively, assets that belong to the same style will inherently share some base characteristic. As such the impact of an exogenous event will affect the entire portfolio either positively or negatively. In Modern Portfolio Theory terminology, the portfolio does not have a high level of diversification, which can be captured by the high correlation and covariance amongst the portfolio constituents. The driving force behind the initiation of new styles and the ending of old styles is largely due to financial innovation and sentiment (or popularity). For example, in the years following 2003, the Credit Default Swap (CDS) has gained in popularity. Consequently, a new style of investing would be to allocate greater proportions of capital to a CDS. Similarly, following the works of Banz (1979) and Basu (1977), small stocks would have increased in popularity.

Style investing is pleasing to both individual and institutional investors for two reasons. First, the categorisation of assets significantly reduces the amount of time and effort required to process information efficiently (Mullainathan, 2000). For example, an investor would prefer to allocate capital amongst say, five asset styles, as opposed to across every listed security. Second, by segmenting assets, performance evaluation is simplified, especially when peer group comparisons are used (Sharpe, 1992). From an institutional perspective, style investing provides a great benefit to funds that are required to follow a mandate.

Barberis and Shleifer (2003) present a simple model for an assessment of style investing. Under the assumption that investors follow a momentum strategy, they find that the investment styles follow a specific life cycle. Prices deviate from their fundamental values as styles become popular or unpopular. According to the authors, in an inefficient market, an arbitrageur can earn substantial profits by following a combination of a momentum and contrarian strategy. However, with extremely volatile prices, the popularity of a particular style is sometimes clouded. Thus, arbitrage becomes risky and consistent profits are less likely to be realised. Consistent with this implication, one can also conclude that these results imply an efficient market in that arbitrage activity decreases consistent profits to the point of eliminating them - prices thereby reflect their fundamental values. Barberis and Shleifer (2003) are particularly careful in using such terms and simply present stylised facts of their study, without overemphasising the importance of their results. One can also relate their results to the AMH described earlier. As the AMH offers a cyclical view of efficiency, one could infer that the popularity (and performance) of a particular style will follow a cyclical pattern.

2.8.2 The over- and under- reaction hypotheses

The phenomena of over- and under- reaction are well documented in the literature. The over-reaction hypothesis of De Bondt and Thaler (1985) suggests that investors overweight current (or short term) information and underweight historic (or long term) information. Thus, investors can cause prices to overshoot fundamental values. Hence, over-reaction leads past losers to become underpriced and past winners to become overpriced, leading to a reversal in the future. This hypothesis is tested by the authors who find that the reaction is more severe for loser shares than winner shares and more apparent over longer term horizons of between three to five years. Further, a strategy which bought loser shares outperformed winner shares by 24.6% over three years, excluding costs. This strategy has grown to become known as value (or contrarian) investing, which was discussed earlier.

Page and Way (1992) document over-reaction on the JSE. The authors found that loser shares outperformed winner shares by 14.5% over a three year holding period, excluding costs. This implied that the JSE was weak-form inefficient. However, in both De Bondt and Thaler (1985) and Page and Way (1992), returns were found to be seasonal during January (although Page & Way, 1992, found that it is less pronounced). Muller (1999) also tests for over-reaction on the JSE but restricts the analysis to the 200 largest shares, given by market capitalisation over the period 1985 to 1998. By adopting a methodology which overcame the seasonality effect of other studies, the author confirmed the presence of over-reaction on the JSE. In a more recent study, Hsieh and Hodnett (2011) confirm the previous findings of Page and Way (1992) that share prices on the JSE tend to overshoot their fundamentals and mean revert. The authors also find that the correction back to fundamentals is stronger for loser shares than winner shares – as found in De Bondt and Thaler (1985).

In contrast, the under-reaction hypothesis as explained by Barberis, Shleifer and Vishny (1998) states that prices are gradually updated to reflect new information. Specifically, shares initially under-react to good news, which is corrected at a later stage, and at that later stage the returns of shares which released good news are higher than those that released bad news. As a consequence, these prices exhibit positive autocorrelation over short-term horizons of approximately 12 months. Studies such as Bernard and Thomas (1989; 1990) and Ikenberry, Lakonishok and Vermaelen (1995) show that prices are slow to react to earnings announcements and share repurchases, respectively. If one were to profit from the under-reaction hypothesis, it follows that firms that release good news should be bought and those that release bad news should be sold. This has manifested itself in the form of fundamental investing described earlier. Using fundamental analysis, the investor is able to determine the impact of news releases. The need for timing the market has been addressed via momentum strategies. Jegadeesh and Titman (1993) document that abnormal positive returns generated by their momentum strategies disappear after two years. This implies that the market has fully incorporated the historic information into share prices – the market has achieved a level of efficiency.

Both these phenomena pose a challenge to efficient markets as sophisticated investors can earn superior returns by utilising these concepts. Indeed, the literature presented forms a justifiable response to the order of the screening criteria of the fusion strategy.[18] Fama and French (1996) posit that their three-factor model can account for over-reaction but not under-reaction. Loser shares have positive size (*SMB*) and value (*HML*) slopes and thus have higher average future returns whereas winner shares have negative value (*HML*) slopes and thus have lower average future returns. The differing signs between loser and winner shares imply a long term reversal. Barberis et al. (1998) develop a parsimonious model of investor sentiment - one that incorporates both over-reaction and under-reaction. Their model is consistent with the experimental evidence of Tversky and Kahneman (1974), with respect to representativeness and conservatism bias (both described below). Under an environment of a single asset and single investor, the earnings of the asset follow a random walk. The investor, who is unaware of this, believes that earnings moves between two states. In the first, earnings are mean reverting. In the second, they follow a trend. The transition probabilities between states, as well as the statistical properties, are fixed in the investor's mind. Each period, the investor updates his information based on an observation of earnings. Although the investor's model of earnings is inaccurate, this updating process is Bayesian[19] in nature. Barberis et al. (1998) show that for a plausible range of values, this model works well in generating

[18] Alternatively, the incorporation of these all particular screens may be counter-productive to producing superior returns.

[19] Bayesian statistics interpret and measure probability objectively or subjectively. Both require the assumptions of rationality and consistency, albeit by differing degrees (Bayes & Price, 1763).

predictions observed in the data. In other words, the authors find that investors over-react to negative news and under-react to positive news.

2.8.2.1 Psychological evidence

Conservatism states that individuals are slow to change their beliefs in the face of new evidence (Edwards, 1968). In experiments conducted by the author, the subjects' reactions are benchmarked to that of an idealised rational Bayesian investor. The findings show that individuals do update their beliefs, but by a lower magnitude, relative to the rational Bayesian benchmark. Subjects take between "two to five observations to do one observation's worth of work in inducing a subject to change his opinions" (Edwards, 1968, p. 359).

The evidence on conservatism suggests that, in a financial context, under-reaction could be present. Investors might disregard the full information content of, say, an earnings announcement. As a consequence, revaluation of the share will only partially reflect the full impact of the announcement. Investors tend to underweight useful evidence relative to less useful evidence that they obtained *a priori*. Further, they might exhibit overconfidence in their revaluations (Barberis et al., 1998).

The second relevant phenomenon documented by psychologists is the representativeness heuristic (Tversky and Kahneman, 1974). A person who follows this heuristic will evaluate probabilities based on its similarity to other events and in a manner which reflects the salient features of the process that generated it. An important consequence of the heuristic, as discussed by Tversky and Kahneman (1974) is that people (investors) will perceive to observe patterns in truly random sequences. As conservatism is suggestive of under-reaction, representativeness is suggestive of over-reaction. To continue with the example of earnings announcements, a consistent history of unusually positive announcements will lead investors to believe that this past history is predictive of future performance. They would thus disregard the pertinent fact of these high earning firms not being able to repeat this performance in the future. When the expected earnings growth is not realised, investors penalise the firm by means of a drop in share price.

Griffin and Tversky (1992) attempt to reconcile conservatism with representativeness. They find that when people focus too much on the strength of the evidence and too little on its weight, forecasts are usually revised downwards – an observance of conservatism.

Conversely, when too much focus is given on weight and not enough on strength, over-reaction occurs. In the world of finance, investors might underweight the information contained in quarterly earnings announcements, since a single number cannot contain much information. They ignore the weight that the news has on forecasting future earnings. Alternatively, investors can overweight the information content of consistently high or low earnings growth, not realising the low impact this has on forecasting.

It is important to note that the psychological evidence does not indicate how to quantitatively differentiate between information that leads to over-reaction and information that leads to under-reaction. Thus, any consecutive finance related literature is not *per se* based on psychological evidence as opposed to being motivated by it. Studies conducted on simulated financial experiments (such as that by Andreassen & Kraus, 1990 and De Bondt, 1993) show that these two phenomena of over- and under- reaction do exist.

2.8.3 The overconfident investor

Daniel et al. (1998) present a behavioural model similar to that of Barberis et al. (1998), with a different psychological foundation. The model by Daniel et al. (1998) is based on overconfidence and biased self-attribution[20]. They define an overconfident investor as one who is quasi-rational – the investor is a Bayesian optimiser except for his over-assessment of valid private information, but not of publicly received information, and his biased updating of this precision. Further, when investors observe the outcomes of their actions, they update their confidence in their own ability in a biased manner. According to Attribution Theory (Heider, 1958), individuals strongly attribute events that confirm the validity of their actions to high ability and those that negate their actions to external noise or sabotage.[21] The authors find that share prices over-react to private information and under-react to public information.

2.8.4 A unified theory of over- and under- reaction

Hong and Stein (1999) follow in the spirit of Barberis et al. (1998) and Daniel et al. (1998) in developing a behavioural model. They place considerably more emphasis on the interaction of heterogeneous agents and less on the psychology of said agents. Their model features two types of agents – news watchers and momentum traders, both of which are boundedly

[20] Also referred to as self-serving bias, this is the tendency of people to attribute their success to endogenous factors and failures to exogenous factors (Miller & Ross, 1975).

[21] Psychologists refer to this phenomenon as cognitive dissonance (Festinger, 1956).

rational.[22] News watchers make forecasts based on some subset of publicly available information and do not condition forecasts on current or past prices. Momentum traders, however, do condition forecasts on past prices. Hong and Stein (1999) impose the assumption that the forecasts by momentum traders are simple in nature – in other words, they are univariate functions. Further, the authors assume that private information diffuses gradually amongst the news watcher population (a violation of market efficiency). Hong and Stein (1999) show that when only news watchers are active, prices adjust slowly to new information, more specifically, there is only under-reaction and never over-reaction. When momentum traders are added to the model, the initial reaction of prices is accelerated but at the expense of creating eventual over-reaction.

The model presented by Hong and Stein (1999) unifies the under- and over-reaction hypotheses by showing that the presence of under-reaction creates the need for over-reaction and *vice versa*. If one group of traders under-react to private information, a second group of traders tries to exploit this under-reaction via an arbitrage strategy. Whilst they partially eliminate the under-reaction, they create excessive price momentum in the process that eventually culminates into over-reaction.

2.9 Summary

This chapter has covered various aspects of finance literature – some of which seem unrelated. However, under closer examination, it is found that these aspects are intertwined. An overview of the literature on market efficiency led to an alternative hypothesis (the AMH) as well as the use of semi-deviation and the Sortino ratio as a more appropriate measure of risk and performance, respectively (both from a statistical and psychological perspective). The anomalies of value investing, fundamental investing and momentum investing were then investigated from an empirical perspective and from the perspective of behavioural finance. Indeed, these anomalies can be seen to have roots in the over- and under- reaction hypotheses. Further, an alternative statistical technique was explored in testing financial series. Stochastic dominance seems a good fit to the challenges presented in the literature surrounding the traditional finance framework of examining risk and returns.

[22] In decision making, an individual's rationality is limited by the information available, the cognitive limitations of his mind, and the finite amount of time available to make the decision. The phrase was first introduced by Simon (1957).

3 Data and Methodology

This chapter proceeds with a description of the data and sample used, followed by an outline of the methodology. From the current literature, a fusion strategy begins with selecting those shares that show value characteristics. These shares are then screened using various filters to select those that show the greatest profit potential. A typical value strategy will be discussed followed by the various screens. It should be noted that value investing can (and has) been enhanced by each of the screens discussed (albeit *independently*), to earn superior profits. It is logical to assess the performance of sequential screening, thereby creating a fusion strategy.

3.1 Data

Data was obtained from FinData@Wits[23], I-Net and McGregor BFA. The data consisted of B/M ratios, fundamental (financial statement) data and monthly closing prices for all firms that were listed and subsequently delisted on the Johannesburg Securities Exchange Ltd. (JSE) during the period January 1989 to December 2010. It is crucial to note that the inclusion of delisted firms is done to prevent any look-ahead bias. Whilst this may seem counterintuitive, the following scenario is assumed to hold. At a point in time, the investor (or portfolio manager) has access to public information regarding those firms currently listed. Based on this dynamic sample, he makes his selection of shares via the fusion strategy. Thus, he does not know in advance which shares will be either suspended or delisted. Once the portfolio is formed, should delisting or suspension occur, the share is immediately removed from the portfolio and assigned a zero percentage return. Data for unit trusts were also collected from McGregor BFA. As bid and offer prices on these unit trusts were unavailable, closing prices are used in all comparisons.

3.2 Value investing

All value strategies select those shares that have low fundamentals relative to price. The shares are then sorted and grouped in descending order. This study uses book-to-market (B/M) ratios as the value indicator as Auret and Sinclaire (2006) find this proxy to be a highly significant variable in identifying value shares listed on the JSE. From the sample, those firms with negative B/M ratios[24] were excluded. Thus, each financial year, all shares that qualified (had a non-negative B/M ratio) were ranked and sorted into quartiles according

[23] FinData@Wits is a database compiled internally by the University of the Witwatersrand.

[24] A share can have a negative B/M ratio if the firm has experienced a series of financial losses.

to their B/M values. At the point of forming the portfolio, the B/M value that applies to the previous financial year end would be used. For example, if a firm has a B/M value of 1.5 during its 1995 financial year end, this value will be used in the ranking for the 1996 financial year end. It is important to note that each share (more specifically the firm) would have differing financial year ends. At the end of each firm's financial year end, new B/M values are used in ranking shares. Using prior year distributions to create the value portfolios eliminates look ahead bias; however, this methodology also leads to larger (smaller) samples of value firms in years where the overall market declines (rises). Piotroski (2000) finds that these time-specific patterns do not affect the results.

3.3 Fundamental investing

Fama and French (1995) identify that the average high B/M (value) firm is financially distressed. By simply implementing a value strategy, one cannot easily distinguish between those firms that are financially sound from those that are not. Typically, firms that are financially distressed are associated with declining or persistently low margins of profits, cash flows and liquidity. If one can identify which firms are in financial distress (or near approaching financial distress), one can then filter out those that are unsound from those that are sound. In this spirit, fundamental investing was developed.

The Piotroski score (Piotroski, 2000) relies on examining historical financial statement information to filter out financially sound firms from their counterparts. The variables are then converted to binary signals – if the firm's ratio surpasses the benchmark, it takes on a value of either *0* or *1* (dependent upon the variable in question). The binary signals are then aggregated. The aggregate score ranges from *0* to *9* where *0* indicates a financially unsound firm and *9* indicates a financially sound firm. The fundamental signals chosen are related to: profitability, financial leverage, liquidity and operating efficiency. Piotroski (2000) stresses that these signals were chosen from both academic and practitioner circles and that they do not purport to represent the only signals to indicate the financial soundness of a firm.[25]

Whilst this approach seems relatively efficient, the effect of any signal on the share's price may be ambiguous. Therefore, an *ex ante* implication must be stated. Each signal is conditioned on the premise that the firm is financially distressed to some degree. Myers and

[25] Various statistical methodologies, such as factor analysis, can be used to determine the optimal choice of signals to be used.

Majluf (1984) describe how an increase in leverage can be considered a negative signal whereas Harris and Raviv (1990) find that an increase in leverage can be considered a positive signal. Thus, the extent of these signals may not be uniform across firms with high B/M values. This ultimately will reduce the power of the Piotroski score to differentiate between financially sound and financially unsound firms.

Each of the signals will now be discussed followed by the composite score.

3.3.1 Profitability

The profitability of a firm provides information about the firm's ability to generate funds internally. A positive earnings trend suggests an improvement of the firm's ability to generate cash in the future. Similarly, a negative earnings trend is suggestive of future performance deterioration.

The Piotroski score uses four performance measures on profitability:

1. ROA: The return on assets of a firm, defined as net income before extraordinary items as a percentage of average assets for the year.

2. CFO: Cash flow from operations as a percentage of average assets for the year.

3. ΔROA: The difference between the current year's ROA and the previous year's ROA.

If ROA, CFO and ΔROA are positive, their respective dummy variables take on a value of *1*, and *0* otherwise. The benchmarks of zero profit and zero cash flow were chosen by Piotroski (2000) as they are independent of industry level, market level and time specification.[26] Sloan (1996) finds that firms that have positive accrual adjustments (profits that are greater than cash flow from operations) actually convey a negative signal to investors, whereas a negative accrual adjustment conveys a positive signal. This result could have possibly gained credence from the Free Cash Flow Hypothesis of Jensen (1986). Amongst value firms (firms with high B/M values) this relationship becomes important in managing earnings, where the incentive to do so is strong (Sweeney, 1994). As such, the relationship between cash flow and earnings is considered.

[26] Zero profit or zero cash flow can occur at any point in time, irrespective of industry-wide profit levels or market-wide profit levels. These benchmarks are thus independent and also easy to implement.

4. Accrual[27]: The variable Accrual is defined as the current year's net income less extraordinary items and less cash flow from operations as a percentage of average assets for the year. The associated dummy variable is assigned a value of *1* if Accrual is positive (CFO > ROA) and *0* otherwise.

3.3.2 Leverage, liquidity and source of funds

Since most value firms are financially constrained, it is logical to examine their capital structure and ability to meet future obligations. Further if these financially constrained firms were to increase leverage via external financing or decreasing liquidity, it has a negative impact on the firm's management of financial risk (financial risk is thus greater).

1. ΔLever captures changes in long term capital structure. It is the change in the historical ratio of long term debt to average total assets. An increase in the ratio is seen as a negative signal. Myers and Majluf (1984) and Miller and Rock (1985) argue that the use of external financing conveys a signal that the firm is unable to generate sufficient internal funds. An increase in long term debt is also likely to place further constraints on the firm's financial flexibility. Thus, the associated dummy variable takes on a value of *1*, if ΔLever is negative and *0* otherwise.

2. ΔLiquid measures the change in liquidity. It is defined as the difference between the current year's current ratio (current assets as a percentage of current liabilities) to the previous year's current ratio. A positive change implies a positive signal and consequently has a value of *1* for the dummy variable. A negative change has a value of *0* for the dummy variable.

3. Eq_offer is simply a dummy variable which takes on the value of *1* if the firm did not issue equity in the prior year and *0* otherwise. As discussed in Myers and Majluf (1984), the use of external financing (debt, hybrid securities or common equity) signals a firm's inability to generate sufficient cash flow to meet obligations.

[27] Piotroski's (2000) definition of accrual includes depreciation, where depreciation is considered a negative accrual.

3.3.3 Operating efficiency

The last two measures used are components included in a DuPont model.[28]

1. ΔMargin is defined as the firm's current gross margin ratio (gross margin as a percentage of total sales) less the prior year's gross margin ratio. If the associated change is positive, the dummy variable takes on a value of *1* and *0* otherwise. The associated positive change could indicate an increase in the firm's product price or a decrease in operating or input costs.

2. ΔTurn is defined as the firm's current year's asset turnover ratio (total sales as a percentage of average total assets for the year) less the prior year's asset turnover ratio. An improvement in this ratio signifies greater productivity of assets and has a value of *1* for the dummy variable; and *0* otherwise.

3.3.4 Composite score

Thus, the nine dummy variables in equation form are:

$$F_{Score}=F_{ROA}+F_{\Delta ROA}+F_{CFO}+F_{ACCRUAL}+F_{\Delta MARGIN}+F_{\Delta TURN}+F_{\Delta LEVER}+F_{\Delta LIQUID}+EQOFFER \quad \{2\}$$

A fundamental investment strategy will rely on selecting firms with high F_Scores. This differs from the probability models and data fitting models of Ou and Penman (1989) and Holthausen and Larcker (1992). The Piotroski Score is straightforward to implement and can be recalculated with little effort.

As the F_Score is an aggregate measure of performance, it presents a simplified investment strategy when using fundamentals. However, given this simplicity, two complications arise. First, the conversion of information into binary signals does ultimately lead to a loss of that information. Thus, potentially valuable information can be overlooked. Second, there is no theoretical justification for the above model. It is an *ad hoc* approach to selecting those firms that are fundamentally stable.[29]

Once the Piotroski scores are calculated, those firms that have scores greater than or equal to *7* are selected to implement a momentum strategy. It is hypothesised that these firms will

[28] The Du Pont model deconstructs return on equity into three components – financial leverage, operating efficiency and asset use efficiency. The model was introduced by the Du Pont Corporation in 1920.

[29] Alternative measures would be the use of Altman's z-statistic (Altman, 1968), the historical change in profitability or a decomposition of ROA.

have strong subsequent performance. The choice of the cut-off score represents the highest tercile of firms – in other words, the top 33% of value firms. Thus, out of the sub-population of value firms (some of which may be financially distressed) the Piotroski score selects those which possess strong historical financial soundness.

3.4 Momentum investing

Momentum investing has received much attention from finance academics and practitioners since the seminal work of Jegadeesh and Titman (1993). Momentum strategies can be used for almost any tradable security and can be implemented on either prices (returns) or earnings announcements (see Jegadeesh & Titman, 1993). Not surprisingly, many trading platforms now provide momentum indicators in trading charts to assist those who wish to follow this strategy. This study follows the "traditional" approach – namely using share returns to base a buy or sell decision without the use of trading charts.

Using those shares that pass both of the above screening criteria (the value screen and Piotroski screen), a momentum strategy is implemented. This study uses a *J=12*, *K=12* momentum strategy. Fraser and Page (2000) find that 12 month past returns provide the highest returns for a momentum strategy. Further, for a typical investor, a holding period of 12 months is appropriate. The original approach is described as per Jegadeesh and Titman (1993). Historic share returns are calculated each month for a 12 month horizon – in other words, on a rolling 12 month horizon. The shares are then sorted based on these historic returns, in ascending order, into quintiles. The bottom quintile is referred to as the loser portfolio and the top quintile is referred to as the winner portfolio. Typically one would long the top quintile and short the bottom quintile. However, this study only utilises the long strategy. Given that historic 12 month returns are calculated monthly, the sorting procedure is also conducted monthly. Thus, each month the top quintile is bought. Returns to buying the top quintile are calculated 12 months later (effectively creating a buy-and-hold strategy). As the portfolio in month *t* is held for a period of 12 months, the overall portfolio will consist of the winner portfolio for the current month, as well as the winner portfolios for the previous 11 months – the overall portfolio will consist of 12 buy-and-hold returns. The return of this overall portfolio is the equally weighted average of the monthly winner portfolios (the arithmetic average of the twelve 12 month buy-and-hold returns). Adherence to differing financial year ends leads to a tedious check each month to determine if the correct shares are evaluated (as the share will have a different B/M and Piotroski score each financial year).

It can be deduced that the longer the holding period, the lower the transaction costs. However, the drawback with extending the holding period is that opportunities to rebalance the portfolio (especially in a volatile market) will be missed. It then becomes a typical economic conundrum of weighing the (transaction) costs with the benefit of realising (potentially) greater returns.

3.5 Statistical methodology

Stochastic Dominance (SD) refers to set of relations which hold between two distributions, characterised by their Cumulative Distribution Functions (CDFs). Consider the CDFs of two functions, *A* and *B*. If for any argument (or point), x, $CDF_A(x) \geq CDF_B(x)$, then *B* is said to stochastically dominate *A*. At first, the conclusion appears counterintuitive. It is important to note that CDF(x) represents the proportion of all observations that lie below x – in other words, the area under the curve with a vertical asymptote at x. Thus, the CDF which has the greater area under the curve up to and including x has a greater proportion of observations that lie below x. This can be further illustrated if x is considered to represent a level of return. If any return below x is considered to be below the minimum acceptable return, then, according to the above relation, *A* will have a greater proportion of returns that are below the minimum acceptable level. Thus *A* is dominated by *B* at first order.

The use of SD in finance circumvents the investigation of distributional properties and yet still presents utility-based interpretations that are economically justifiable. As it is beyond the scope of this study to specify the utility function of the investor who follows the fusion strategy, it is found that

...in the absence of any specification of the utility function, to say that prospect P is larger than P' in the sense of first order dominance is equivalent to saying that P is preferred to P' for all monotonic utility functions; and given risk aversion, to say that P is larger than P' in the sense of second order dominance is equivalent to saying that P is preferred to P' for all concave utility functions (Hadar & Russell, 1969, p. 34).

Fong, Wong and Lean (2005) are the first to use SD to analyse a momentum strategy. Their primary focus is on the higher orders of SD, due to the compelling utility interpretations these orders contribute. The first three orders of stochastic dominance each have a different interpretation of the utility function of the investor. As such, the concept of proper risk aversion (the precept of first order dominance) and then the higher orders of SD will now be discussed.

3.5.1 Proper risk aversion

"Proper risk aversion is the property that an undesirable lottery can never become desirable by the presence of an independent undesirable lottery" (Pratt and Zeckhauser, 1987). Thus, if an investor is forced to choose between two undesirable outcomes, the outcome *not* chosen should still remain undesirable, independent of his level of wealth.

Utility functions that are monotone obey the above definition. Examples of monotone utility functions include the power and concave exponential utility functions. Consider the following utility function:

$$U(w) = \int_0^\infty [g(s) - e^{-sw}]dF(s) \tag{3}$$

Where g is an arbitrary function of any non-decreasing value of *s*, *F* is non-decreasing and e^{-sw}can be replaced by *w* when $s=0$. This monotone utility function can be expressed as:

$$U(w) = U(w_1) + \int_0^\infty [e^{-sw_1} - e^{-sw}]dF(s) \tag{4}$$

for any w_1, where $U(w_1)$ is finite. After differentiating with respect to *w* and applying Bernstein's Theorem (S. Bernstein, 1928), the following expressions are obtained:

$$U^n(w) > 0\ for\ all\ n \geq 1\ and\ n\ odd \tag{5}$$

$$U^n(w) < 0\ for\ all\ n \geq 1\ and\ n\ even \tag{6}$$

In other words, the above expressions imply that investors prefer more positively skewed return distributions.

3.5.2 Orders of stochastic dominance

Orders of stochastic dominance can be defined as follows:

$$\mathrm{D}^{s+1}(x) = \int_0^x \mathrm{D}^s(\mathrm{z})\mathrm{dz}, \text{ for s=1,2,3,...} \tag{7}$$

where $D^{s+1}(x)$ represents a CDF of order $s+1$. If a distribution dominates another at first order, then it is sufficient (yet not necessary)[30] to infer that it will dominate that distribution for any successive order. Definitions are now offered for first, second and third order SD.

Definition 1: First order stochastic dominance (FSD)

Let F and G be the cumulative distributions of two risky assets, x be the uncertain[31] return and U be the utility function. Further, assume that all investors are non-satiated ($U'(x) \geq 0$). F is said to dominate G at first order if:

$$F(x) \leq G(x) for\ all\ x \qquad \{8\}$$

If the investor picks the asset whose returns are given by G, there is a higher probability he will earn lower returns than if he were to pick the asset whose returns are given by F. In realistic scenarios, FSD is a stringent criterion to rely upon as it does not describe the risk appetite of the investor – only that the investor prefers more wealth to less wealth. In Figure 4 below, option A dominates option B as A has a smaller area under its curve.

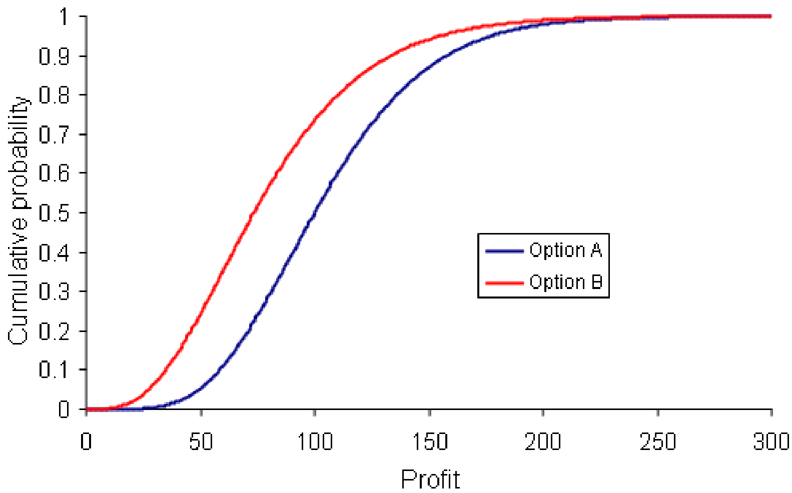

Figure 4 – First order stochastic dominance

[30] A sufficient condition, if satisfied, assures the validity of the statement. In contrast, a necessary condition must be satisfied to assure the validity of the statement.

[31] Uncertainty refers to both an unknown outcome, x, and an unknown distribution of x. This is in contrast to risk which refers to an unknown outcome x with a known distribution of x (Knight, 1921). One could argue that financial returns have log-normal distributions but there is no prevailing consensus on this point (see Campbell, Lo and MacKinlay, 1997).

Definition 2: Second order stochastic dominance (SSD)

Let F and G be defined as above for Definition 1. Then, F is said to dominate G at second order for all investors with utility functions satisfying $U'(x) \geq 0$ and $U''(x) \leq 0$ if:

$$\int_{-\infty}^{x} [G(z) - F(z)]\, dz \geq 0 \; for\; all\; x \tag{9}$$

SSD applies to investors who are non-satiated and risk-averse. In Figure 5 below, option A has second order dominance over option B as function *D(z)* is positive for all *x*. However, option A does not have first order dominance over option B as A has a larger area under its curve.

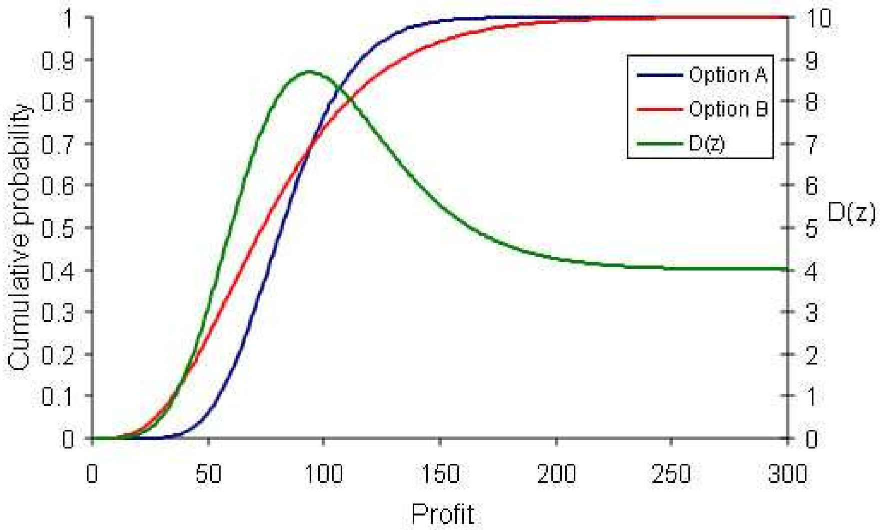

Figure 5 – Second order stochastic dominance

Definition 3: Third order stochastic dominance (TSD)

Let F and G be defined as above for Definition 1. Then, F is said to dominate G at third order for all investors with utility functions satisfying $U'(x) \geq 0$, $U''(x) \leq 0$ and $U'''(x) \geq 0$ if: $m_F > m_G$ and

$$\int_{-\infty}^{x} \int_{-\infty}^{v} [G(z) - F(z)]\, dzdv \geq 0 \; for\; all\; x \tag{10}$$

where m denotes expected return. For an investor who is non-satiated, risk-averse and has a decreasing absolute risk aversion, third order SD provides the criterion for ranking returns.

3.5.3 The link to mean-variance analysis

As discussed in Section 2.2, the use of standard deviation as measure of risk is tenuous at best. However, in two particular scenarios, the use of standard deviation is acceptable – when returns are normally distributed or when investors have quadratic utility functions. SD analysis relaxes these assumptions and provides a more general framework for analysing the risk-return framework. Similar to mean-variance analysis, SD analysis provides a means of ranking portfolios but within a less restrictive framework.

3.5.4 Methods of analysing performance

3.5.4.1 Stochastic dominance tests

Tests for stochastic dominance are non-parametric (there is no fixed structure of the model used), make no assumptions about the distribution of asset returns and minimal assumptions on investor utility (namely, that the investor prefer more wealth to less). However, it is quite sensitive to outliers in the distribution. The use of stochastic dominance testing allows for variation in the screening protocol. The order of the screens can then be changed to determine if a particular order performs better than another. However, this avenue is left for future research.

Linton, Massoumi and Whang (2005) present a generalised procedure for estimating first and second order dominance where observations are allowed to be autocorrelated and there is dependence amongst observations.[32] These relaxations of the independence and identical observations assumptions fit well when returns of different funds are compared in the same market.

The authors offer a procedure for estimation that consists of finding at least one observation that results in a strictly positive value. In other words, it searches for that observation which results in the smallest positive area between two graphs. The estimation procedure for first and second order dominance, respectively, is given by:

$$d^* = \min\max[G(z) - F(z)] \tag{11}$$

$$s^* = \min\max \int_{-\infty}^{z} [G(t) - F(t)]dt \tag{12}$$

As such, the hypotheses to be tested are:

1. H_0^d: d* ≤ 0 against H_1^d: d* > 0
2. H_0^s: s* ≤ 0 against H_1^s: s* > 0

The first hypothesis tests for first order dominance, whilst the second tests for higher order dominance. The critical values for these distributions are obtained via a sub-sampling

[32] Another common alternative is the test offered by Davidson and Duclous (2000), described in Appendix A.

approach. The results obtained from these smaller samples construct the distribution of possible values for d^* and s^*. Thereafter, using the entire sample, one determines if these values lie at the appropriate significance level in the distribution.[33] The authors acknowledge that the use of the sub-sampling approach makes their test conservative. These tests are conducted in the statistical software, Model Risk 4.0, by Vose Software (Vose, 2011).

3.5.4.2 Performance-based measurement

In addition to statistical testing, the portfolio manager would be more interested in specific performance ratios. This study employs three such ratios. The Treynor and Sharpe ratios are used to determine exposure (if any) to unsystematic and total risk; and the Sortino ratio is used as a ranking criterion. These ratios are calculated on a rolling window period using a minimum return period of 12 months. The risk-free rate used in this study is 3-month T-bill rate.

The Treynor ratio is given as:

$$Treynor = \frac{(r_p - r_f)}{\beta} \tag{13}$$

Where r_p is the return on the portfolio at time t, r_f is the risk free rate and β is the relationship of systematic risk between the portfolio and the market proxy (given by the ALSI).

The Sharpe ratio is defined analogously:

$$Sharpe = \frac{(r_p - r_f)}{\sigma} \tag{14}$$

where σ is a measure of standard deviation (or total risk).

Lastly, the Sortino ratio is given as:

$$Sortino = \frac{R - B}{O_B} \tag{15}$$

$$O_B = \sqrt{E\{\min[(R - B)\,,0]^2\}} \tag{16}$$

Where O_B is defined as downside risk (as before), R is the return of the portfolio and B is the target return.

[33] The interested reader is referred to Linton, Massoumi and Whang (2005) for a detailed discussion.

3.5.4.3 Summary

In summary, the fusion strategy can neatly be described by five procedures.

Procedure 1: Form and rank portfolios based on the B/M ratio.

Procedure 2: Calculate the Piotroski Score for the highest quartile of the B/M ranking and rank firms according to this score.

Procedure 3: Calculate the 12 month price momentum for the top 33% of Piotroski score shares and rank shares according to this score.

Procedure 4: Initiate a 12 month buy and hold based on the top quintile of momentum rankings. Repeat the momentum ranking for each calendar month.

Procedure 5: Evaluate the returns from the fusion strategy via stochastic dominance tests and performance ratios.

4 Results

Analysis of the results obtained from the fusion strategy begins with an examination of each screening criterion. Portfolio returns are investigated, ending with tests for stochastic dominance and robustness tests.

4.1 Screening criteria

As the number of firms in the sample varied each year, the sample of value firms would thus change each year. Table 1 below shows pertinent figures of the value screen. As the number of value firms increase each year, their maximum B/M value is erratic, whilst their minimum B/M value is relatively low. Downward revisions to this ratio seem to occur at the pre-emptive stage for a recession, such as during 1995 and 2005.

Table 1 – The value screen

Year	Sample total	Size of value quartile	Maximum B/M ratio	Minimum B/M ratio of
1990	113	24	9.42	1.69
1991	120	30	8.09	1.42
1992	134	33	13.41	1.50
1993	138	34	32.09	1.83
1994	143	35	11.51	1.42
1995	144	36	9.83	0.92
1996	154	38	18.17	0.80
1997	158	39	7.68	0.92
1998	167	41	7.77	1.16
1999	188	48	11.60	1.59
2000	228	57	12.95	1.58
2001	239	59	11.86	1.46
2002	241	60	20.72	1.47
2003	246	61	44.81	1.52
2004	244	61	18.41	1.46
2005	244	61	34.59	1.00
2006	260	65	11.30	0.33
2007	272	68	18.29	0.19
2008	307	76	9.42	0.17
2009	340	85	7.66	0.20

Note: The respective year's B/M value relates to the respective fiscal year end. For example, the first row of Table 1 shows the number of firms in the 1990 fiscal year regardless of when the firm's fiscal year ends.

For a graphical representation of the above table, the B/M ratios are logarithmically differenced and are shown in Figure 6 below. The decline in the minimum log(B/M) value for the value quartile is an interesting observation. This decline begins in 2005 and seems to correspond to the global recession experienced thereafter. Further analysis (left for future research) should be conducted to determine if there were any common characteristics shared between these firms (for example, they could be classified as defensive firms – firms that perform well during a recession).

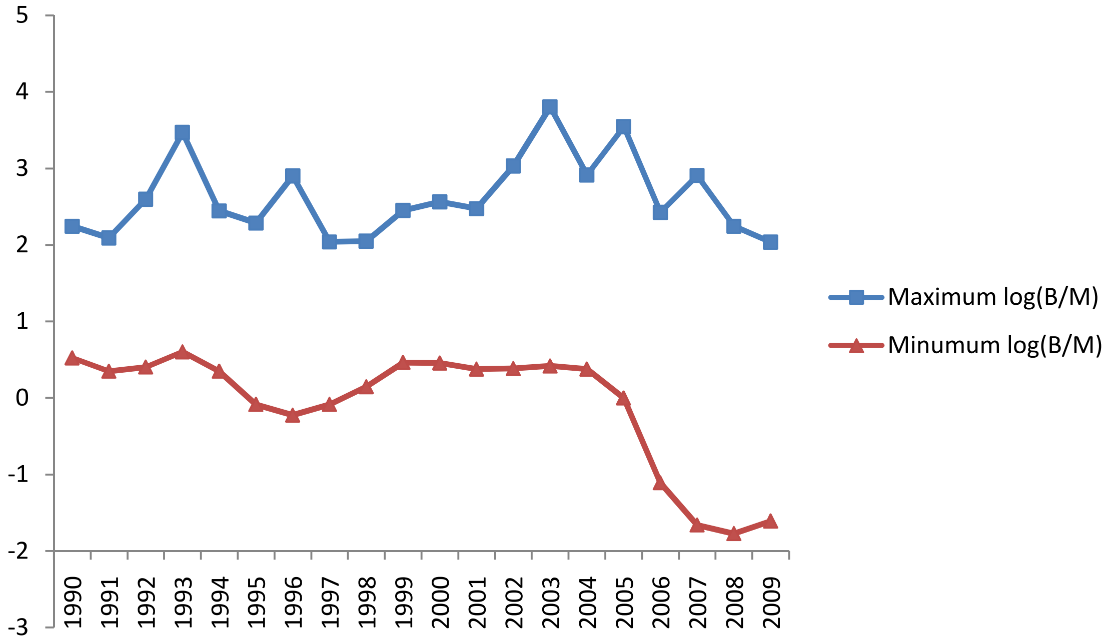

Figure 6 – Logarithm of maximum and minimum B/M ratios

For this study, those firms that had a Piotroski in the top 33rd percentile (in other words, a score of 7 or more) passed the Piotroski screen. Table 2 shows these results. As the fusion strategy relies on sequential screening, Piotroski scores are calculated for the value quartile only.

Table 2 – The Piotroski screen

Year	Total number of value firms	Number of firms with a score of 7 or more	% of firms that passed the screening criterion
1990	24	0	0
1991	30	2	6.67
1992	33	2	6.06
1993	34	5	14.71
1994	35	8	22.86

1995	36	6	16.67
1996	38	6	15.79
1997	39	4	10.26
1998	41	7	17.01
1999	48	7	14.58
2000	57	5	8.77
2001	59	8	13.56
2002	60	16	26.67
2003	61	16	26.23
2004	61	11	18.03
2005	61	9	14.75
2006	65	12	18.46
2007	68	5	7.35
2008	76	5	6.58
2009	85	15	17.65

The number of firms that pass the Piotroski screen seems to roughly follow a cyclical pattern, as shown in Figure 7 below. During periods of prosperity, such as the mid-2000s, more firms are financially sound whereas during periods of austerity, fewer firms are financially sound.

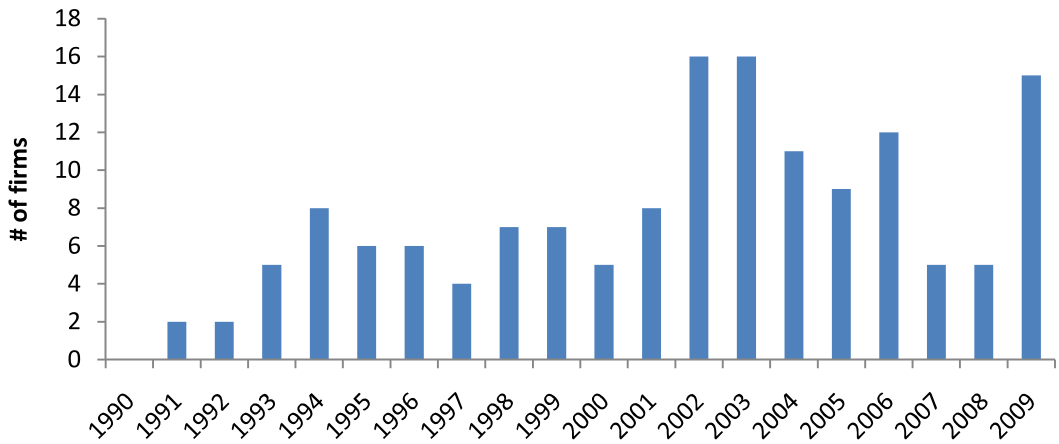

Figure 7 – Number of firms with a Piotroski score of 7 or more

Closing prices for each month were used in calculating the discrete returns for those shares that remained. The 12 month past return was used to rank shares each month. The top quintile is referred to as the winner portfolio, whilst the bottom quintile is referred to as the loser portfolio. Table 3 below shows the size of the top quintile. Whilst the absolute number of firms may appear small, note that the composition of the top quintile is not necessarily the same each month. Due to monthly rankings, a particular share may enter the top quintile in month one and exit in month two, while another share may exit at a later date. Given that the strategy employs strict criteria, if a larger number of shares passed all criteria, it would provide a greater likelihood of (relatively) poor performance of the portfolio. By examination of the last column, the 95th percentile of shares forms the portfolio.

Table 3 – The momentum screen

Year	Size of the winner portfolio	Number of firms in after the Piotroski Screen	Number of firms after the Value Screen	% of winner firms to the Piotroski Screen	% firms that passed all screening criteria.
1990	0	0	24	0.00	0
1991	1	2	30	50.00	3.33
1992	1	2	33	50.00	3.03
1993	1	5	34	20.00	2.94
1994	2	8	35	25.00	5.71
1995	1	6	36	16.67	2.78
1996	1	6	38	16.67	2.63
1997	1	4	39	25.00	2.56
1998	1	7	41	14.29	2.44
1999	1	7	48	14.29	2.08
2000	1	5	57	20.00	1.75
2001	2	8	59	25.00	3.39
2002	3	16	60	18.75	5.00
2003	3	16	61	18.75	4.92
2004	2	11	61	18.18	3.28
2005	2	9	61	22.22	3.28
2006	2	12	65	16.67	3.08
2007	1	5	68	20.00	1.47
2008	1	5	76	20.00	1.32
2009	3	15	85	20.00	3.53

In contrast to the number of firms in the Piotroski screen, the momentum screen (shown in Figure 8 below) does not have any discernable cyclicality present that can be explained via the business cycle. The number of shares in the fusion strategy appears independent of any business cycle (or rather independent of prosperous and austere periods).

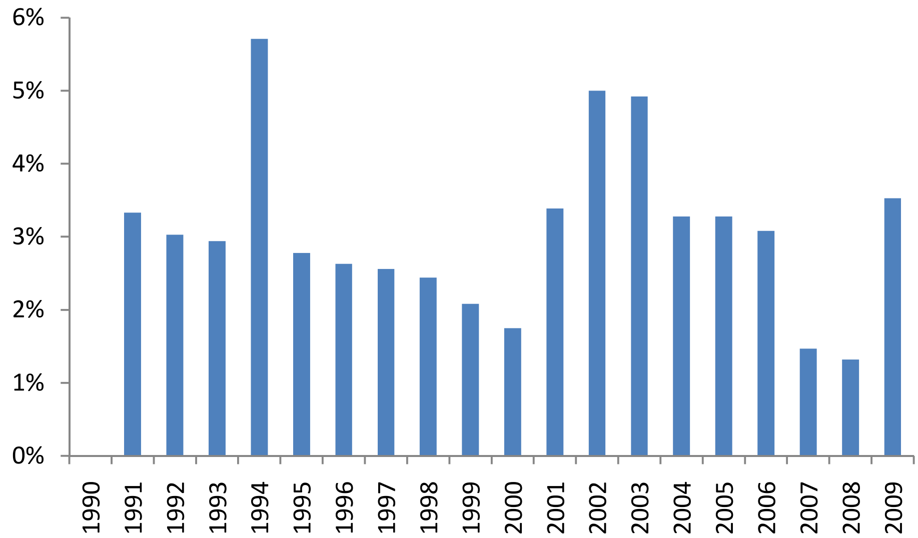

Figure 8 – Number of firms that pass all three screening criteria

4.2 Portfolio returns

Using those shares that passed all screening criteria, the 12 month momentum strategy is examined. Transaction costs of 1% per each return in the cross-sectional average are imposed, initially. Sensitivity analysis of the level of transaction costs is also conducted. Throughout this study, these 12 month momentum strategy returns are referred to as the "fusion strategy" returns. An apparent caveat in this calculation lies in the feasibility of these returns in a real world scenario. Thus far, these transaction returns inherently ignore the amount of funds available to the investor – the investor could very well invest large amounts of money into each share and be highly leveraged.

An alternative (and perhaps more realistic) indication of the results would be to consider a hypothetical mutual fund that invests according to the fusion strategy. These results would be more beneficial to a typical investor who can enter or exit the fund at any point in time. In this hypothetical fund, capital is either invested in domestic equity or risk-free government bonds. The fund's mandate allows it to invest 3% of available capital into a share. If five shares are bought in a particular month, then 15% of capital is invested in equity. This rule still applies when a particular share is bought for any number of consecutive months. For example, if share X is bought for 3 consecutive months, the fund has invested 15% of capital into share X. Transaction costs of 1% are imposed on each percentage holding in the portfolio every month, initially. This accounts for the scenario where the fund liquidates its position at the end of every month. Whilst this is not an entirely accurate description of returns of the strategy, it does provide the benefit of a worst-case scenario. The remaining capital is invested in risk-free government bonds. Thus, the return to this fund is a linear combination of the returns from equity and the returns from fixed income. Returns for equity are calculated as the monthly changes in share prices in which the fund holds a percentage and are equally weighted.[34] Throughout this study, these returns are referred to as the "fusion fund" returns.

The performance of the fusion strategy is now compared to several benchmarks. The benchmarks selected can be categorised into active and passive benchmarks. The passive benchmarks used were the All Share Index (ALSI) (JSE code: J203) and the Small Cap Index (JSE code: J202). The ALSI can be considered representative of the South African market for share trading (barring any finer points on its efficiency or the extent of this representativeness). From the perspective of the average investor, the ALSI represents the market. The first screening criterion for the fusion strategy selects those shares that are inexpensive based on their B/M values – some of which could have small capitalisation values. This is the primary motivation for selecting the Small Cap Index as the other passive benchmark. In a South African context, the ALSI is dominated by large capitalisation firms. If the fusion strategy primarily selects small capitalisation firms, it is logical to compare performance against a suitable index. The active benchmarks were selected from the universe of unit trusts[35]. Those unit trusts that are advertised as "moderate to high risk", invest only in domestic equity and follow a semblance of a typical value strategy were selected to be compared with the fusion strategy. As unit trusts are actively managed instruments, the Total Expense Ratio (TER)[36] as well as management fees were considered in performance comparison. In total, the fusion strategy is compared against two passive benchmarks and four active benchmarks[37]. An important caveat in the comparison relates to the data points

[34] Arguably, one could use value-weightings to calculate returns. As such, a comparison between the equally weighted return of the fusion strategy (fund) and an artificial equally weighted ALSI is conducted in Appendix C.

[35] Unit trusts are open-ended collective investments that offer access to a wide range of securities. Each unit trust follows a mandate and investment objective, typically given by a style of investing.

[36] TER is a measure of the total cost of the fund to an investor. It includes a variety of administrative costs.

[37] Details on the active benchmarks are obtainable upon request.

used in the testing. The passive benchmarks contain data for at least 15 years whilst the active benchmarks (ranging in data points) contain data for at least 4 years.

Assuming returns to be normally distributed, Table 4 below shows the descriptive statistics of the fusion strategy and fund returns. The mean return of the fusion strategy is 2.75% per month. Whilst this is impressive, the high standard deviation shows that the strategy is quite volatile (indeed the highest when compared to its benchmarks), also given by the large range between maximum and minimum returns. Overall, the fusion strategy generates positive returns (given by skewness) and high returns (given by kurtosis).

The ALSI and Small Cap benchmarks both have similar means and standard deviations. Whilst there are differences between their skewness and kurtosis, the distributions appear approximately normal, relative to some of the active benchmarks. The Small Cap index does have a smaller beta than the ALSI. As beta is a measure of systematic risk only, it does not adequately capture the risks prevalent in small capitalisation firms. Three of the four active benchmarks exhibit greater mean returns and standard deviations than the passive benchmarks. The exception of Fund B’s lower mean and standard deviation is most likely a result of the low number of observations. Each of the benchmarks (both passive and active) all have a lower number of observations than the fusion strategy. This is due to data collection constraints.

Lastly, it can be seen that all of the active benchmarks possess lower betas than the ALSI, indicative of good defensive strategies (which inherently implies good diversification according to MPT). The fusion strategy has a high beta of 1.70, indicative of its aggressiveness (and perhaps poor diversification – to be examined later).

Table 4 – Descriptive statistics with the fusion strategy

Descriptive Statistic	Value						
	ALSI	Small Cap	Fund A	Fund B	Fund C	Fund D	Fusion
Mean (%)	0.79	0.75	1.19	0.01	1.04	0.88	2.75
Standard Deviation (%)	1.32	1.63	1.45	0.13	1.72	1.54	4.00
Skewness	-0.52	-0.01	-0.66	-0.31	-1.09	-0.68	1.06
Kurtosis	-0.44	-0.96	-0.94	-1.06	-0.26	-0.93	3.09
Maximum (%)	2.87	3.28%	2.98	0.23	2.64	2.67	18.47

Minimum (%)	-2.56	-2.73	-1.58	-0.23	-2.70	-2.08	-5.10
Observations	165	165	61	36	64	64	195
β (Beta)*	1.00	0.84	0.84	0.05	1.00	0.90	1.70

*Note: $\beta = \frac{covar(i,j)}{\sigma(i)*\sigma(j)}$. Calculations for beta used the ALSI as the market proxy and restricted the number of observations to the minimum present in both data series.

The returns for the fund, given in Table 5 below, are (expectedly) more realistic. The mean return for the fund is 0.42% with a standard deviation of 0.38%. The performance of most of the active benchmarks appears poor when using monthly differences, also coupled with their higher standard deviations. It is surprising to observe that the range between maximum and minimum values (notwithstanding the values themselves) reflect poorly on the benchmarks' performance and high volatility present in monthly fluctuating prices. The fund shows some negative skewness and some excess kurtosis, indicative that the returns are close to approximating a normal distribution. It has the lowest beta (of approximately zero). The large difference between the fusion strategy and fusion fund beta could be a result of the return calculation employed. The higher number of observations for the fund method is due to the manner in which returns were calculated. The fund method does not require 12 month buy and hold returns but rather monthly changes in the fund's value. As such, the number of observations is higher.

Table 5 – Descriptive statistics with the fusion fund

Descriptive Statistic	Value						
	ALSI	Small Cap	Fund A	Fund B	Fund C	Fund D	Fund
Mean (%)	0.51	0.48	0.11	-0.88	-0.27	-0.13	0.42
Standard Deviation (%)	5.09	5.16	3.87	4.08	4.25	3.94	0.39
Skewness	-1.06	-1.11	-1.30	-0.88	-1.07	-1.77	-0.45
Kurtosis	2.47	4.30	2.19	1.10	2.24	5.77	1.67
Maximum (%)	11.60	13.40	5.78	7.79	7.48	6.13	1.49
Minimum (%)	-20.44	-27.71	-14.60	-13.50	-16.59	-19.35	-0.90
Observations	186	186	82	57	85	85	217
β (Beta)*	1.00	0.80	0.78	0.70	0.80	0.780	0.03

Figure 9 below plots the returns over the sample period of the fusion strategy. With the exception of relatively abnormally high returns during the 1994 to 1995 period, the fusion strategy returns seem to exhibit cyclical behaviour. This indicates that the shares selected are still prone to systematic risk. This can be seen by the negative returns during the 2009 period – coinciding with the global financial recession.

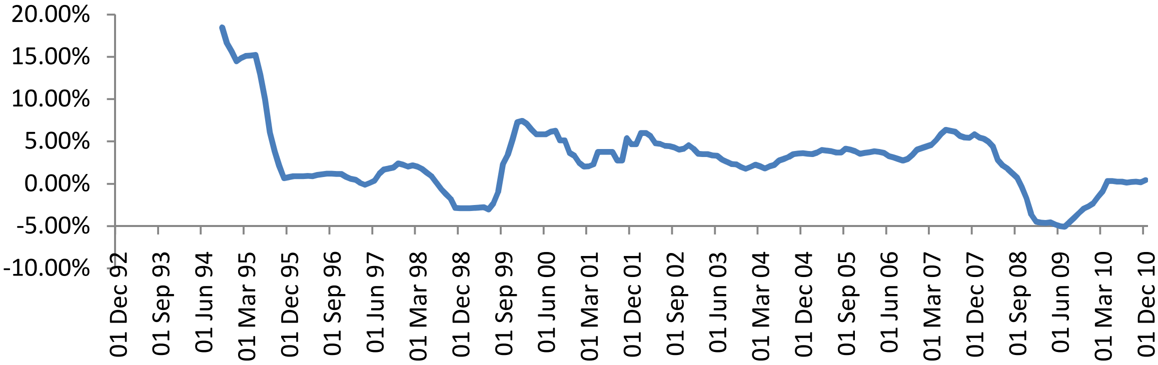

Figure 9 – Fusion strategy returns

In Figure 10 below, the returns of the fusion fund exhibit the typical volatility of share returns. The returns however still seem to weakly follow the fusion strategy returns. Periods of low returns for the fusion fund do not completely correspond to periods of low returns for the fusion strategy. This could imply that by calculating returns as monthly fluctuations, the investor may be tempted to prematurely exit the fusion fund due to high volatility.

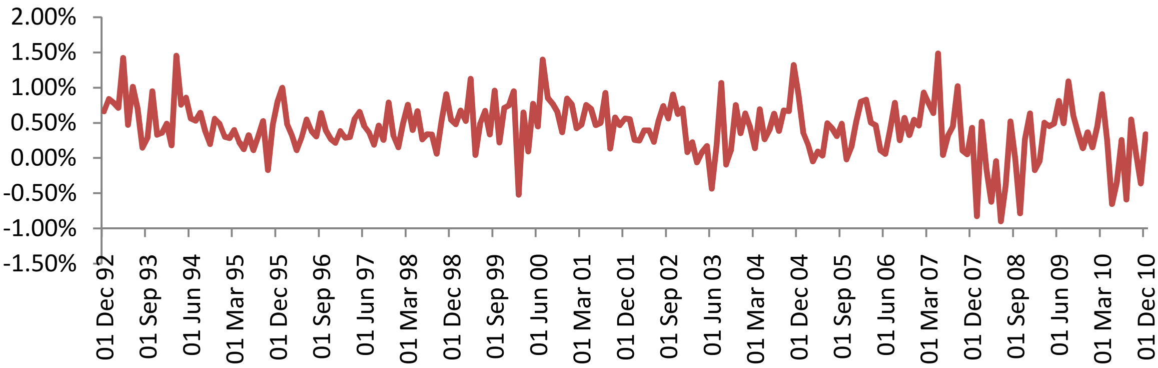

Figure 10 – Fusion fund returns

4.3 Risk-adjusted performance

A portfolio manager would have his fund's performance measured via performance ratios, such as the Sharpe and Treynor ratios. From a risk-based perspective, market (or systematic) risk is always present in portfolios. The benefit of diversification to portfolios assists in eliminating firm-specific (unsystematic) risk. To informally examine the amount of exposure to either systematic or unsystematic risk, these measures are calculated for the fusion strategy, the fusion fund, as well its comparative benchmarks. As such, one would expect, *a priori,* that the Sharpe ratio would be higher than the Treynor ratio. This can be explained as follows. If the excess return, the numerator in both of the above ratios, is held constant, a lower denominator (given either by β or σ) would translate into a higher overall ratio. Further, if systematic risk is always present in any portfolio, undiversified portfolios will have a higher standard deviations (σ's). Thus, the Sharpe ratio would be higher than the Treynor ratio.

Upon examination of Table 6 below, the majority of Treynor ratios are lower than their corresponding Sharpe ratios, with the exception of Fund B (with its associated fusion strategy comparison) and the Small Cap index only. This implies that the fusion strategy and the benchmarks have relatively good levels of diversification. The large negative values for the Sharpe ratio of Fund B (as well as the fusion strategy) could be explained by the measurement period used for the fund. Returns to Fund B were calculated with the initial data point beginning in January 2008. At the onset of a global recession, the returns to Fund B were particularly low.

The fusion strategy performs better than the passive benchmarks (the ALSI and Small Cap Index) under the Sharpe ratio. In the parlance of portfolio management language, the fusion strategy provides greater returns per unit of total risk (given by σ) against both the passive benchmarks. The fusion strategy performs better than the ALSI and worse than the Small Cap index under the Treynor ratio. The results for the active benchmarks are somewhat unfavourable towards the fusion strategy. Funds A, C and D all perform better than the fusion strategy, as given by the Sharpe and Treynor ratios (the exception being the lower Treynor ratio for Fund C than the fusion strategy). The ratios for Fund B indicate that it performed drastically worse than the fusion strategy. As expressed earlier, this could possibly be due to the measurement period of returns for Fund B.

If the ratios were examined from a cross-sectional, risk-based perspective, it can be seen that (again with the exception of the Small Cap index and Fund B) all remaining benchmarks as well as the fusion strategy possess greater Sharpe ratios than Treynor ratios. This indicates that unsystematic risk is present, as the portfolios are not well diversified. Further, the fusion strategy is less diversified when compared to the ALSI, Small Cap index and Fund A; and lower levels of unsystematic risk when compared to Funds B, C and D.

Table 6 – Sharpe and Treynor ratios using returns from the fusion strategy

	Sharpe Ratio	Treynor Ratio	Difference (Sharpe - Treynor)
Fusion	0.68	0.01	0.67
ALSI	0.01	0.00	0.01
Fusion	0.68	0.01	0.67
Small Cap	-0.16	0.03	-0.19
Fusion	2.29	0.01	2.28
Fund A	3.90	0.03	3.87
Fusion	-0.28	-0.01	-0.27
Fund B	-4.11	-0.09	-4.02
Fusion	2.69	0.00	2.69
Fund C	4.09	-0.03	4.12
Fusion	2.69	0.00	2.69
Fund D	4.62	0.02	4.60

Using the fusion's fund based returns, the results from Table 7 below are less than encouraging. In all comparisons, the fusion fund performs worse than its benchmarks under both the Sharpe and Treynor ratios (the exception, albeit minor, is that Fund B's Sharpe ratio is more negative than the fusion strategy). Once again, the fusion fund is less diversified than its peers.

Table 7 – Sharpe and Treynor ratios using returns from the fusion fund

	Sharpe Ratio	Treynor Ratio	Difference (Sharpe - Treynor)
Fund	-0.06	-0.01	-0.04
ALSI	0.00	0.00	0.00
Fund	-0.05	-0.01	-0.04
Small Cap	-0.03	0.00	-0.03
Fund	-0.13	-0.01	-0.12
Fund A	0.10	0.00	0.10
Fund	-0.23	-0.02	-0.21
Fund B	-0.23	-0.01	-0.22
Fund	-0.10	-0.01	-0.09
Fund C	-0.01	0.00	-0.01

Fund	-0.10	-0.01	-0.09
Fund D	0.03	0.00	0.03

Attention is now turned to the Sortino ratio in Table 8 below. This ratio provides a measure of return per unit of downside risk. A higher Sortino ratio is indicative of a better managed investment portfolio. In contrast to the mixed results presented earlier, performance according to the Sortino ratio is more in favour of the fusion strategy. The strategy has higher Sortino ratios for all benchmarks except Fund A[38]. The fusion strategy offers better capital preservation than the benchmarks used. This is particularly appealing to investors who wish to seek a form of assurance in financial returns (as counter-factual as the analogy may seem).

Table 8 – Sortino ratios with the fusion strategy

Portfolio	Sortino Ratio
Fusion	0.70
ALSI	-0.40
Fusion	0.70
Small Cap	-0.68
Fusion	0.35
Fund A	0.57
Fusion	-0.64
Fund B	-10.01
Fusion	0.29
Fund C	0.27
Fusion	0.31
Fund D	0.24

When comparing performance using the fusion fund, the results are disappointing. The fusion fund has a lower Sortino ratio than all benchmarks, shown in Table 9 below. This implies that the fusion fund does not offer better downside risk protection (capital preservation).

Table 9 – Sortino ratios with the fusion fund

Portfolio	Sortino Ratio
Fund	-0.28
ALSI	-0.03

[38] This also serves as an indirect validation of the superior performance of Fund A, given by the accolades this fund has earned.

Fund	-0.27
Small Cap	-0.06
Fund	-0.39
Fund A	-0.02
Fund	-0.57
Fund B	-0.45
Fund	-0.37
Fund C	-0.08
Fund	-0.38
Fund D	-0.09

The mixed set of results between the fusion strategy and fusion fund can be explained via the return calculation method. For the fusion fund, the use of monthly calculations clearly leads to different results. Whilst the fusion fund may be more practical for the investor, the monthly observation of price fluctuations could induce the fund's participants to prematurely exit the fund. Thus, the results of the fusion strategy are preferred over that of the fusion fund, as it, in effect, behoves the investor to have funds that cannot be liquidated until the holding period expires.

4.4 Statistical results

The tests for stochastic dominance were conducted in Microsoft Excel®, using the add-in Model Risk 4.0 by Vose Software (Vose, 2011). This statistical tool is designed to work in a similar manner to other formulae present in Microsoft Excel and provide the user with a final outcome. Using the function, *vosedominance*, one of three outcomes is possible. The first distribution can show first or second order dominance over the second distribution, or the result could be inconclusive – indicative that perhaps higher order dominance is possible. These results are also presented in graphical form, in the manner shown in Section 3.5.2. It is important to note that due to differing measurement periods used, whichever strategy is found to be the stochastically dominant one, does not imply that over the entire sample period, the said relationship will hold.

The test for stochastic dominance shows inconclusive results for the fusion strategy and all benchmarks, except Fund B. With Fund B, the fusion strategy is second order dominated by Fund B, shown in Figure 11 below. The difference in area under the curves of the fusion strategy and Fund B shows that Fund B has a lower area. In summary, the risk-averse investor will choose Fund B over the fusion strategy whilst a risk-averse investor with decreasing risk aversion may (at the very least) choose the fusion strategy over all other benchmarks.[39] These results conform to the stated objectives of Fund B – to outperform the market without taking on greater risk. The remaining cumulative distribution functions are shown in Appendix B.

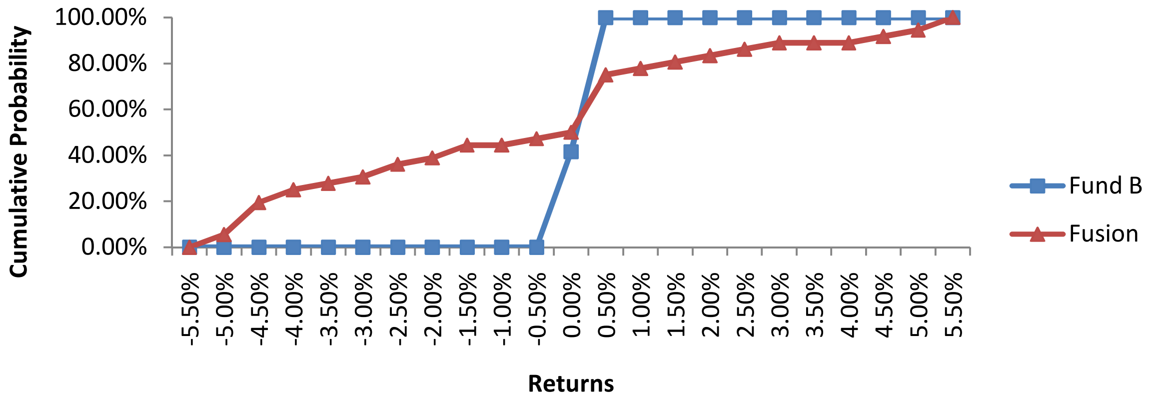

Figure 11 – CDFs of the fusion strategy and Fund B

When using the returns of the fusion fund in place of the fusion strategy, the results are surprising. The results are inconclusive for the passive benchmarks (the ALSI and Small Cap index). This result is shown in Figure 12 below. In Figure 12, the area under the curve of both distributions does not provide a clear indication of superiority.

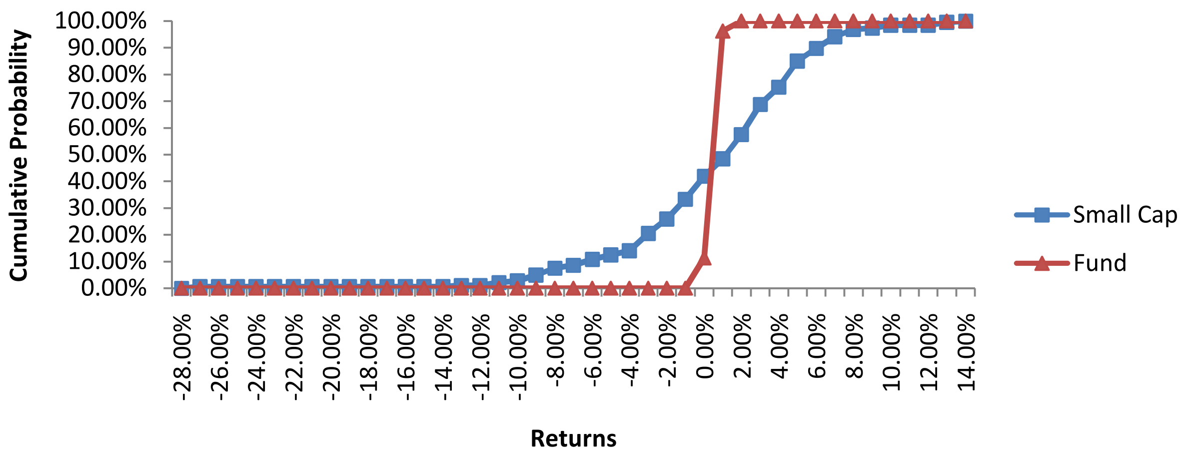

Figure 12 – CDFs of the fusion fund and the Small Cap Index

[39] Recall that an inconclusive result could imply dominance at higher orders. At the very least, third order dominance is thus possible.

However, with all active benchmarks, the fusion strategy exhibits second order dominance. One of these results is shown in Figure 13 below. The difference in the area under the curves of the fusion fund and Fund B show that the fusion fund has the lower area. All remaining CDF plots are shown in Appendix B.

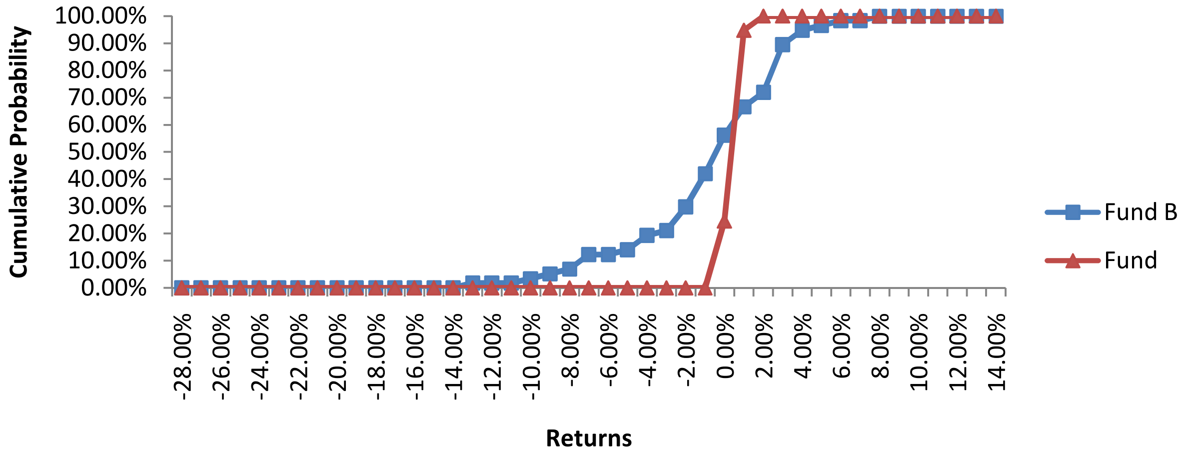

Figure 13 – CDFs of the fusion fund and Fund B

From a utility perspective, the risk-averse investor with decreasing risk aversion may (at the very least) choose the fusion fund over the passive benchmarks used whilst the risk-averse investor will choose the fusion fund over all active benchmarks used. This implies that the active benchmarks are better at preserving capital than the fusion fund; and the fusion fund offers better downside protection than the passive benchmarks used, with greater upside potential. This could possibly be due to the lack of diversification (or rather the lack of an objective to diversify) on the part of the fusion fund. Once again, for reasons outlined previously, the results from the fusion strategy are preferred over the fusion fund.

4.5 Robustness tests

4.5.1 Comparison with the business cycle

Finance theory posits which shares perform best over stages of the business cycle. This view is often agreed upon and followed by many practitioners. The inherent difficulty in following a sector rotation strategy is to determine at which point the business cycle is currently in. Stangl, Jacobsen and Visaltanachoti (2009) test a sector rotation strategy to determine if there is any merit to following such an approach. A sector rotation strategy, like any other market timing strategy, relies on the accuracy of the forecaster in anticipating the correct stage of the business cycle. If the forecaster achieves this, he can outperform a simple buy-and-hold strategy. Stangl et al. (2009) investigate the sector rotation strategy from this perspective (by assuming the forecaster has complete accuracy) and then investigate the strategy by relaxing the above assumption. Over the period 1948 to 2007, Stangl et al. (2009) find that the "perfect" forecaster earns risk-adjusted returns of 2.3% annually, excluding transaction costs. When the forecaster's ability is less than perfect, this performance is significantly lowered to approximately 1% annually, excluding transaction costs. When outperformance is measured against other asset pricing models (such as the Fama-French three factor model (Fama & French, 1993)) or the Carhart four-factor model (Carhart, 1997), the results are largely unchanged. Thus, a sector rotation strategy was found to not earn significantly large abnormal returns.

To disentangle the effects (if any) between the fusion strategy and market timing, a descriptive analysis is conducted. The figure and accompanying table below, from Stangl, Jacobsen and Visaltanachoti (2009) show which sectors display the best performance at each stage of the business cycle.

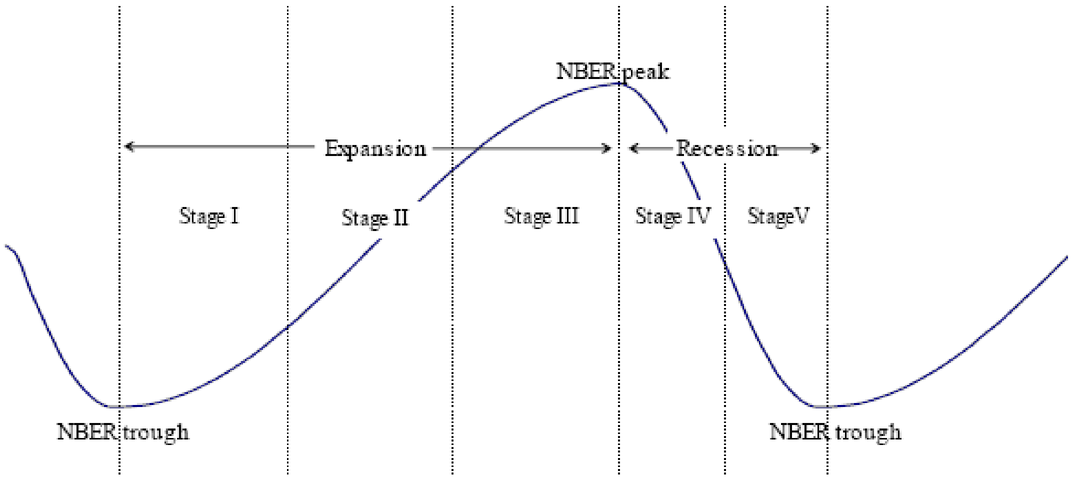

Figure 14 – Stylised depiction of the business cycle

Table 10 – Sector rotation according to the business cycle

Three Stages of Expansion			Two Stages of Recession	
Stage I	Stage II	Stage III	Stage IV	Stage V
Technology:	**Basic materials:**	**Consumer staples:**	**Utilities:**	**Consumer cyclical:**
Computer software	Precious metals	Agriculture	Power and water utilities	Apparel
Measuring and control equipment	Chemicals	Beer and liquor	Telecommunication	Automobiles and trucks
Computers	Ore and metal processing	Food products		Business supplies
Electronic equipment	Non-metallic and	Healthcare		Construction

	metal mining			
Transportation:	**Capital Goods**	Medical equipment		Construction materials
General transportation	Fabricated products	Pharmaceutical products		Consumer goods
Shipping containers	Defence	Tobacco products		Entertainment
	Machinery	**Energy:**		Printing and publishing
	Ships and railroad equipment	Coal		Recreation
	Aircraft	Petroleum and natural gas		Retail
	Electrical equipment			Rubber and plastic products
	Services:			Textiles
	Business services			**Financial:**
	Personal services			Banking
				Insurance
				Real estate

For each of the firms bought in the fusion strategy, the sector classification (as given by the JSE), is noted. Thereafter, the date of purchase is compared alongside the business cycle to examine any similarities that may exist. To determine South Africa’s progression through each stage of the business cycle, Composite Business Cycle indicators, supplied by the South African Reserve Bank, were used.

A simple comparison of when the share was purchased relative to the stage of the business cycle shows that 15.4% of shares in the fusion strategy (fund) were bought at the time suggested by a sector rotation strategy. Arguably, if the fusion strategy did follow a sector rotation strategy, the above value would be higher. Thus, the fusion strategy’s performance is not necessarily due to following a sector rotation approach.

4.5.2 Calendar effects

Another anomaly in financial markets is the seasonality of share returns over distinct calendar periods (days, weeks or months). The best cited example would be the January effect – the tendency for shares to earn abnormal returns in the month of January for no viable reason. French (1980) shows that returns on the S&P500 are negative on Mondays. Keim and Stambaugh (1984) relate the Monday effect to the January effect – returns on Mondays during the month of January are positive, yet become negative for the remainder of the year. Some of these effects can be explained. For example, many firms in the United States have a tax year that ends in December. Thus, the January effect has been linked to the year-end pressure of tax-loss selling. This would suppress share prices in December to have them revert and sometimes overshoot in January. In South Africa, most firms have a tax year that ends in February. By the same reasoning, one would expect South African shares (belonging to South African companies) to have unusually high returns in March. There is also a line of (irrational) thought that posits that share prices in October tend to decline. As many catastrophic financial events have occurred in October, investors fear that every October, some catastrophic event will occur which will drive down prices.

If the fusion strategy earns significantly higher returns in a particular month for exogenous reasons, it would not be a clear reflection of the performance of the fusion strategy. To examine if any calendar effect is present, the returns for each calendar month are arithmetically averaged and then plotted in Figure 15 (the fusion strategy). Clearly there is no graphical evidence of the January effect in both figures. The fusion strategy appears to have the lowest returns in October, indirectly confirming the intuition outlined above.

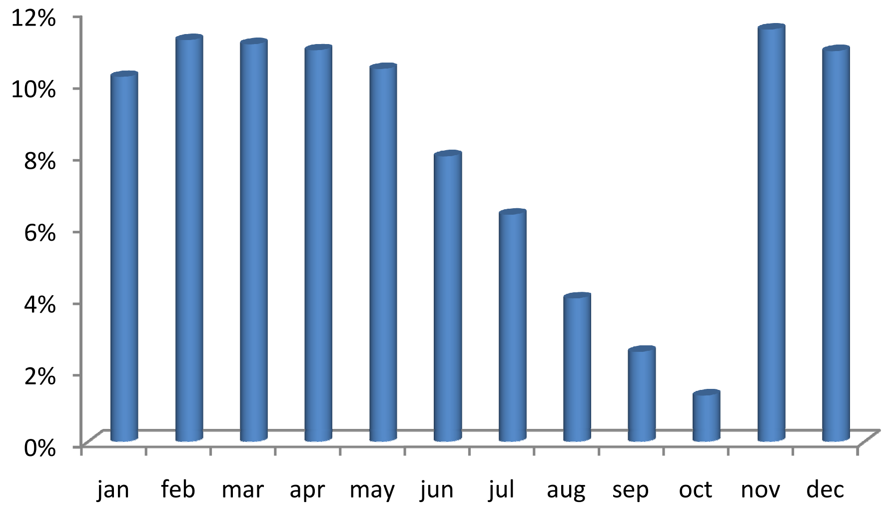

Figure 15 – Analysis of calendar month returns of the fusion strategy

In Figure 16 below, the fusion fund appears to have the lowest return in June. These findings are corroborated by other South African studies, such as Auret and Cline (2011), who find no significant January effect (in addition to no significant size or value effect) on the JSE for the sample period of January 1996 to December 2006.

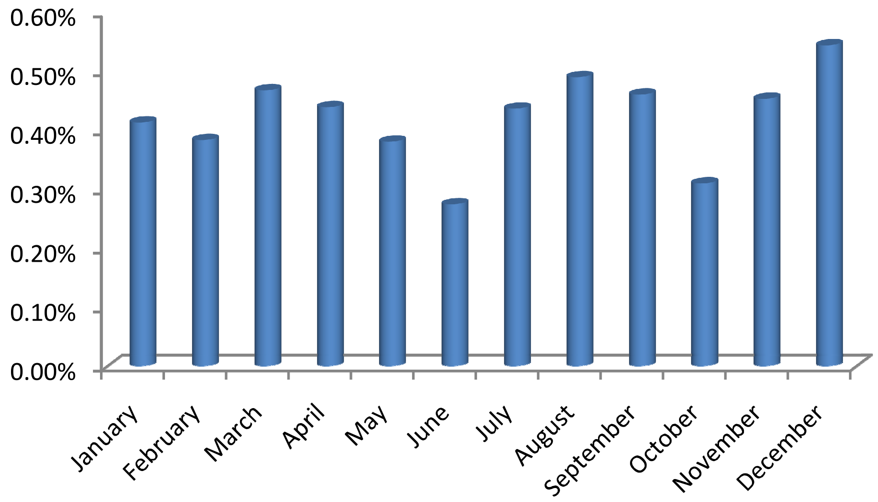

Figure 16 – Analysis of calendar month returns of the fusion fund

4.5.3 Sensitivity to transaction costs

Under a 1% transaction cost regime, the results of the fusion strategy and fund are promising. However, if this regime assumption is inappropriate given the nature of the fusion strategy, it follows that the sensitivity of transaction costs should then be investigated. Lower levels of transaction costs, namely 0.75% and 0.5% per month per share are now imposed. It is hypothesised that a lower transaction cost regime will improve the (already positive) outcome with respect to the success of the fusion strategy.

The results for the portfolio performance measures are displayed in Table 11 and Table 12 below. In Table 11, the results show that as the transaction costs decrease, the respective performance evaluation ratios increase in value (or decrease if the ratio is negative). However, these new values are not sufficient to change the conclusions reported previously.

Table 11 – Sensitivity analysis of transaction costs for the fusion strategy

	Sharpe Ratio		Treynor Ratio		Sortino Ratio	
	0.75%	0.5%	0.75%	0.5%	0.75%	0.5%
Fusion	0.74	0.79	0.01	0.01	0.77	0.83
ALSI	0.01	0.01	0.00	0.00	-0.40	-0.40
Fusion	0.74	0.79	0.01	0.01	0.77	0.83
Small Cap	-0.16	-0.16	0.03	0.03	-0.68	-0.68
Fusion	2.38	2.47	0.01	0.01	0.40	0.44
Fund A	3.90	3.90	0.03	0.03	0.57	0.57

Fusion	-0.23	-0.21	0.00	0.00	-0.59	-0.54
Fund B	-4.11	-4.11	-0.09	-0.09	-10.01	-10.01
Fusion	2.80	2.90	0.00	0.00	0.36	0.41
Fund C	4.09	4.09	-0.03	-0.03	0.27	0.27
Fusion	2.80	2.90	0.00	0.00	0.36	0.41
Fund D	4.62	4.62	0.02	0.02	0.24	0.24

A similar conclusion can be drawn from the evaluation of the fusion fund's returns in Table 12 below. While the fusion fund does have more favourable portfolio performance ratios, most comparisons yield the results reported previously. There are, however, marginal differences in a few of these comparisons. For example, under a 0.5% transaction cost regime, the fusion fund does have a better Sharpe ratio than Fund B – a different conclusion to that reached under the 1% transaction cost regime. Under this same regime (of 0.5%), the fusion fund performs on par to the Small Cap index under the Sharpe ratio.

Table 12 – Sensitivity analysis of transaction costs for the fusion fund

	Sharpe Ratio		Treynor Ratio		Sortino Ratio	
	0.75%	0.5%	0.75%	0.5%	0.75%	0.5%
Fund	-0.06	-0.03	-0.01	0.00	-0.28	-0.23
ALSI	0.00	0.00	0.00	0.00	-0.03	-0.03
Fund	-0.06	-0.03	-0.01	0.00	-0.28	-0.23
Small Cap	-0.03	-0.03	0.00	0.00	-0.06	-0.06
Fund	-0.14	-0.11	-0.01	-0.01	-0.40	-0.36
Fund A	0.10	0.10	0.00	0.00	-0.02	-0.02
Fund	-0.24	-0.21	-0.02	-0.02	-0.58	-0.55
Fund B	-0.23	-0.23	-0.01	-0.01	-0.45	-0.45
Fund	-0.11	-0.08	-0.01	-0.01	-0.39	-0.34
Fund C	-0.01	-0.01	0.00	0.00	-0.08	-0.08
Fund	-0.11	-0.08	-0.01	-0.01	-0.39	-0.34
Fund D	0.03	0.03	0.00	0.00	-0.09	-0.09

Indeed, the results for stochastic dominance tests remain identical to that of the 1% transaction cost regime. Namely, the tests for stochastic dominance show inconclusive results for the fusion strategy and all benchmarks, except Fund B. With Fund B, the fusion strategy is second order dominated by Fund B. When using the returns of the fusion fund in place of the fusion strategy, the results are inconclusive for the passive benchmarks (the ALSI and Small Cap index). However, with all active benchmarks, the fusion strategy exhibits second order dominance.

The regime that results in a break-even (or zero percentage) return presents an optimisation problem to solve. Using a 5% tolerance level and the quasi-Newton search method[40], the level of monthly transaction costs that results in a 0% return, is 6.50% for the fusion strategy and 10.71% for the fusion fund. It is important to note that these figures are economically significant, not necessarily statistically significant.[41] As such, these amounts are difficult to justify in reality. However, one should note that these levels are maxima. For the fusion strategy to perform worse than its benchmarks, transaction costs would have to be greater than 1% and will differ for each comparison with a benchmark as each has a different average return. In other words, the level of transaction costs to enable the fusion strategy to perform worse than the ALSI would be different to that of Fund A, and so on.

4.6 Statistical caveats

4.6.1 Data mining bias

The performance of the fusion strategy may simply be a result of data mining. Whilst this is an easy criticism to level against this study, the methodology and testing criteria are both robust and complete.

4.6.2 Non-synchronous trading bias

As the prices used to calculate returns are based on close of the last business day of the month, there can be a mismatch between the actual return each share earns. Further, as some of the shares are infrequently traded, the closing prices in the dataset may not be an accurate reflection of the actual closing prices at those specific points in time.

4.6.3 Small sample bias

Both the study period and the number of firms initially used are large enough to counter any claims against the use of a small sample. Upon formation of the portfolios, the number of shares included does not *per se* incorporate an adequate sample size. Thus, whilst the number of shares used in the fusion strategy is small, the process of arriving at the best shares to invest in is sufficiently large to curtail any small sample bias.

[40] A mathematical algorithm for finding local maxima and minima of functions.

[41] Statistical significance would require a distribution to be fit to the data.

4.6.4 Time period bias

As the study period incorporates many phases of the business cycle, the time period under investigation does not present any difficulty. Whilst structural breaks in the data (for example in 1994 and 1995 due to political instability and the elimination of the financial rand[42], respectively) should have been incorporated, it is not paramount to the results generated.

4.7 Potential causes of portfolio (under-) performance

The profitability of any strategy needs to be examined in the context of any possible reasons for its performance. This section discusses some causes of the performance of the fusion strategy.

Portfolio turnover relates to how often a manager buys and sells the constituents of the portfolio. The higher the turnover, the more often the manager engages in trading. Intuitively, a higher turnover will imply higher transaction costs. Jegadeesh and Titman (1993) find that their $J=6$, $K=6$ momentum strategy generates significant turnover of 84.8% semi-annually. Not surprisingly, Lesmond, Schill and Zhou (2004) find that the turnover generated from momentum strategies significantly affects the profits obtained from such strategies. Thus, the high turnover of the fusion strategy would have impacted its performance negatively. In the presence of the results outlined previously, this serves to strengthen the potential success of this strategy. An exercise of determining the optimal momentum strategy to use in the fusion strategy should be conducted in future research.

Market capitalisation can be considered a proxy for liquidity. Those shares that have large market capitalisations generally trade more frequently than those with small market capitalisations. By the very nature of the fusion strategy, shares that are illiquid on the JSE are sometimes chosen. These illiquid shares do increase already high transaction costs which are sometimes mitigated by superior performance. It thus became necessary to not include a liquidity filter to exclude shares based on trading volume as a low trading volume could also lend credence to the neglected firm effect.

A potential shortcoming in the implementation of the fusion strategy relates to the diffusion of financial statement information. A firm's financial statements are not immediately released

[42] The financial rand was implemented in 1985 and abolished in 1995. It allowed for exchange rates on the rand, one for current account transactions and another for capital account transactions for non-residents (Jonnson, 2001)

at their fiscal year end – there is a lag of approximately two months (or more). When the financial statements become publicly available, one would expect a revision (in either direction) of the firm's share price. The methodology followed in this study raises a concern on not explicitly taking this lag into account. If financial statements are released after their fiscal year end, the first two screening criteria can only be evaluated at a later stage. In applying the fusion strategy to historical data, a lag of perhaps three months could be introduced.

This study has offered an interpretation of a fusion strategy – a strategy which incorporates over- and under- reaction. Inherent in any new strategy, there will be flaws in the design process. First, the delineation points chosen for each screening criterion can be modified to produce another set of results. When analysing value shares, a quartile grouping provides enough diversification in the relative valuation ratios as well as allowing an appropriate amount of shares to be included therein. The minimum allowable Piotroski Score was chosen to be the top 33% of the score range as this allows the most fundamentally sound firms to be passed through the screen. For the momentum screen, a stricter grouping, that of quintiles, was chosen as the one year holding period could include exogenous events that could erroneously affect the ranking. The intuition underlying the stricter ranking rests on the premise that better quality shares will be passed through to be used in the strategy.

The proxy used in the value screen could not be the most ideal. Perhaps other proxies such as Price to Earnings or Price to Cash Flow would provide better results. Further, Asness and Stevens (1995) show that value strategies are more effective when the proxy used is measured within the industry as opposed to across the market, as in this study.

4.8 Discussion and inferences

Asness (1997) investigates whether value and momentum strategies are independent or related. The author finds that a value strategy is particularly strong among low momentum (loser) shares and weak among high momentum (winner) shares. Similarly, a momentum strategy is strong among value shares and weak among growth shares. Whilst both strategies work independently, Asness (1997) finds that the returns generated from these independent strategies are negatively correlated; each strategy performs best when the other is held constant. In other words, a value strategy works best when momentum is held constant and a momentum strategy works best when the value proxy is held constant. This presents an interesting caveat for this study. In the initial screen, those shares that were value shares were selected, with the growth shares (amongst the other quartiles) being discarded. Thus, the momentum strategy was effectively implemented on a value quartile. Of the value quartile, those shares that were inexpensive and had good levels of financial health were utilised in a momentum strategy. One would expect the results of Asness (1997) to not hold in this regard as the value shares used in Asness (1997) were not differentiated. It is plausible that firms examined by Asness (1997) were fundamentally weak and were included in the same quartile as those that were neglected. Indeed, the fusion strategy can be enhanced by short selling those shares that are value and low momentum whilst buying those shares that are growth and high momentum.

A question asked by academics is whether performance should be interpreted as a behavioural phenomenon or an information-driven process. Studies such as Coval and Moskowitz (2001) indentify information as the primary reason for investment performance. Chen (2004) provides a theory of information relating to finance. This "Informational Theory of Investment" is based on the work of Shannon (1948) and aims to provide an understanding of observed market behaviours. The theory describes the investor (market participant) as having limited information processing capacity - the investor is boundedly rational (Sims, 2003). Whilst the behavioural models offer compelling psychological evidence of certain phenomena, they often disagree on which phenomena are considered irrational. Information Theory, whilst not contradictory to the behavioural models, offers another viewpoint on the behaviour of market participants via mathematical systems. This theory can offer interesting avenues of research into the AMH discussed previously. Indeed, as discussed in Chapter 2, the fusion strategy incorporates both the under- and over- reaction hypotheses in a seemingly amiable manner. Further research, under the pretext of information theory, should be conducted as to the "inflection point" of where one hypothesis becomes the other.

The investor who follows the above fusion strategy (in its current state) is indirectly conforming to the Behavioural Portfolio Theory of Shefrin and Statman (2000). This descriptive theory explores the construction of portfolios and the design of securities with relation to behavioural finance. The mean-variance investor will: evaluate a portfolio based on covariances between assets; care about expected returns and variance of the overall portfolio; have consistent attitudes towards risk and will always be risk-averse. The behavioural investor, in contrast, will build his portfolio as a pyramid of assets, where each layer represents a different risk and reward profile. In doing so, the role of covariance in portfolio construction is significantly lower compared to its role in mean-variance optimisation. This does not imply however that covariances are ignored. They simply take less precedence in portfolio construction. Cash and bonds are held in the lowest level of the pyramid as protection against adverse outcomes, whereas growth shares are held in the higher levels to represent the profit potential of the portfolio. In practice, financial advisors suggest this approach to their clients (Fisher & Statman, 1997). The use of the fusion fund (with a percentage of capital invested in risk-free bonds) conforms to the idea of "pyramid portfolio construction". It would be interesting to determine the optimum level of capital to hold in risk-free bonds which will maximise the returns of the fusion strategy.

The predictions of behavioural portfolio theory (as per Shefrin & Statman, 1997) are as follows. Investors will (1) have a reluctance to invest in short or margined positions, (2) will exhibit home bias[43] when selecting assets, (3) will utilise mental accounting in labelling securities (for example, growth and value), (4) will prefer assets with a minimum stated return and (5) will participate in risk seeking activities with some portion of their investment (such as the purchase of lottery tickets). Without an *a priori* objective of doing so, the fusion strategy, *prima facie*, meets the predictions of behavioural portfolio theory – there are no short positions, domestic equity (and bonds) are the only invested securities, labels are applied to portfolios, a minimum return was utilised in measuring performance according to the Sortino ratio and (perhaps) some of the shares chosen are more risky.

[43] An empirical anomaly in finance that states that domestic investors prefer to hold less than optimal amounts of foreign securities despite the benefits from international diversification (French and Poterba, 1991).

5 Conclusion

This chapter provides concluding remarks on the study conducted and provides possible avenues for future research.

5.1 Summary of findings

The fusion strategy developed in this study utilised three screening criteria – a value, fundamental and momentum screen. Returns were calculated net of transaction costs, initially set to 1% per month, and were compared against two passive benchmarks and four active benchmarks after costs. To provide greater tractability, a fusion fund was constructed as a more realistic means of investing to the typical investor. This fusion fund allocated 3% of capital to each share held in its portfolio at any given time. Returns were also calculated net of transaction costs of 1% per share, yet were done so on a monthly basis (in contrast to the 12 month buy-and-hold returns of the fusion strategy). The fusion strategy (fund) was also compared against an (artificial) equally weighted ALSI. This comparison is found in Appendix C.

Summary statistics show that the fusion strategy has the highest mean and standard deviation of all comparisons, whilst the fusion fund differs. Statistical testing, done via stochastic dominance, yielded inconclusive results in the majority of cases. The exception however, was that Fund B stochastically dominated the fusion strategy at second order. This implies that a risk-averse investor would prefer to invest in Fund B and that Fund B has a greater probability of achieving higher returns than the fusion strategy. When using the returns from the fusion fund, the results are inconclusive compared to the passive benchmarks used yet the fusion fund dominates all active benchmarks at second order. This implies that a risk-averse investor will prefer the fusion fund compared to all active benchmarks used. This surprising result can be reconciled when one observes that the returns for the fusion fund are less volatile than its active peers and have a positive mean.

However, it is interesting to note that the above results, whilst true statistically, do not provide a complete picture. By the use of Sharpe and Treynor measures, the fusion strategy yielded mixed results. However, the Sortino ratio shows that the fusion strategy outperforms all benchmarks chosen, except Fund A. When performance is evaluated using the fusion fund returns, all ratios (Sharpe, Treynor and Sortino) favour the respective benchmark against the fusion fund. The striking difference in performance results could be attributed to the calculation of returns. As returns are measured as monthly fluctuations under the fusion fund, high volatility present in individual value shares may induce a lower mean return, thereby reducing the corresponding portfolio performance measure. Further, the investor may be tempted to pre-maturely exit the fusion fund due to these performance results as the true reflection of the 12 month buy-and-hold strategy may not be adequately captured in monthly fluctuations.

The performance of the fusion strategy was also found to not be induced by either a sector rotation strategy or the existence of the January effect. Sensitivity to the level of transaction costs was also investigated. Lower levels (0.75% and 0.5%) of transaction costs enhanced the success and performance of the fusion strategy. Further, the level of transaction costs that results in a break-even return for the fusion strategy was found to be at least 6.50% per month. This amount is economically significant. Thus, notwithstanding the significant influence of transaction costs, the results are promising.

5.2 Recommendations for future research

An interesting area for future research would be the investigation of share volume with share performance, especially in the context of a fusion strategy. Arguably, the high level of transaction costs or the performance of the shares chosen by the fusion strategy could be linked to the trading volume of those shares. Literature shows that share returns and trading volume are jointly determined by the same market dynamics and are linked in theory (see for example, Blume, Easley & O'Hara, 1994). Lee and Swaminathan (2000) investigate the use of trading volume in predicting cross-sectional returns for momentum-styled portfolios. They find that the price momentum effect of Jegadeesh and Titman (1993) reverses over long horizons. This suggests that price momentum is not only a function of market under-reaction but also of market over-reaction. Lee and Swaminathan (2000) also find that past trading volume predicts the magnitude and persistence of future price momentum. Specifically, high (low) volume winners (losers) experience faster momentum reversals. This result is depicted graphically in Figure 17 and has since become known as the Momentum Life Cycle Hypothesis. This presents yet another extension of this study and will perhaps offer explanations to the performance of the fusion strategy.

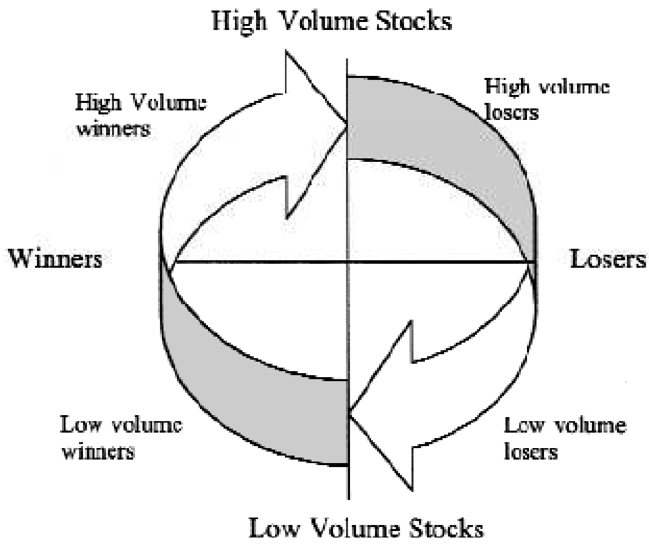

Figure 17 – Momentum life cycle hypothesis

Perhaps the most significant field would be to further define (both mathematically and descriptively) the AMH (Lo, 2004; 2005) using the concepts developed in this study. An initial extension would be to test the fusion strategy in other markets. As South Africa has a relatively small securities exchange, if one were to have a larger initial sample, the fusion strategy can be more accurately assessed. This study has made no firm remarks about the representative agent who could prefer semi-variance or whose utility could be described by stochastic dominance axioms. This theoretical avenue should be pursued and perhaps combined with the extension of the AMH.

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Appendix A

This Appendix describes an alternative test for stochastic dominance developed by Davidson and Duclous (2000). It is important to note that as both the Linton et al. (2005) method as well as the test described here are valid, the choice is determined by the data to be analysed.

The Davidson and Duclous (DD) (2000) test for stochastic dominance that is applicable to both independent and dependent samples from a joint distribution. The test compares the cumulative distribution functions over a grid of points. A potential caveat of the test is that the number of grid points is chosen arbitrarily and the consistency of the test statistic is affected by the use of a finite grid. The test is outlined in detail below.

The following hypotheses are tested:

1.H_0: $D_W^s(x_k) = D_L^s(x_k) \forall\, x_k$, k=1…K

2.H_A: $D_W^s(x_k) \neq D_L^s(x_k)$ for some x_k

3.H_{A1}: $D_W^s(x_k) > D_L^s(x_k)$ for some x_k

4.H_{A2}: $D_W^s(x_k) < D_L^s(x_k)$ for some x_k

Davidson and Duclous (2000) construct the following sample statistics, where to avoid notation clutter; the grid index *k* is suppressed for each statistic:

$$\widehat{D}_W^S(x) = \frac{1}{N(s-1)!}\sum_{i=1}^{N}(x_k - W_i)^{s-1}{}_{+} \quad \{A1\}$$

$$\widehat{D}_L^S(x) = \frac{1}{N(s-1)!}\sum_{i=1}^{N}(x_k - L_i)^{s-1}{}_{+} \quad \{A2\}$$

$$\widehat{V}_W^S = \frac{1}{N}\left[\frac{1}{N((s-1)!)^2}\sum_{i=1}^{N}(x_k - W_i)_{+}^{2(s-1)} - \widehat{D}_W^S(x)^2\right] \quad \{A3\}$$

$$\widehat{V}_L^S = \frac{1}{N}\left[\frac{1}{N((s-1)!)^2}\sum_{i=1}^{N}(x_k - L_i)_{+}^{2(s-1)} - \widehat{D}_L^S(x)^2\right] \quad \{A4\}$$

$$\hat{V}_{W,L}^{S} = \frac{1}{N}\left[\frac{1}{N((s-1)!)^2}\sum_{i=1}^{N}(x_k - W_i)_{+}^{s-1}(x_k - L_i)_{+}^{s-1} - \hat{D}_W^S(x)\hat{D}_L^S(x)\right] \quad \{A5\}$$

$$\hat{V}^s(x) = \hat{V}_W^S(x) + \hat{V}_L^S(x) - 2\hat{V}_{W,L}^S(x) \quad \{A6\}$$

Consider the t-statistic:

$$T^S(x) = \frac{\hat{D}_W^S(x) - \hat{D}_L^S(x)}{\sqrt{\hat{V}^S(x)}} \quad \{A7\}$$

Under the null hypothesis, $T^S(x)$ is asymptotically distributed as a standard normal variate. To implement the DD test, we can compute a t-statistic at each grid point and reject the null hypothesis if the *largest* t-statistic is significant. As suggested by Davidson and Duclous (2000), the joint test size can be controlled by using critical values of the studentised maximum modulus (SMM) distribution in place of the normal distribution. Let $M_{\infty}^{k}(x)$denote the (1- a) percentile of the SMM statistic with k and infinite degrees of freedom. Then, the following decision rules can be used:

1. $If\ |T^s(x_k)| < M_{\infty,a}^{k}\ for\ k = 1, \ldots, K\ then\ accept\ H_0$
2. $If\ T^s(x_k) < M_{\infty,a}^{k}\ for\ all\ k\ and\ -T^s(x_k) > M_{\infty,a}^{k}\ for\ some\ k\ then\ accept\ H_{A1}$
3. $If\ -T^s(x_k) < M_{\infty,a}^{k}\ for\ all\ k\ and\ T^s(x_k) > M_{\infty,a}^{k}\ for\ some\ k\ then\ accept\ H_{A2}$
4. $If\ T^s(x_k) > M_{\infty,a}^{k}\ for\ some\ k\ and - T^s(x_k) > M_{\infty,a}^{k}\ for\ some\ k\ then\ accept\ H_A$

In empirical studies, the number of grid points is usually chosen based on rules of thumb. Barrett and Donald (2003) show that for reasonably large samples (greater than 500 observations), the DD test works well for K = 10. Actual applications may require a finer grid because as Barrett and Donald (2003, p. 91) point out, a coarse grid may miss out important differences in the distributions. The 5% asymptotic critical value is 3.254 from Stoline and Ury (1979).

Appendix B

This appendix provides cumulative distribution plots of those benchmarks not discussed in the text under a 1% transaction cost regime.

In Figure B1 below, the fusion fund is neither first nor second order dominant against the ALSI. This could imply dominance at higher orders.

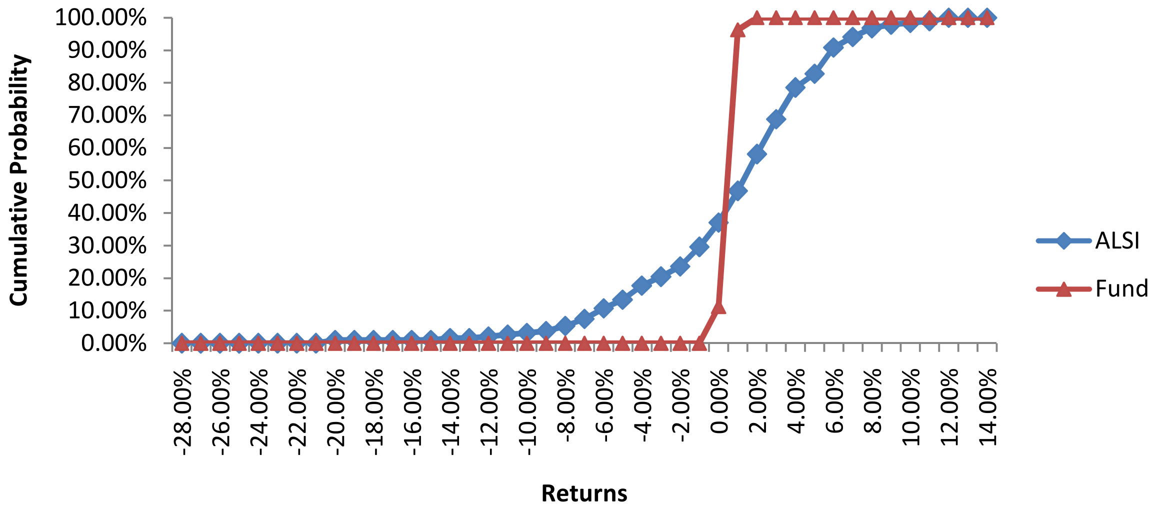

Figure B 1 – CDF of ALSI and fusion fund

In contrast, Figures B2, B3 and B4 all show that the fusion fund is second order dominant against its comparative benchmark.

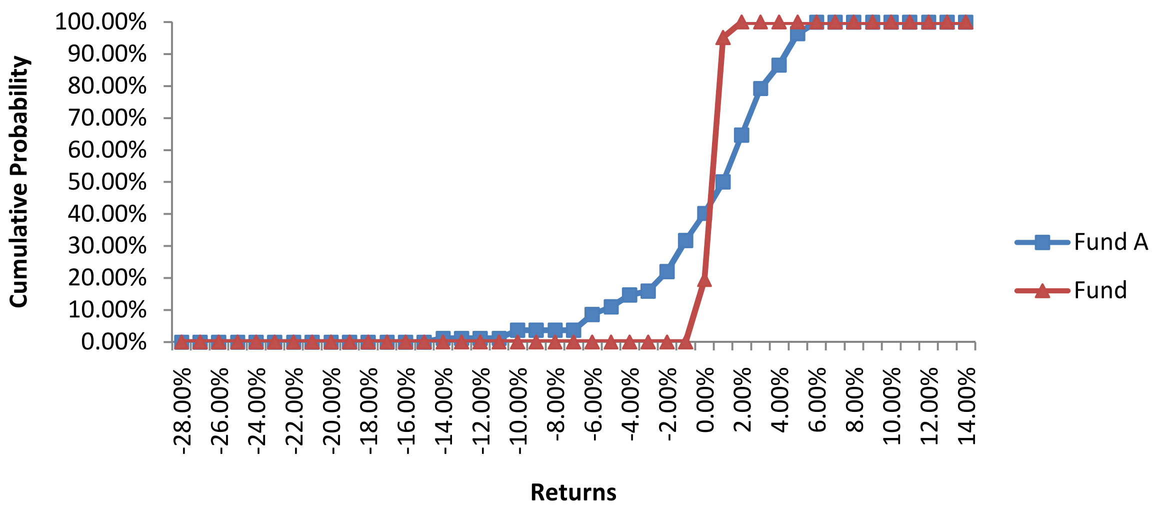

Figure B 2 – CDF of Fund A and fusion fund

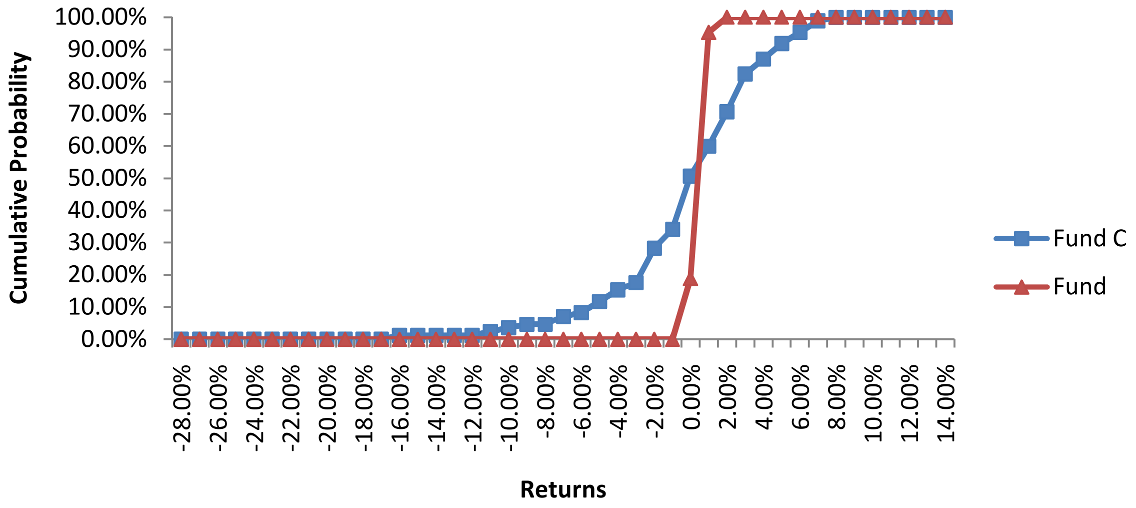

Figure B 3 – CDF of Fund C and fusion fund

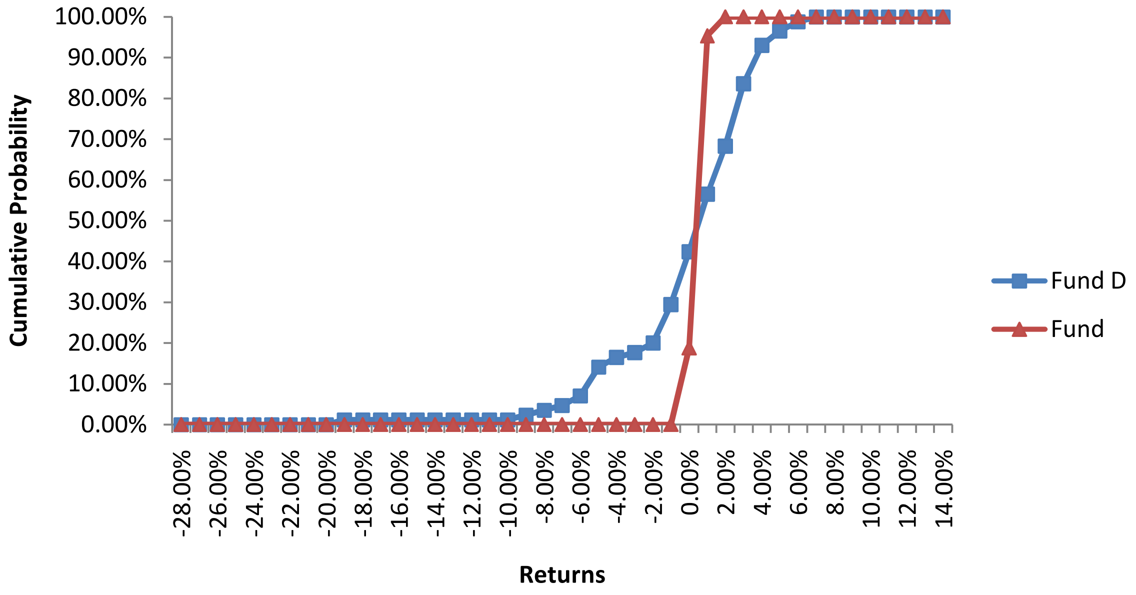

Figure B 4 – CDF of Fund D and fusion fund

In all remaining figures below (Figure B5 to Figure B9), the fusion strategy is neither first nor second order dominant against the comparative benchmark. This could imply dominance at higher orders.

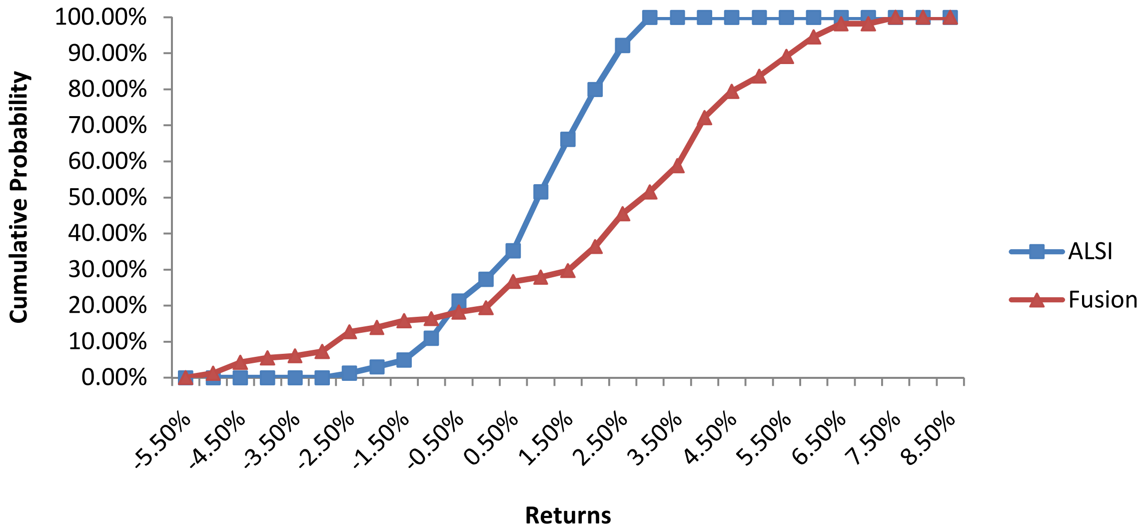

Figure B 5 – CDF of ALSI and fusion strategy

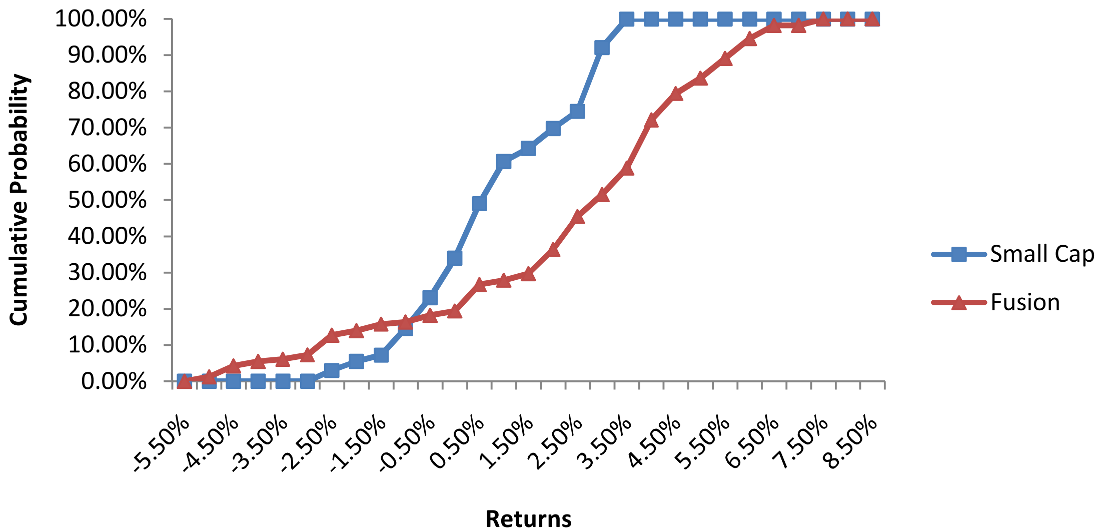

Figure B 6 – CDF of Small Cap Index and fusion strategy

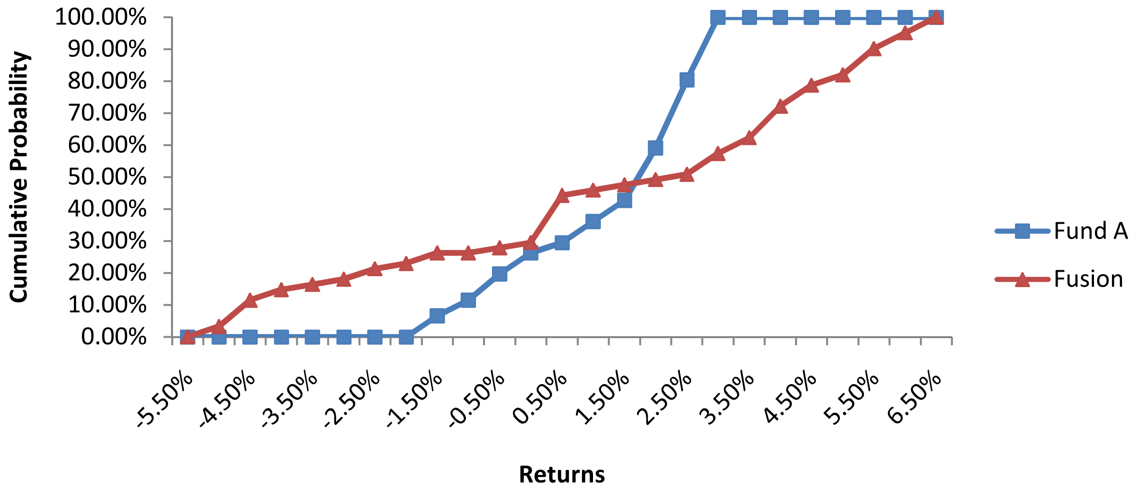

Figure B 7 – CDF of Fund A and fusion strategy

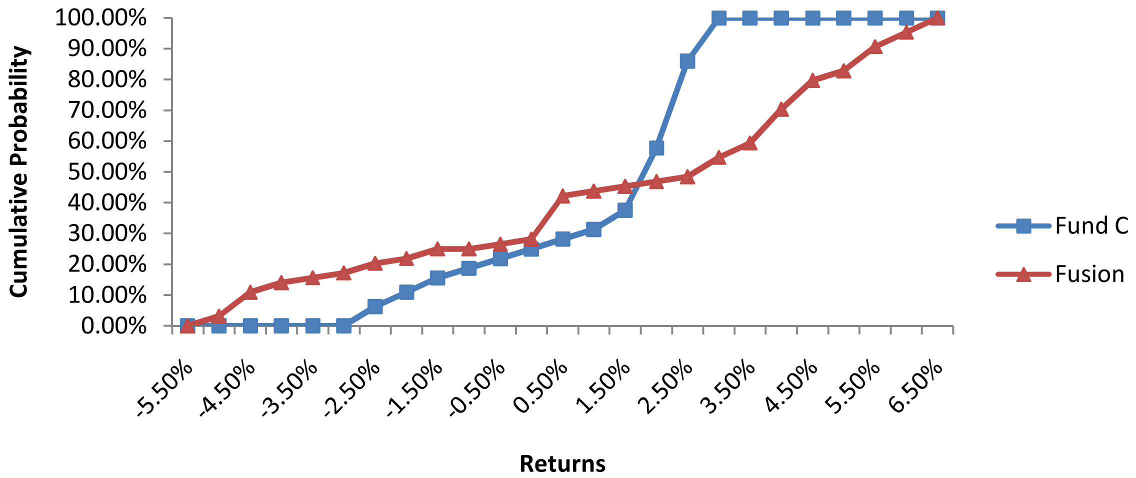

Figure B 8 – CDF of Fund C and fusion strategy

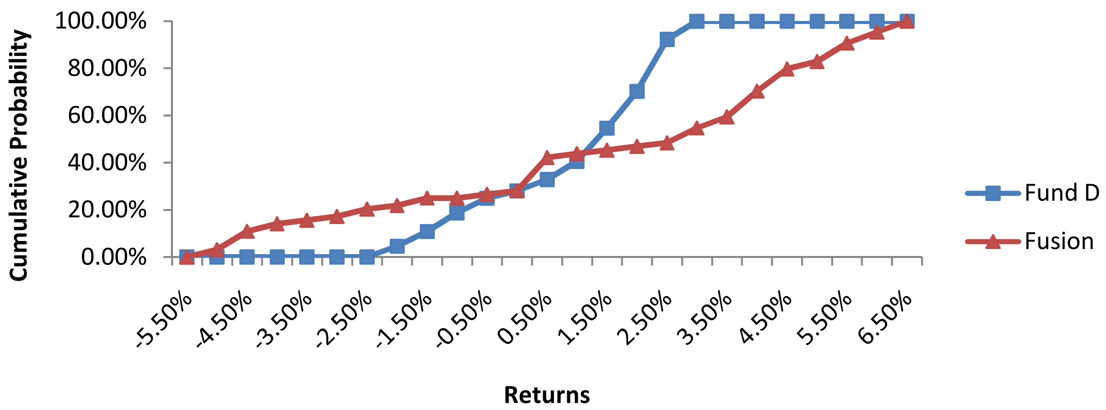

Figure B 9 – CDF of Fund D and fusion strategy

Appendix C

As the fusion strategy (fund) has returns that are equally weighted, perhaps a more accurate comparison would be with an equally weighted passive index. A comparison with an active benchmark is not required at this point as each unit trust, governed by its specific mandate, has the choice of calculating returns using the equally weighted or value weighted method.

In South Africa, indices listed on the JSE are predominantly value weighted. Thus, an equally weighted index consisting of all shares listed on the JSE needed to be constructed. Total returns (inclusive of dividends) were averaged over each month from January 1989 to June 2009. As this data was sourced from FinData@Wits, the end point does not correspond to the end point used in this study. Further, while a comparison of an equally weighted passive index to the equally weighted fusion strategy may be more accurate, it is not realistic *per se* for the typical investor. A typical investor would lack access to this index. Hence, this comparison is conducted for the purposes of a more accurate comparison, albeit at the cost of not being effectively replicated by the typical investor.

The results from Table C1 below are mixed. For varying transaction cost regimes, the fusion strategy performs better than the equally weighted ALSI under the Sharpe and Sortino ratios and on par under the Treynor ratio. However, the fusion fund performs worse than the constructed index under all three performance ratios.

Table C 1 – Performance evaluation ratios

	Sharpe Ratio			Treynor Ratio			Sortino Ratio		
	1%	0.75%	0.5%	1%	0.75%	0.5%	1%	0.75%	0.5%
Fusion	0.68	0.74	0.79	0.01	0.01	0.01	0.70	0.77	0.83
ALSI	0.19	0.19	0.19	0.01	0.01	0.01	0.19	0.19	0.19
Fund	-0.06	-0.05	-0.03	-0.01	-0.01	0.00	-0.28	-0.27	-0.23
ALSI	0.44	0.44	0.44	0.02	0.02	0.02	0.54	0.54	0.54

Tests for stochastic dominance show that the comparisons between the fusion fund and the equally weighted ALSI are inconclusive (implying third order dominance at the very least), while the fusion strategy is second order dominant over the constructed index. These results hold under the three different transaction cost regimes explored. Figure C1 and Figure C2 below show the CDFs for the fusion fund and fusion strategy (both under the 1% transaction cost regime), respectively.

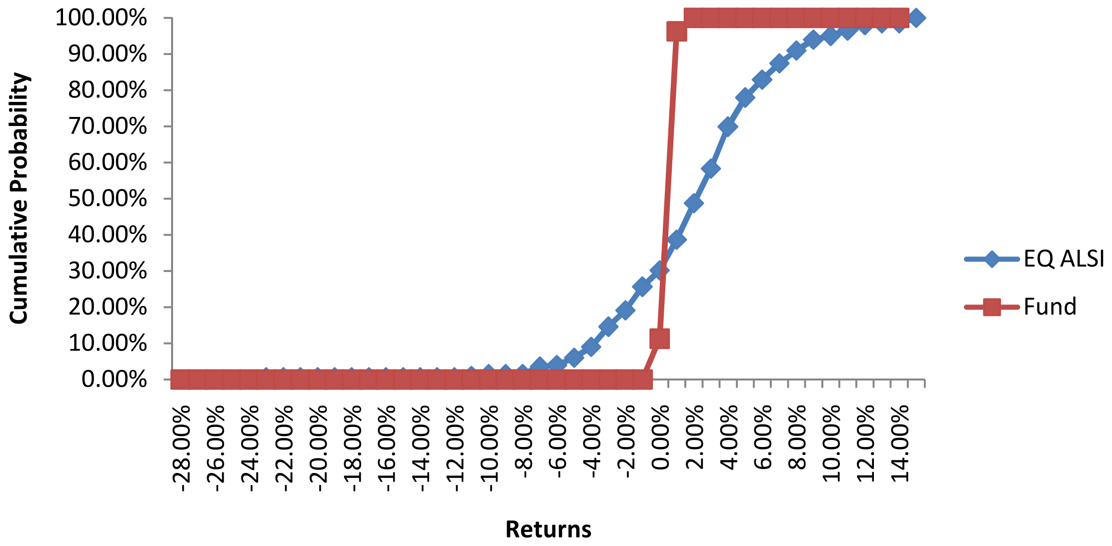

Figure C 1 – CDF of constructed ALSI with fusion fund

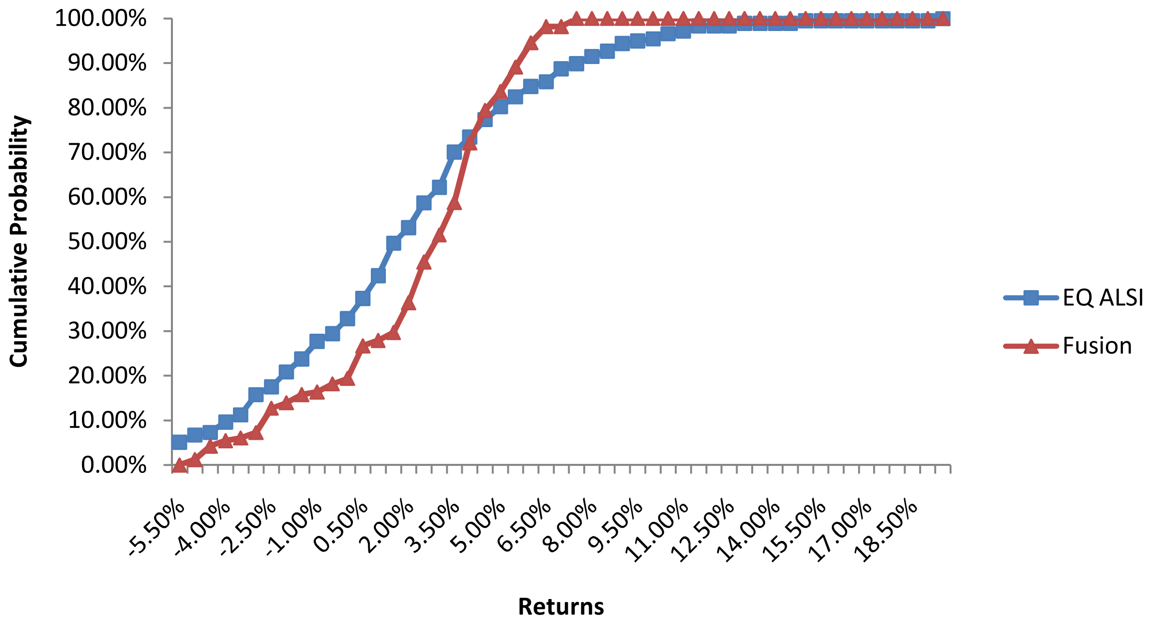

Figure C 2 – CDF of constructed ALSI with fusion strategy