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PASSIVE VERSUS ACTIVE APPLICATIONS OF INDUSTRY EXCHANGE TRADED FUNDS (ETFs): AN EMPIRICAL INVESTIGATION ON THE S&P GLOBAL 1200 INDEX

BY

ARSHAD MUSA
(Student Number: 3108226)

Thesis prepared under the supervision of Professor Heng-Hsing Hsieh and submitted in full fulfilment of the requirements for the Degree of Master of Commerce in Finance in the School of Business and Finance of the Faculty of Economic and Management Sciences at the University of the Western Cape.

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1. I declare that this research thesis has been completed under the guidance and instruction of Professor Heng-Hsing Hsieh of the University of the Western Cape, South Africa, and that this thesis may not be submitted, in whole or in part, in order to obtain another degree, other than M.Com (Finance) at UWC.

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Arshad Musa

October 2015

Data Declaration

I hereby declare that the data undertaken to conduct this research has been acquired from Bloomberg databases. The data is raw price and volume data of the S&P Global 1200 index, its constituents sectors and the iShares S&P Global 1200 sector ETF's, downloaded as at February 20th, 2015 and has been filtered to provide the relevant data required for the research. I acknowledge that I am fully aware that any use of the data, other than for the purpose of this research thesis is strictly prohibited.

Arshad Musa

October 2015

Dedication

This thesis is dedicated to my parents; Mr. Ishaq Musa and Mrs. Yasmin Musa, and my siblings; Mrs. Nasreen Musa and Mr. Ifzaal Musa.

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Utmost thanks to my supervisor, Professor Heng-Hsing Hsieh for the guidance throughout my studies, the opportunities created, as well as the theoretical and practical finance, investments and modelling knowledge that he imparted on me. His academic advice and supervision as well as the practical and applied industry knowledge that he shared was unequivocally appreciated.

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All mistakes in this thesis are mine.

Abstract

The notion of market efficiency posits that stock prices fully reflect all available information in a timely manner. The efficient market hypothesis (EMH) proposed by Fama (1970) systematically rules out the profitability of information driven investing, and implicitly promulgates a passive market capitalisation weighted investment strategy such as indexing. The appeal of passive strategies has largely been driven by the growth of passive tracking instruments, which allow investors to earn underlying index performance by purchasing a single security such as an exchange traded fund (ETF). On the contrary, proponents of behavioural finance suggest that investors are irrational and subject to psychological biases. Furthermore, the noisy market hypothesis of Siegel (2006) asserts that the deviations from the economic ideal of rationality proposed by the EMH, introduces noise in the market which could lead prices to deviate from their intrinsic values. The resultant drag in performance of market capitalisation weighted indices suggests that the optimal cap-weighted market portfolio promulgated by the modern portfolio theory (MPT) of Markowitz (1952), ceases to be the most mean-variance approach to asset allocation. With the goal of testing the applications of ETF's, this study first evaluates the performance of passive sector ETF's in the global equity market. In addition, motivated by the potential inefficiencies of cap-weighted portfolios, the study tests optimisation based asset allocation techniques, and technical analysis based market timing strategies.

The study employs the S&P Global 1200 sector indices and their respective sector ETF's to test their performances and applications in passive and active investment strategies, over the period from July 5th, 2002 to February 6th, 2015. The ETF's are evaluated based on their tracking ability and price efficiency. All 10 sector ETF's possess insignificant tracking errors and successfully replicate the performance of their underlying indices. In addition, the global sector ETF's are not price efficient over the study period, as they possess persistent price deviations from their net asset values (NAV's). Furthermore, the ETF trading strategy based on the relationship between ETF returns and price deviations, proves to be effective in outperforming the passive buy and hold strategy in the majority of the sectors.

The sector decomposition of the cap-weighted S&P Global 1200 index which is employed as the market proxy, reveals that its sector allocation remains fairly stable throughout the study period. In contrast, the optimal historical sector composition incurs large changes in sector exposure from year to year and provides substantially superior performance relative to the cap-weighted market portfolio. The cap-weighted portfolio tends to overweight cyclical sectors and underweight resilient sectors during major economic downturns. The long-only, long-short and market neutral strategies developed from the S&P Global 1200 index and its constituent sector indices provide exceptional risk-adjusted performance, and more mean-variance efficient portfolios than the cap-weighted market proxy. The relaxation of the long-only constraint also improves the optimised portfolios risk-adjusted performance, mainly through risk reduction benefits. The performance of the optimised global sector based portfolios also resembles the performances of the global style based optimised portfolios developed by Hsieh (2010), thereby suggesting that the two approaches are analogous.

The 3 technical market timing strategies tested in this research provide varying results. The sector momentum portfolios experience significant positive returns during bull markets, however the portfolios incur significant drawdowns during periods of economic turmoil such as the 2008 global financial crisis. As a result, all sector momentum portfolios provide inferior risk-adjusted returns relative to the passive cap-weighted buy and hold strategy. The exponential moving average (EMA) trend timing strategy promulgated by Hsieh (2010) provides impressive risk-management attributes and superior risk-adjusted performance relative to passive buy and hold benchmarks. Similarly, the alternative technical charting heuristics trend timing strategy helps reduce drawdowns during market crashes, however the charting strategy provides inferior cost and risk-adjusted performance relative to the cap-weighted buy and hold approach due to larger timing errors and longer hedging periods in comparison to the EMA strategy. In addition, the global tactical sector allocation (GTSA) model tests the EMA and technical charting trend timing tools in the context of a global sector portfolio, and the model provides outstanding cost and risk-adjusted performances relative to the passive investing alternatives. The portfolio based GTSA model highlights the benefits of portfolio diversification and successfully hedges market exposure during economic downturns.

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Introduction

1.1. Background

The modern portfolio theory (MPT) pioneered by Markowitz (1952) introduces the concept of risk and diversification in the portfolio selection process. The MPT asserts that the market portfolio that weights all risky assets in proportion to their market capitalisation is the optimal portfolio of risky assets that all investors should invest in. The separation theorem of Tobin (1958) extends upon the MPT and suggests that investors can split the investment between the risk-free asset and the market portfolio, in order to tailor the investment to the individuals risk appetite. Subsequently, Sharpe (1964), Lintner (1965) and Mossin (1965) independently contribute towards the development of the capital asset pricing model (CAPM). The CAPM provides a tool for pricing assets in an efficient market based on the assets return and beta coefficient, which is the measure of sensitivity of asset returns to changes in market returns. The MPT and CAPM are underpinned by the efficient market hypothesis (EMH) promulgated by Fama (1970, 1991). The EMH states that investors are rational and stock prices fully and fairly reflect all available information in a timely manner, thereby ruling out the ability to consistently outperform the cap-weighted optimal market portfolio using information driven active management strategies.

In contrast, proponents of active portfolio management argue that the assumptions of the EMH are extremely restrictive and unrealistic, such as assuming that all investors are rational at all times. According to the behavioural finance school of thought, investors are irrational as they are subject to cognitive errors, feelings and emotions. The prospect theory of Kahneman and Tversky (1979) provides a model that explains investor decision making based on irrationality, and highlights that an investors decisions are largely inconsistent with rational economic theory. Similarly, psychological biases such as emotional loss of control, heuristics simplification and self-deception proposed by Hirshleifer (2001), as well as the familiarity bias of Ritter (2003) can culminate into investor over-optimism and overconfidence. As a result, asset prices could overshoot, as suggested by the overreaction hypothesis of De Bondt and Thaler (1985).

The presence of investor irrationality and well documented anomalies such as investor overreaction and the subsequent mean reversion in asset prices introduces noise in the market, thereby causing prices to deviate from their true fundamental values. The deviation of prices results in a performance drag of cap-weighted indices, as assets are over or underweighted due to pricing errors. The potential presence of the cap-drag in a market characterised by irrationality and market noise suggests that the cap-weighted market portfolio, which is stated to be the optimal portfolio by the MPT, ceases to be the most mean-variance efficient approach to asset allocation.

Potential mispricing cycles in the market support active management strategies such as alternative asset allocation and market timing strategies, which differentiate the portfolio and place it out of sync of the market consensus as suggested by Kao and Schumaker (1999). Investors could develop more mean-variance efficient portfolios than the cap-weighted strategy by employing alternative asset allocation techniques such as fundamental indexation promulgated by Arnott, Hsu and Moore (2005). Fundamental indexation avoids the distorting effect of market noise by weighting portfolio constituents based on their price insensitive fundamental metrics. Investors could also utilise other portfolio allocation mechanisms such as equal weighting or portfolio optimisation strategies that are conditioned to achieve a pre-specified objective. In addition to alternative asset allocation, investors could improve portfolio performance beyond the cap-weighted strategy by employing technical analysis. Technical analysts utilise information extrapolated from past price and volume data in order to time market trends and identify optimal trading points.

1.2. Overview

This research undertakes to test the practicality of incorporating global sector or industry exchange traded funds (ETF's) and indices in passive and active management strategies, over the study period from July 5th, 2002 to February 6th, 2015. The objective of this study is to test the performance of passive global ETF's and to search for practical sector based mean-variance efficient strategies in the global equity market. The study employs the Standard and Poor's (S&P) Global 1200 index and its 10 constituent sectors as defined by the Global Industry Classification Standard (GICS). The research database also includes the 10 iShares S&P Global 1200 sector ETF's listed by Blackrock Investments.

Chapter 2 provides an overview of the pertinent theories underpinning the research which encapsulates the modern portfolio theory (MPT), the capital asset pricing model (CAPM) and the efficient market hypothesis (EMH). The implications of behavioural finance, and the theories supporting the use of alternative asset allocation and technical analysis based market timing strategies are also discussed. Chapter 3 reviews prior literature on the performance of ETF's based on their tracking ability and pricing efficiency. The chapter also reviews empirical evidence on portfolio optimisation strategies in active management. Furthermore, empirical tests of various technical analysis based market timing strategies are discussed.

Chapter 4 details the problem statement and the research objectives undertaken to answer the research question. The chapter also provides a motivation for the selected research database, the statistics of the research sample, an outline of the tests conducted in the ensuing chapters and the potential biases in the research as well as how they are mitigated. Chapter 5 commences by assessing the risk-return characteristics of the 10 global sector indices over the examination period. The chapter subsequently focuses on assessing the performance of the global sector ETF's. The ability of each ETF to track its underlying index is evaluated to determine whether the ETF's replicate their benchmarks performance. The chapter also examines the price efficiency of the ETF's, and develops a technical trading rule based arbitrage model to profit from the information contained in the deviations between the ETF's market price and net asset value (NAV).

Chapter 6 decomposes and evaluates the cap-weighted sector composition of the benchmark S&P Global 1200 index relative to the retrospective optimised compositions. In addition, the chapter develops and evaluates the performance of global sector based optimised portfolios with different optimisation objectives and portfolio constraints in terms of short selling and portfolio leverage. Chapter 7 investigates the performance of 3 distinct technical analysis strategies, namely the global sector momentum strategy, the exponential moving average (EMA) timing strategy and the technical charting heuristics trend timing strategy. Motivated by the potential lack of correlation between global sector indices, the research also develops a global tactical sector allocation (GTSA) model which applies the EMA and technical charting tools in the context of an investor’s portfolio. Chapter 8 consolidates and summarises the findings from the tests conducted in this research and provides recommendations based on the results of the study.

1.3. Contributions

The results and analysis of the tests conducted in this research contribute to the existing literature on the performance of global ETF’s as well as application of global sector indices within various investment strategies. Firstly, motivated by the evidence that sector based factors have a stronger bearing on investment returns than country based factors, the study selects a database with sufficient sector representation that can provide greater diversification and timing benefits. The presence of systematic country specific risks that affect all sectors of an economy also suggests that sector based allocation is more effective in a global rather than domestic equity market context. Although several studies have explored the characteristics of sector based portfolios, the majority of the studies focus on domestic sector investing benefits or global sector diversification. To the author’s knowledge, there is no extensive research on the applications of global sector based investment strategies that are explored in this research.

ETF’s provide an attractive and cost-effective means of buying into a basket of securities in the same way a stock is traded on an exchange. The number of ETF's has grown exponentially over the past decade, with the approximate count at the end of 2013 estimated to be around 3,581 worldwide (Statista, 2015). The increased popularity of ETF's has seen an increase in global ETF assets from $205.3 billion in 2003 to $2253.8 billion at the end of 2013 (Statista, 2015). Similarly, passive sector ETF’s are designed to provide investors with the sector returns by investing in a single index tracking instrument. To the best knowledge of the author, although domestic and country ETF’s have been widely studied, there is limited literature on the tracking ability and pricing efficiency of global sector based ETF’s. The evaluation of the deviations between ETF prices and NAV’s is expected to provide an indication of the degree of efficiency of ETF’s in global equity markets.

The majority of the ETF's are traditionally developed as passive tracking instruments, however they can also be incorporated into active management strategies. Consequently, the study explores the practicality of applying active sector based asset allocation and market timing strategies. Although significant research by Yu (2008) and Hsieh (2010) has been conducted on the development of style based optimised portfolios under various portfolio constraints, no prior studies have explored the potential benefits of global sector based portfolio optimisation strategies with real-life optimisation objectives and constraints using tradable ETF's. The focus on sector representation rather than market capitalisation in the case of both the Dow Jones Sector Titans Composite index employed by Hsieh (2010) and the S&P Global 1200 index employed in this research allows for an ideal comparative analysis in global equities. Furthermore, although the study by Hsieh (2010) is based on the global equity market, the market coverage of this research is much greater as the study incorporates a more representative global index in the form of the S&P Global 1200 index. Unlike the Dow Jones Sector Titans Composite that only selects the 30 largest constituents per sector; the S&P Global 1200 index employed in this research selects an average of 120 constituents per sector, with the mother index covering almost 70% of the global equity market capitalisation. This study also focusses on a more recent time period than the prior studies and encapsulates both the 2008 global financial crisis and the post-2009 European debt crisis. However, it is important to note that the real-life optimisation constraints adopted in this study differ from prior studies, as they are based on global sector indices and prevailing regulations in the United States (U.S.) equity market. Overall, the results from the optimised sector allocation strategies will speak to the attractiveness of the relative correlation between global sectors, and the potential benefits of optimisation strategies relative to the traditional market capitalisation investment strategy.

Empirical literature suggests that market crashes such as the 2008 financial crisis pose a systematic risk that affects all asset classes, investment styles, sectors and markets, thereby rendering many investment strategies such as style or sector diversification and portfolio optimisation to be ineffective (Hsieh, Hodnett and van Rensburg, 2012). Consequently, the study tests two comparative technical analysis based trend timing tools on the global sector indices from 2002 to 2015, that could potentially help identify and avoid losses during bear market phases. Firstly, the study tests the exponential moving average (EMA) trend timing strategy proposed by Faber (2007) and Hsieh (2010). However, their tests focus on the U.S. market and on global style indices respectively, rather on the global sector indices tested in this research. Secondly, the study develops a novel trend timing strategy based on technical charting heuristics proposed by Leigh, Purvis and Regusa (2002c). The technical charting strategy is tested as an alternative to the EMA trend timing strategy developed by Hsieh (2010). Technical charting uses representative price patterns to indicate expected bull and bear market phases. Prior literature on technical charting heuristics using the template or pattern matching technique has focused on the predictive ability of charting patterns, which is assessed using exogenous or fixed holding periods. However, this research tests the application of technical charting heuristics by using the representative pattern templates to generate both endogenous market entry and hedge signals. The results of the technical analysis strategies are assessed relative to the passive buy and hold strategies to infer the benefit of timing sector trends. Henceforth, the results will assist in identifying prospective market timing tools that can increase an investor’s portfolio value during bull markets while safeguarding the portfolio from substantial losses and drawdown experienced during market downturns.

Lastly, the research develops a global tactical sector allocation (GTSA) model which employs the technical hedging mechanisms proposed by Faber (2007) and Hsieh (2010). Significant prior research on a similar model is conducted by Faber (2013), who tests an equally weighted simple moving average crossover model across different U.S. asset classes and investment styles. This research incorporates the exponential moving average (EMA) and technical charting heuristics based trend timing tools in the context of an equally weighted global sector portfolio. The GTSA models employing the technical trend timing tools will highlight the potential benefits for investors from avoiding significant drawdown during bear markets, while simultaneously benefiting from portfolio diversification as a result of investing in supposedly uncorrelated global sector indices.

2

Theoretical Overview

2.1. Introduction

This chapter provides a review of the pertinent theories supporting the research, which encapsulate the principles of the Modern Portfolio Theory (MPT), implications of the Random Walk Hypothesis, forms of the Efficient Market Hypothesis (EMH) and the theory of active asset allocation and timing strategies. The background of technical analysis and the characteristics of trending markets, market inefficiencies and investors behavioural biases are analysed to decipher the development of trends. The gains from market timing as well as applications of technical analysis within tactical asset allocation (TAA) models are discussed.

The MPT pioneered by Markowitz (1952) describes the risk-return relationship within the investment opportunity set available to investors. The separation theorem by Tobin (1958) extends on the MPT by providing a means for investors to tailor investments to their individual risk appetites. The MPT assumes that investors are risk-averse as suggested by the expected utility theorem and would therefore require higher returns for taking on higher risk in order to maximise their utility (Von Neumann and Morgenstern, 1944). The MPT is underpinned by the EMH promulgated and formalised by Fama (1970) which assumes that investors are rational and not affected by behavioural biases.

The EMH states that prices fully and fairly reflect all available information in a timely manner. As a result investors cannot consistently outperform the market and should therefore adopt a passive investment approach. In contrast, active investors believe that markets are not perfectly efficient for instance due to behavioural biases such as herding and conservatism, or market anomalies such as overreactions and momentum which leads prices to stray from their intrinsic values. Therefore, active portfolio managers are presented with an opportunity to improve performance by exploiting market inefficiencies with the objective to outperform a passive buy and hold investment strategy.

Active portfolio management includes alternative asset allocation and market timing strategies amongst other techniques. Alternative asset allocation strategies deviate from the traditional market capitalisation weighting by systematically over-weighting or under-weighting certain assets with the aim of achieving a particular objective such as outperforming a pre-specified benchmark. Alternatively, active portfolio managers frequently use information-driven forecasting techniques to determine appropriate trading signals based on technical analysis. Technical analysis focuses on past and current stock market price and volume data in order to predict the market's direction. This includes the use of various quantitative or charting tools to time the optimal market entry and exit points. One of the main objectives of using technical analysis is to benefit from bull market trends and avoid significant losses and drawdown during bear markets. The advent of tactical asset allocation (TAA) models designed to shift portfolio exposures towards attractive assets, has also furthered the application of technical indicators from single index forecasting to diverse portfolio management tools.

2.2. The Modern Portfolio Theory (MPT)

The Modern Portfolio Theory (MPT) pioneered by Markowitz (1952) incorporates the concept of risk and diversification in the portfolio selection process. The MPT is based on the premise that investor's possess a risk-averse attitude towards portfolio selection as suggested by the expected utility theorem of Von Neumann and Morgenstern (1944). The expected utility theorem states that investors expected utility increases with increasing wealth levels; however, expected utility increases at a decreasing rate as investors are risk-averse. Therefore risk-averse investors would reject risky investments if returns do not adequately justify the additional risks borne. Alternatively, risk-averse investors would require additional compensation for taking on additional risk and would prefer an expected outcome to any riskier position with the same expected outcome. In the context of portfolio selection, rational risk-averse investors will select portfolios that provide the highest level of return for a given level of risk or lowest level of risk for a given level of return. This is commonly known as the mean-variance efficient property.

The expected return of a portfolio is simply the weighted average of the individual asset or security returns as depicted in Equation 2.1. However, the total risk of the portfolio which is measured by the standard deviation of the returns is influenced by the correlation between the asset classes. The variance (standard deviation squared) of a portfolio consisting of two assets is computed using Equation 2.2.

$$E(R_p) = (w_i\, E(R_i)\,) + \left(w_j\, E(R_j)\,\right) \qquad (2.1)$$

$$\sigma_p{}^2 = (w_i{}^2\sigma_i{}^2) + \left(w_j{}^2\sigma_j{}^2\right) + 2\left(w_i\, w_j\sigma_i\ \sigma_j\, \rho_{ij}\right) \qquad (2.2)$$

where

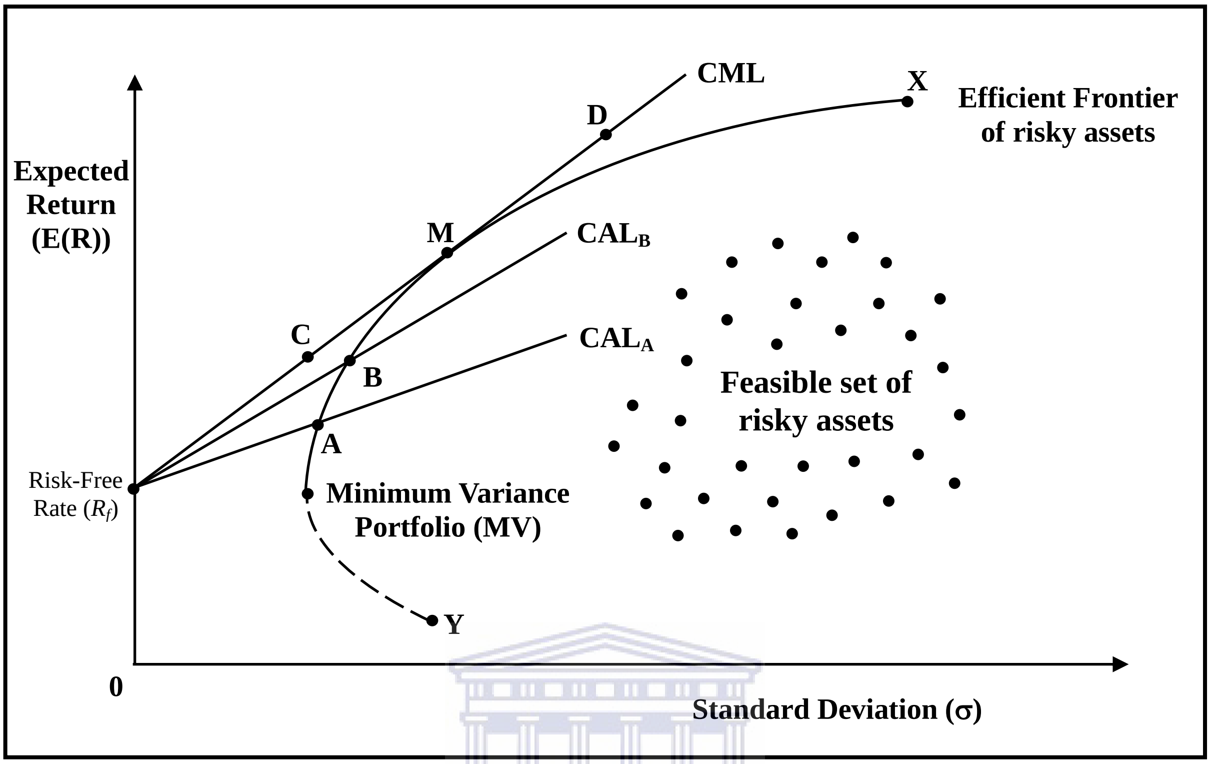
w_i the weight of asset *i* in portfolio *P*;
w_j the weight of asset *j* in portfolio *P*;
σ_i the standard deviation of asset *i*'s returns;
σ_j the standard deviation of asset *j*'s returns; and
ρ_{ij} the correlation coefficients between the returns of asset *i* and *j* in portfolio *P*.

Markowitz (1952; 79) states, *"There is a rate at which the investor can gain expected return by taking on variance, or reduce variance by giving up expected return."* Therefore, the goal of a rational utility maximising investor is to select portfolios that can gain expected return at a higher rate than the level of additional variance borne. Alternatively, investors can reduce variance at a higher rate than expected returns. This is made possible by the concept of portfolio diversification supported by Equation 2.2, which highlights that the lower the correlation between assets i and j, ρ_{ij}, the lower the variance of the portfolio, σ_p^2, as firm specific risk is diversified away. Therefore, the expected return and risk of a portfolio are not likely to move in perfect lockstep movements and with greater diversification through lower correlations, portfolio return can increase at a higher rate than portfolio risk.

Investors can achieve portfolio diversification by employing a vast array of investment techniques. Some of the techniques include diversification based on asset class allocation for instance between stocks, bonds, commodities and currencies; or including assets of different investment styles such as value, growth, momentum and size. Alternatively, investors can employ a sector based diversification approach for instance between energy, utility and financial sectors amongst others. These approaches to portfolio diversification incorporate the basic tenets that different asset classes, investment styles or sectors are expected to be in favour at different times during the economic cycle.

The concept of diversification is also captured in the Markowitz efficient frontier of risky assets depicted in Figure 2.1. The portfolios that are plotted on the efficient frontier between point *MV* and *X* denote the most mean-variance efficient portfolios developed from the feasible set of risky assets. Portfolios that lie on the efficient frontier provide the highest return for given levels of risk or lowest risk for given levels of return in the feasible set. The concave shape of the efficient frontier of risky assets is attributed to the imperfect correlation between assets within the feasible set of risky assets, thus risk and return do not increase proportionately. On the other hand, assets or portfolios that fall below the efficient frontier of risky assets are inefficient. Hypothetical portfolios beyond the efficient frontier of risky assets are unattainable (Bodie, Kane and Marcus, 2008).

Figure 2.1: Markowitz Efficient Frontier of Risky Assets



Source: Figure Modified from Hodnett and Hsieh (2012:852)

The dashed portion below the efficient, frontier from the minimum variance portfolio (*MV*) to point *Y* in Figure 2.1 denotes inefficient portfolios, as investors can achieve higher returns for the same level of risk on the corresponding solid segment of the efficient frontier. Furthermore, some investors may have a lower risk appetite and would like to minimise exposure to risky assets. The separation theorem of Tobin (1958) suggests that investors can invest a fraction of the portfolio in the risky asset and the remainder in the risk-free proxy which has high liquidity, low default risk and low maturity risk. The combination of the risk-free asset and risky portfolio can be graphically depicted as the capital allocation line (CAL). For instance, CAL_A is a linear combination of the risk-free asset (R_f) and risky portfolio *A*, and CAL_B is a linear combination of the risk-free asset (R_f) and risky portfolio *B*.

Rational utility maximising investors will prefer higher CAL's as they provide a higher return for any given level of risk in comparison to a lower CAL. Thus, CAL_B dominates CAL_A. Henceforth, the highest attainable CAL is the CML which occurs at the point of tangency between the efficient frontier of risky assets and the CAL. The portfolio of risky assets at the point of tangency is referred to as the market portfolio denoted by point *M*, and is assumed to be the most mean-variance efficient portfolio within the attainable set of risky assets. As a result, the market portfolio is characterised by the highest attainable return per unit of risk.

Tobin's (1958) separation theorem furthers the application of the market portfolio by separating the asset allocation process into two distinct steps. The first step involves identification of the market portfolio, *M*, which occurs at the point of tangency of the CML and the efficient frontier of risky assets. The separation theorem is based on the assumption that all investors are rational and therefore will choose to invest in the optimal market portfolio. The second step is the determination of the appropriate mix between the risk-free asset and the market portfolio, *M*, in order to match the investment profile with the risk preference of the investor. Risk-averse investors will select portfolios such as portfolio *C* in Figure 2.1, that are partly invested in the risk-free asset and the balance invested in the market portfolio. On the other hand, investors who are less risk-averse can implement active extension strategies that borrow at the risk-free rate and invest the entire sum of capital into the market portfolio as indicated by point *D* on the CML (Tobin, 1958).

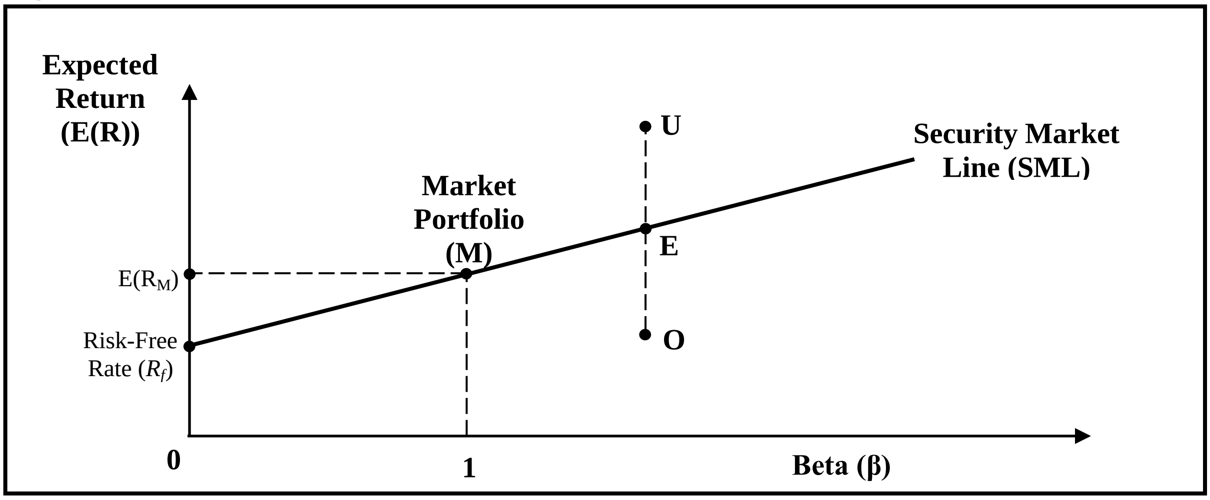
2.3. The Capital Asset Pricing Model (CAPM)

Sharpe (1964), Lintner (1965) and Mossin (1965) independently contribute towards the development of the Capital Asset Pricing Model (CAPM) which extends upon the MPT by providing a tool for pricing assets. According to the CAPM, investors should only be concerned about systematic risk of an asset, as firm specific risks can be diversified away by holding a well diversified portfolio characterised by imperfect correlation between assets. The expected return-risk relationship proposed by the CAPM is expressed in Equation 2.3.

$$E(R_i) = R_f + \beta_i\big(E(R_M) - R_f\big) \tag{2.3}$$

Equation 2.3 shows that the expected return on asset *i* ($E(R_i)$) is equal to the risk-free rate (R_f) plus the market risk premium ($E(R_M) - R_f$) in proportion to asset *i*'s systematic risk as measured by beta (β_i) (Hodnett and Hsieh, 2012). The CAPM equation is also referred to as the Security Market Line (SML) which is depicted in Figure 2.2. The SML indicates the equilibrium price of assets, therefore in efficient markets all assets must plot on the SML. Any asset plotted above the SML is undervalued such as asset U as it provides higher returns than expected, given its systematic risk. On the other hand, assets the plot below the SML are overvalued such as asset O as it provides lower returns than expected, given its systematic risk. Over time, investors will drive up the price of asset U and push down the price of asset O by buying asset U and selling asset O. This will lead to a reduction in the return of asset U and increase in the return on asset O, until equilibrium point E on the SML is reached.

Figure 2.2: Security Market Line



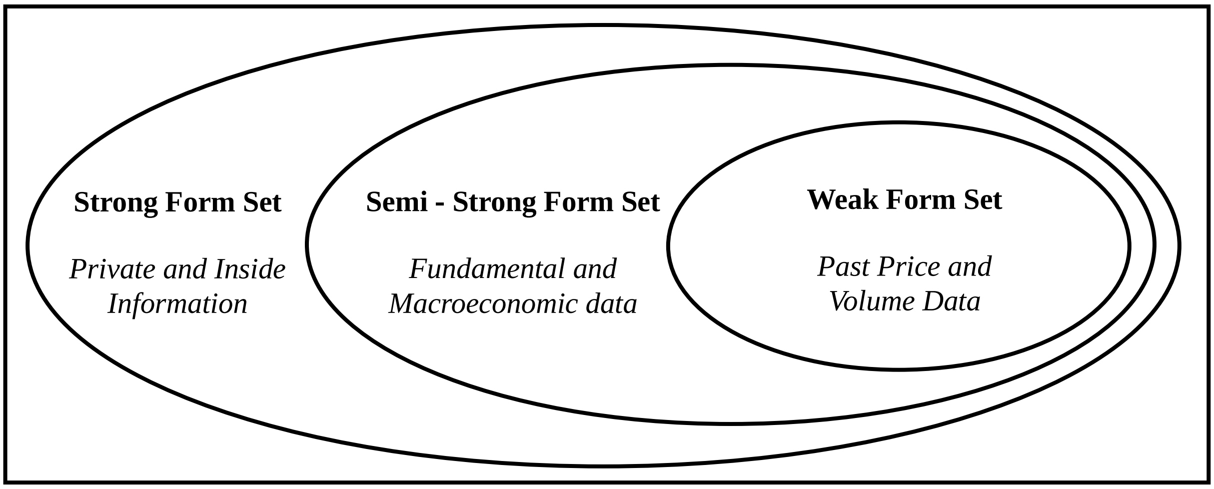
Source: Figure Modified from Hodnett and Hsieh (2012:855)

2.4. The Efficient Market Hypothesis (EMH)

An efficient market refers to a market in which stock prices fully and fairly reflect all available information and therefore, rules out investors' ability to consistently earn abnormal returns. In efficient markets investors are assumed to be rational and unaffected by psychological and behavioural biases. Consequently, the concept of efficiency is a cornerstone of many financial theories such as the MPT and CAPM. Rational utility maximising investors aim to use available information to determine investment approaches that will assist with optimal resource allocation (Fama, 1970). Investors are subject to three main types of information which includes past price and volume data, publicly available information such as firm fundamentals, and inside information or as termed by Fama (1970; 383), "*monopolistic access to any information relevant to price formation*."

The EMH pioneered by Fama (1970, 1991) states that stock prices fully reflect all available information in a timely manner. The EMH depicts three levels of market efficiency based on the type of information reflected in stock prices, namely the weak, semi-strong and strong form efficiency of the market. The weak form EMH asserts that all historical price and volume data has already been reflected in asset prices. Therefore, the weak form EMH rules out the ability of using technical analysis to identify market trends and cycles. This is congruent with the Random Walk Hypothesis which states that stock price movements in one period are independent from the previous period (Kendall, 1953). This is the case as new information enters the market unsystematically, which causes price changes to be random. Therefore, technical analysts cannot use past prices to predict future trends. The semi-strong form EMH states that all public information such as firm fundamentals and macroeconomic factors are reflected in asset prices. Therefore, fundamental analysts cannot consistently earn abnormal returns in a semi-strong form efficient market. The strong form EMH is the most restrictive form of the EMH and posits that all knowable information, that is past, public and private information is reflected in asset prices. As a result, the strong form efficiency of markets eliminates the possibility of earning abnormal returns even in the presence of inside information. Strong form efficiency is considered an extreme model that is unlikely to materialise in the real world, however, it serves as a benchmark for perfect efficiency (Fama, 1970). Figure 2.3 depicts the three forms of the EMH and the information sets pertaining to each form. The weak form EMH is encapsulated within the semi-strong form EMH, which is encompassed within the strong form EMH.

Figure 2.3: The 3 Forms of the EMH and Respective Information Sets



Source: Figure Modified from Bodie, Kane and Marcus (2008; 261)

The implication of the EMH is that active portfolio management is a wasted effort. The EMH posits that active investing is riddled with extra trading costs and expenses that are not justifiable. Henceforth, according to the EMH a passive investment strategy that simply tracks a market is due to outperform an active strategy that attempts to identify optimal trading points and mispriced securities. Passive investment strategies have advanced significantly and investors can easily track the market, sectors or desired asset classes through easily tradable securities such as passive mutual funds and exchange traded funds (ETF's).

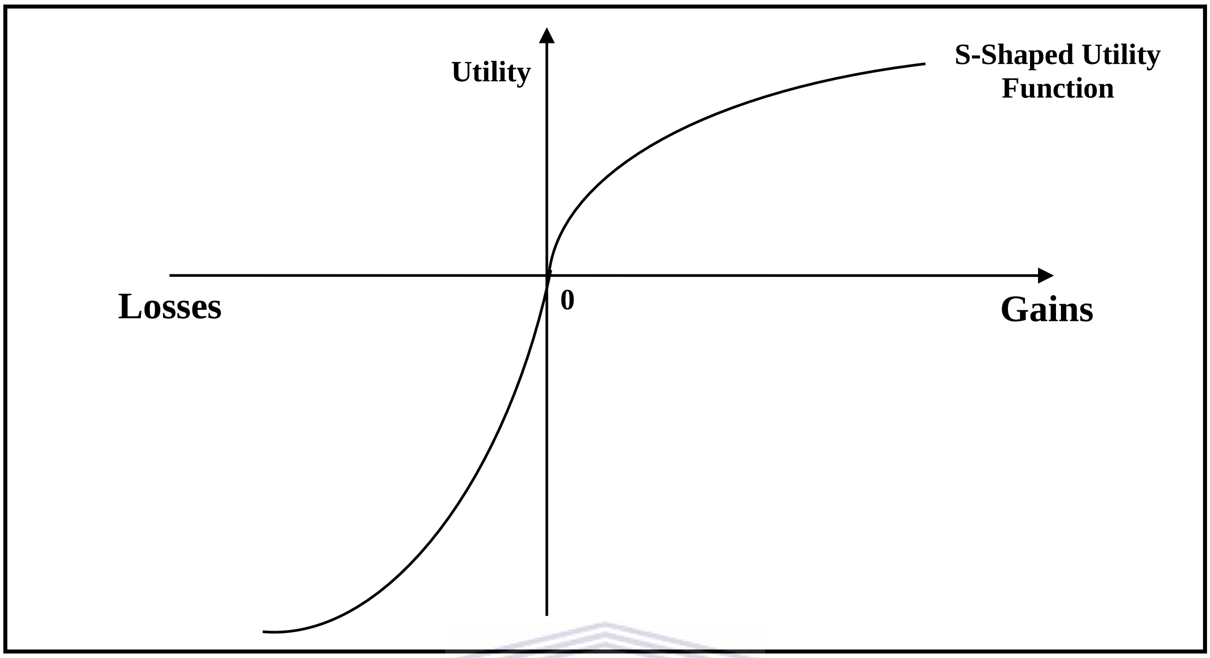
On the contrary, active portfolio managers argue that certain requirements and assumptions of the EMH proposed by Fama (1970, 1991) are restrictive and unrealistic, such as rationality of all investors. Investors are subject to behavioural biases and irrationality which translates into systematic errors within their investment activities. As a result, financial markets are not necessarily efficient and experience cycles of mispricing. Furthermore, given that different asset classes or sectors are expected to be in favour at different points of the economic cycle, investment managers constantly attempt to benefit from alternative asset allocation and/or market timing strategies. The goal of deviating from traditional passive investing strategies is to differentiate the portfolios returns from the market or benchmark in order to place the portfolio out of sync of the general market consensus (Kao and Schumaker, 1999).

2.5. Behavioural Finance

The underpinnings of behavioural finance are best summarised by Statman (1999; 26) who states, *"People in standard finance are rational. People in behavioural finance are normal"*. Behavioural finance studies the effects of psychological biases on the behaviour and decision making process of financial practitioners. Behaviourists purport that investors are likely to be influenced by cognitive errors and emotions when making investment decisions. As a result, investors are not expected to have homogenous expectations under behavioural finance and thus, will not arrive at the same optimal risky portfolio also known as the market portfolio suggested by Tobin (1958). Therefore, in a market that is not underpinned by rationality, the asset allocation decision proposed by the MPT and the asset pricing relationship promulgated by the CAPM, are likely to provide portfolios that are not mean-variance efficient (Hodnett and Hsieh, 2012). The presence of investor irrationality is best understood through cognitive theories that focus on investor beliefs, preferences and the decision making process such as the prospect theory pioneered by Kahneman and Tversky (1979).

The prospect theory provides a critique of the expected utility theory of Von Neumann and Morgenstern (1944) and develops an alternative model to explain how investors manage risk under uncertainty. Unlike the expected utility theory which is bound by investor rationality, the prospect theory is based on irrationality as investors could make decisions that are inconsistent with economic theory. The prospect theory builds upon the expected utility theory which states that investors are risk-averse, by introducing the concept of loss-aversion. Loss-aversion entails that investors prefer avoiding losses in comparison to acquiring gains. The concepts of risk and loss-aversion are captured in the S-shaped utility function depicted in Figure 2.4. The concave shape of the utility function in the positive domain captures risk-aversion as utility increases at a decreasing rate for gains. The convex shape of the utility function in the negative domain shows the negative diminishing utility experienced by loss making investors. The steeper slope of the utility function in the negative domain highlights the concept of loss-aversion as investors experience greater disutility from losses in comparison to equal gains.

Figure 2.4: Prospect Theory Utility Function



Source: Figure Adapted from Kahneman and Tversky (1979:279)

Furthermore, the prospect theory asserts that investors are not consistently risk-averse, instead investors are risk-averse with regard to gains but risk-seeking with regard to losses. Kahneman and Tversky (1979) document a certainty effect, whereby investors tend to underweight probable positive outcomes in comparison to guaranteed positive outcomes. For instance, an investor's risk-averse attitude would lead him/her to select $3,000 gain with certainty over an alternative with an 80% chance of winning $4,000 or 20% chance of winning nothing. However, when the signs of the outcomes are reversed from gains to losses, investors tend to be risk seeking, thereby preferring the option that has an 80% chance of losing $4,000 or 20% chance of losing nothing, rather than a guaranteed loss of $3,000. This is referred to as the reflection effect (Kahneman and Tversky, 1979).

Investor irrationality can be traced to various different psychological biases. Hirshleifer (2001) argues that three sources namely, emotional loss of control, heuristic simplification and self-deception, can provide a holistic explanation for most decision biases. Emotions and feelings are found to be the core source of behavioural biases as they tend to influence rational considerations, for instance related to investment horizon and investors risk appetite. Investors adopt risk-averse and loss-averse attitudes in order to avoid unpleasant future feelings. Furthermore, investors moods also affect their current decisions, for instance a good mood is found to be correlated with over-optimism. Similarly, fear of regret may deter investors from undertaking risky investments. Investors may also engage in decision making based on social interaction and conversation, as it provides a feeling of self-reinforcement (Hirshleifer, 2001).

Heuristic simplification arises due to investors limited attention, memory and processing capacity. Therefore, investors choose to simplify investment decisions and tend to use a rule of thumb approach. Investors also fall prey to the availability heuristic as they focus on available information sets and believe that recent information that is easier to recall is more common. Similarly, investors may become subject to the representativeness bias by using most recent past performance as indicator of future performance, without assessing the sustainability of past performance. For example, if equity returns have been successively high in the past few years, investors may believe that it is normal for equity returns to continue being high. Investors may also be subject to mental accounting, whereby they view each investment individually relative to its purchase price rather than viewing all assets owned in terms of a portfolio. Investor overconfidence may culminate into the familiarity bias suggested by Ritter (2003), as investors overweight local firms or firms that they associate with, thus reducing portfolio diversification.

Self-deception refers to investors overconfidence or over-optimism, and the overestimation of the precision of their knowledge and abilities. Barberis, Shleifer and Vishny (1998) present a model of investor sentiment which depicts investors tendency to overreact to a series of congruent events such as good returns, while under-reacting to public information such as earnings announcements. Similarly, Daniel, Hirshleifer and Subrahmanyam (1998) attribute investor overreaction to overconfidence in private information and perception of its superiority over public information. Furthermore, the biased self-attribution process prevents investors from rational learning that could eliminate self-deception. Biased self-attribution refers to investors tendency to attribute positive outcomes to own abilities and negative outcomes to external factors or conditions. Thus, self-attribution could exaggerate investors overconfidence, which could subsequently translate into asset prices overshooting their fundamental values as investors overreact in the short to intermediate-term, before experiencing long-term reversals.

2.6. Alternative Asset Allocation Techniques

The MPT and CAPM infer that the cap-weighted market portfolio is the most mean-variance efficient portfolio. This premise is based on the assumption of efficient markets in which asset prices equal their intrinsic values and therefore, prices increase or decrease based on sound economic reasoning. Cap-weighting is the industry norm and is widely used to construct equity indices such as the S&P 500, Russell 1000, Wilshire 5000 and South Africa's JSE/FTSE All Share Index (ALSI). The advantage of cap-weighted indices is that they automatically rebalance the weightings of the index constituents as market prices fluctuate, thus providing a convenient, passive and diversified strategy to invest in the broad equity market. The passive nature of tracking cap-weighted indices necessitates little trading, lower transaction costs and lower turnover costs in comparison to active indexing strategies. The correlation between market capitalisation and trading liquidity also entails the benefit of lower costs, as cap-weighted indices emphasize stocks with high trading volumes (Arnott, Hsu and Moore, 2005).

Although cap-weighting has several benefits, it is perceived as a theoretically sound weighting approach that is effective only in perfectly efficient markets. However, financial markets are subject to well documented pricing anomalies such as the overreactions, investor irrationality and insider trading unrelated to the fundamental values of a stock, which introduces noise into the market. The noise refers to the subsequent temporal shocks in security prices, causing them to deviate from their true fundamental values as suggested by the Noisy Market Hypothesis of Siegel (2006). As cap-weighted indices assign higher (lower) weightings to constituents that experience a price increase (decrease), the index has a tendency of assigning higher weightings to overvalued stocks and underweighting undervalued constituents in a market where prices overshoot their intrinsic values. Therefore, cap-weighted indices tend to underperform over time due to their higher exposure to stocks with pricing errors which are expected to disappear, as prices return to their fair values (Hsu and Campollo, 2006). Furthermore, the underperformance of cap-weighted indices is expected to be higher for larger deviations between prices and fundamentals. The likelihood of the performance drag in cap-weighted indices challenges the MPT's assertion that the cap-weighted market portfolio is the most mean-variance efficient approach to asset allocation.

Although market capitalisation is a widely used measure of firm size, the arguments against cap-weighting suggest that in a noisy market investors ought to use an alternative metric for measuring firm size and performance. Consequently, Arnott, *et al.* (2005) propose the use of fundamental values of a firm. Some of the fundamentals suggested by Arnott, *et al.* (2005) include book value, cash flow, revenue, sales, gross dividends and total employment. The key characteristic that differentiates these metrics from traditional market capitalisation is that they are price-insensitive and therefore, they are not affected by market noise.

Fundamental Indexation suggested by Arnott, *et al.* (2005) assigns weights to index constituents based on relative values of the fundamental metrics. The pioneering study by Arnott, *et al.* (2005) developed indices using the fundamental attributes listed above for 1,000 stocks in the United States, over a 43 year examination period from 1962 to 2004. The study employed the S&P500 as the benchmark and also developed a comparative cap-weighted reference portfolio from the same 1,000 stock universe. The findings of the study show that fundamental-weighted indices exhibit similar risks as cap-weighted benchmarks, with the dividend weighted index being the only exception. The dividend-weighted index has significantly lower volatility and systematic risk (beta) which can be attributed to the mature, low growth companies that are expected to dominate such an index. On average, the fundamental-weighted indices also achieve 1.97% higher returns than the S&P500 and 2.15% higher returns than the cap-weighted reference portfolio over the examination period.

Arnott, *et al*. (2005) also test a composite fundamental index employing book value, cash flow, dividends and sales metrics. The constituent weights are computed based on the average values of the four metrics. The composite index provides similar results as the single-metric fundamental indices and outperforms the cap-weighted benchmarks. Even after taking transaction costs into consideration, the fundamental-weighted indices provide higher returns than the reference portfolio by almost 2.00%. Furthermore, all fundamental-weighted indices provide higher Sharpe ratios (excess return per unit of total risk) than cap-weighted benchmarks over the entire study period, as well as during expansionary and recessionary periods. Therefore, indices that are weighted based on fundamental attributes of a firm provide a more mean-variance efficient method for asset allocation in comparison to cap-weighted strategies. Hsu and Campollo (2006) further the study of Arnott, *et al.* (2005) by applying composite fundamental indices in 23 global markets from 1984 to 2004. The results are similar to Arnott, *et al.* (2005), with the fundamental indices providing higher returns and lower overall risks than the cap-weighted MSCI World index. Fundamental indices are also found to be more mean-variance efficient than cap-weighted indices by Estrada (2006) in 16 international countries, Mar, Bird, Casavecchia & Yeung (2009) on the Australian Stock Exchange and by Ferreira and Krige (2011) on South Africa's JSE Limited.

In a subsequent study, Hsieh, Hodnett and van Rensburg (2012) address whether fundamental-weighted indices are better mean-variance efficient proxies for large established firms compared to cap-weighted proxies in the global equity market. The study employs the Dow Jones Sector Titans Composite Index data over an 18 year period from 1991 to 2008. The authors develop four cap-weighted benchmark indices consisting of the top 200, 100, 50 and 30 stocks based on market capitalisation in addition to the cap-weighted MSCI World Index that is used as a market proxy. The study also computes four fundamental indices consisting of the top 200, 100, 50 and 30 stocks based on the average of five fundamental attributes namely; book value, earnings after tax, dividends, sales and cash flows. The empirical results show that for the same number of constituents, the fundamental-weighted indices outperform their cap-weighted counterparts and the MSCI World Index. The fundamental indices also possess higher risk-adjusted performance than the MSCI World Index and cap-weighted indices as denoted by the Sharpe ratio, Treynor ratio and Jensen's alpha. The level of portfolio concentration also has minimal effect on fundamental indices, whereas the performance of cap-weighted indices exhibit the presence of the small firm effect as cost and risk-adjusted performance deteriorates with higher concentration.

Other than fundamental indexation, equal-weighted indexing is one of the most notable price insensitive alternatives to the traditional cap-weighted method. Equal-weighted indices assume that investors have zero forecasting ability. Therefore, as the name suggests, it allocates equal weights to all constituents regardless of their market capitalisation or fundamental attributes and assigns no value to public or private information that differentiates firms (Arnott, Kalesnik, Moghtader and Scholl, 2010). The advantage of using equal weighting is that it is unaffected by market noise, pricing errors are random and tends to be highly diversified. Arnott, *et al.* (2010) test alternative weighting strategies on the global equity market, using data from 23 developed economies contained in the FTSE and MSCI World Indexes over the period 1993 to 2009. The equal-weighted indexes provide higher returns and marginally higher volatility than cap-weighted indexes. Equal-weighting also provides higher risk adjusted performance as denoted by the Sharpe ratio. The findings are congruent with studies by Chow, Hsu, Kalesnik and Little (2011) in the US and Global markets, and Aked, Kalesnik, Kose, Lawton and Moroz's (2014) in Australia and the G-7 countries. However, all three studies show that the equal-weighted strategies underperform relative to the fundamental-weighted strategy. This can be attributed to the lack of liquidity and capacity of equal- weighted small stocks that result in higher transaction costs.

The use of optimisation based asset allocation models has also been gaining traction amongst investment management practitioners. The optimal weights allocated to each asset can be determined using optimisation techniques that are conditioned to obtain a particular objective, such as maximising the mean-variance criterion or minimising downside risks. Portfolio optimisation strategies can either be static or dynamic models. Static optimisation models select the structure and weights of the portfolio at the beginning of the period and the weights are held constant thereafter. The advantage of static optimisation is that they avoid significant transaction costs that tend to wipe out profits, as static models do not undergo significant changes in portfolio weightings over a short period of time. Alternatively, a dynamic model continuously adjusts the portfolio composition and weights based on rolling time series market analysis. Therefore, as suggested by the proponents of dynamic models, investors are likely to profit from tilting the portfolio towards assets, styles or sectors that are in favour at different points of the economic cycle regardless of the additional transaction costs.

Amenc, Goltz, Martellini and Retkowsky (2010) of the EDHEC Risk Institute test a mean-variance optimised asset allocation strategy across S&P500 stocks from 1959 to 2008. A 2-year rolling model is adopted to determine the most optimal weights that can be applied at the next rebalancing period. The study tests both quarterly rebalancing as well as an ad-hoc rebalancing dependent on the arrival of significant new information. The findings of the study show that the optimisation technique provides more efficient asset allocations than cap-weighting, as suggested by higher Sharpe ratios across different time periods and throughout the business cycle. Henceforth, the technique is accordingly coined the Efficient-Indexing technique. In another study, Hsieh, Hodnett and van Rensburg (2012) evaluate an optimised Tactical Style Allocation (TSA) strategy that employs Dow Jones Sector Titans Composite Index data to develop global value and momentum style portfolios from 1994 to 2008. The TSA model uses a series of 36 month weighted least-squares (WLS) regressions to identify optimal style allocations that will maximise the Sharpe ratio. The results of the study show that the optimised style based portfolio provides higher returns than individual style portfolios and the cap-weighted MSCI World Index, which is used as a market proxy. The optimised TSA portfolios also achieve higher risk-adjusted returns as measured by the Jensen's alpha, Sharpe and Treynor ratios.

2.7. Market Timing Strategies and Technical Analysis

In addition to alternative asset allocation strategies, investors can also employ technical analysis to time market trends as part of their active portfolio management strategies. Market timing involves predicting financial market cycles and turning points, which act as indicators or triggers for shifting into and out of the market. The technical analysis process can be likened to that of market timing, in that technical analysts use historical price and/or volume information to predict the optimal timing of trades. One of the primary objectives of market timers is maximising returns by investing during bull markets and avoiding bear market phases. Although determining market turning points can be rewarding, it is not easy as, *"clearly any investor who bought and sold the market at its turning points would outperform (by a vast margin)...unfortunately, nobody can call market turning points with anything approaching certainty"* (Treynor, 1980; 2).

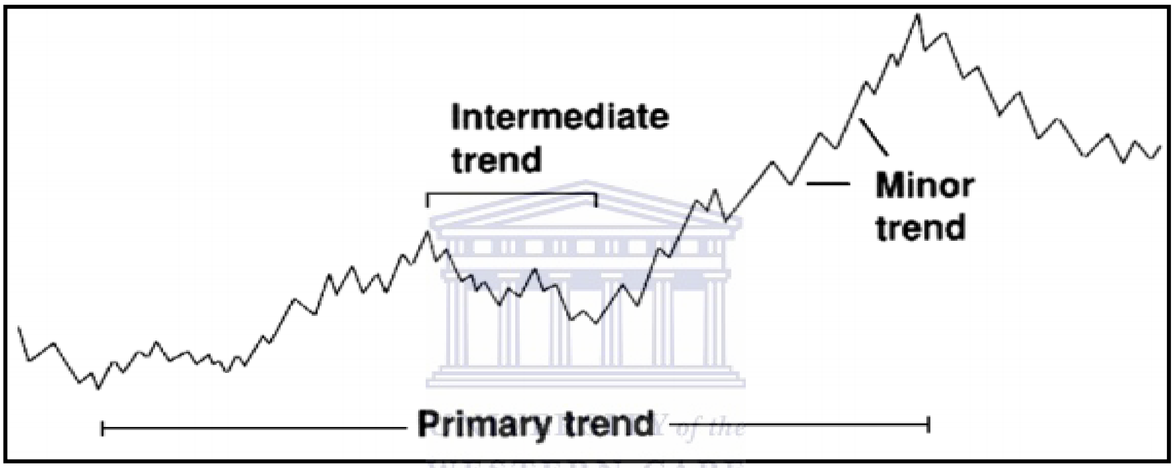
Chua, To and Woodward (1987) test and highlight the potential gains from accurately predicting bull and bear market trends in the Canadian stock market from 1950 to 1983. The results of their study confirm the importance of correctly forecasting bull market trends in comparison to bear markets. Investors with good bull market timing ability will on average earn higher returns than investors with high bear market timing accuracy. Drom's (1989) findings are congruent with Chua, *et al,* (1987) and suggest that predicting a bull market phase is more important than predicting a bear market phase. Furthermore, identifying the bull market as early as possible should also be prioritised in order to maximise returns. De Chassart and Firer's (2001) study on the gains from market timing on South Africa's Johannesburg Stock Exchange now the JSE Limited, suggests that market timing is a viable investment strategy.

Although the above studies on market timing prioritise the gains from accurately timing bull markets, technical analysts cannot ignore the risk reduction benefits from avoiding substantial drawdown's during bear markets. Furthermore, emphasis is placed on having a high market timing or predictive ability. Technical analysts are also challenged with the task of selecting and conditioning the most accurate and prompt technique to identify market trends.

2.7.1. Principles of Technical Analysis

The use of technical analysis in the form of price trends dates as far back as the 17th century Dutch markets. Early seminal proponents included Charles Dow who developed the Dow Theory in 1884, which was revised by Edwards and Magee in 1997 (Chen, 2010). Technical analysis revolves around two central principles. Firstly, stock prices move in trends that are persistent over certain periods as suggested by the Dow Theory. Figure 2.5 illustrates the trending nature of stock prices postulated by the Dow Theory.

Figure 2.5: Stock Price Trends According to the Dow Theory

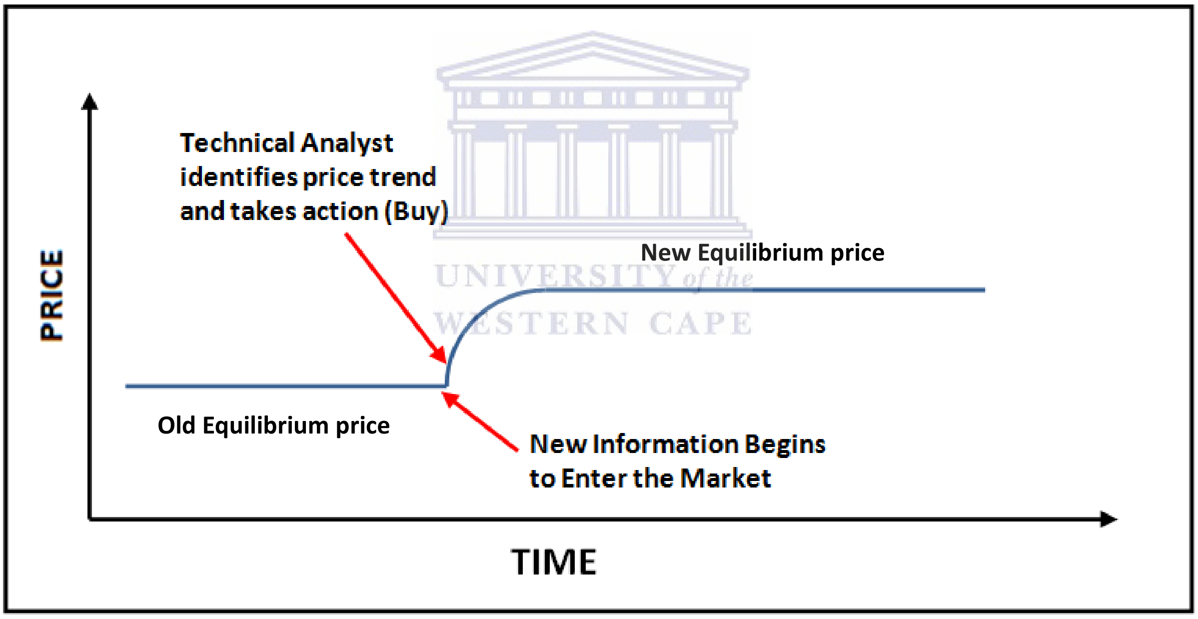


Source: Bowman and Hartle (1990: 690)

The primary trend refers to the broad market trend which is of a long-term nature. The primary trend in Figure 2.5 is upward sloping, signifying a bull market period. A downward sloping primary trend would be indicative of a bear market period. The secondary or intermediate trend is downward sloping, however; it is expected to revert back to the long-term upward sloping primary trend. The secondary trends characterise the medium-term intermediate corrections during bull market phases and recoveries during bear market phases. The short-term minor or primary trends fluctuate on a day to day basis and are mainly attributable to the changes in market demand and supply conditions driven by investor sentiment. Therefore, the key to successful technical analysis is the identification of these trends and recurring price patterns in order to determine the appropriate timing of trades.

Secondly, technical analysts do not reject the value and significance of fundamental data. According to technical analysts, all fundamental information and economic data will be factored into the current stock price. However, the stock prices will only gradually adjust to the new intrinsic value. The success of technical analysts therefore hinges on the exploitable slow response of markets (Chen, 2010). A slow response of the market entails that analysts can identify changes in trends at an early stage and take appropriate action to exploit the price adjustment to its new equilibrium. Figure 2.6 depicts the expected price movements following the entry of new information into the market. As investors assimilate the new information and initiate trades, the market is expected to start trending or moving in a particular direction from its current equilibrium level. Technical analysts endeavour to identify the direction of the price trend at an early stage and take appropriate action in order to capitalise from the shift to the new equilibrium price level.

Figure 2.6: Technical Analysts Reaction to New Trend Information



Source: Figure Modified from Snyman (2011: 14)

Technical analysts are likely to sell stocks when prices are expected to decline and purchase stocks when onsets of bull market trends are identified. Thereafter, technical analysts are bound to maintain investment positions until signs of trend reversals emerge. However, the use of past data to predict trends and the expectation of gradual price changes, challenges the notion of market efficiency postulated by the EMH.

2.7.2. Technical Analysis and Market Efficiency

Many investors primarily rely on past price and volume data to time the market and predict future market trends. However, the Random Walk Hypothesis asserts that price changes are haphazard and not predictable, thus contradicting the profitable use of technical tools and strategies. Similarly, although all forms of the EMH contradict the use of past price and volume data to earn abnormal returns, the weak form EMH particularly asserts that technical analysis is bound to be ineffective.

Proponents of the weak form EMH support the notion of market efficiency through studies that test the strength of technical analysis in improving returns beyond a buy and hold strategy. Early tests by Alexander (1964), Fama and Blume (1966) as well as Jensen and Benington (1970), suggested that technical analysis is a waste of time and effort. The three independent tests took into consideration various filter rules that supposedly capture principles of many technical theories (Jensen and Benington, 1970). The findings of the three studies showed that technical rule based strategies were inferior to and did not consistently outperform a simple buy and hold strategy. This was supported by later studies, for instance Allen and Karjalainen (1999) and Neely (2003) implement genetically optimised technical trading rules on the S&P 500 index in the United States covering data from 1928 to 1995. Both studies failed to provide higher returns than a passive buy and hold strategy, which is inferred to be the optimal investment strategy by the EMH.

On the contrary, various contemporary theorists have challenged the notion of the EMH and have proven the effectiveness of technical trading rules. Brock, Lakonishok and LeBaron (1992), test technical trading rules based on moving averages and trading range break on the Dow Jones Index from 1897 to 1986. The findings of the study support the strength of trading rules in predicting market trends. Campbell (2011) recreated Brock, *et al's* (1992) study in a South African context over the period 1988 to 2007. The findings show that investors can use technical analysis to earn abnormal returns on the JSE, even after accounting for transaction costs. Bessembinder and Chan (1995) also prove that simple technical trading rules can predict stock prices in Asian markets such as Malaysia, Thailand and Taiwan. Chang and Osler (1999) test a technical trading strategy that implements the head and shoulders pattern in the foreign exchange market between 1973 and 1994. The study concludes that the pattern based approach is profitable for certain currencies and supports the predictive ability of simple trading rules, such as the oscillators and momentum rules. Lo, Mamaysky and Wang (2000) test technical pattern recognition across the Nasdaq and New York Stock Exchange (NYSE) from 1962 to 1996. The findings show that technical analysis employing charting patterns can provide incremental information and has practical value in the investment industry. Furthermore, from a total of 95 published modern technical analysis studies that have been considered from both emerging and developed markets between 1960 and 2004, 56 studies (59%) show positive results, 19 (20%) studies show mixed results and only 20 studies (21%) contradict the use of technical analysis (Park & Irwin, 2007).

The success of the above mentioned technical trading strategies challenges the tenets of the weak form EMH. In his book, *'A Random Walk Down Wall Street'*, Malkiel (1999) states that technical analysis is analogous to observing the movement of a pole tied to a pig. The aim of technical analysts is to predict the direction of the poles next movement from a distance, without knowledge of or concern for whether it is a pig. This suggests that there is a high level of subjectivity and the payoffs to technical analysts are due to luck rather than skill. However, technical analysts state that the technical tools such as charting heuristics and quantitative technical indicators objectify technical analysis. Investors' around the world have embraced technical analysis tools; however, academics have been sceptical and have leaned towards justifications based on the EMH. The wealth of research supporting the use and success of technical analysis in assisting with investment timing draws attention to the efficiency of financial markets. Haugen (1995, pp.12), referred to efficient markets as a *"fantasy"* and asserts that *"fantasies are usually gross distortions of reality"*. The increasing literature on stock market inefficiencies challenges the notion of market efficiency and lends a justification to the success of technical trading methods.

The presence of well documented anomalies such as momentum from overreactions and subsequent reversals, suggests that prices do not necessarily follow a random walk. Investors' irrationality, emotions and psychology also influence stock price movements and prices do not instantly reflect new information. Therefore, the new finance stance postulated by Haugen (1995) asserts that markets are not perfectly efficient. De Bondt and Thaler (1985) investigate the overreaction hypothesis on the New York Stock Exchange from 1926 to 1982 and find that investors overreact to new information. Overreaction leads to stock prices moving beyond their fair values before reverting back to the mean which creates a reversal pattern. Haugen (1999) cites the overreaction hypothesis as a reason for the payoffs to technical analysts, as they can purchase stocks following a downward overreaction and profit from the subsequent reversion back to the mean.

Stock market momentum has also been widely cited as one of the factors contributing to the development of trends and success of technical analysis. Momentum can be defined as the persistence of existing market trends. Jegadeesh and Titman (1993) test for momentum in the United States equity market from 1965 to 1989. The notion of momentum posits that winner stocks over the past 12 months continue to do well and loser stocks over the past 12 months continue to do poorly over the short term. The existence of momentum entails that returns in a particular period are correlated to and dependent on previous period returns. Momentum leads asset prices to stray from their fundamental values over the short term; however, asset prices subsequently revert to their mean giving rise to long term reversals as rational investors identify the mispricing (Haugen, 1999). During bull market phases, technical analysts aspire to benefit from the upward momentum and during bear market phases technical analysts aim to identify the onset of reversal back to the mean. Therefore, technical analysts can exploit and profit from market anomalies which are in part attributable to investors' behavioural biases.

2.7.3. Behavioural Finance and Technical Analysis

The advent of behavioural finance has also challenged the underpinnings of the EMH which state that investors are rational. According to the behavioural finance school of thought, investors' are subject to errors, overconfidence and heuristic simplification by overweighting certain information due to restricted memory and attention (Hirshleifer, 2001). Henceforth, according to behaviourists, investors are irrational and influenced by their emotions.

The conservatism bias suggests that investors react slowly to information or market changes over the first twelve months, before possibly overreacting in the medium and long term (Ritter, 2003). This entails that reversals and onset of market trends are not always instantaneous as suggested by the notion of perfect market efficiency. The conservatism bias can be attributed to behavioural biases such as investors being sceptical about new information over the short-term. However, over the long-term investors either better understand the news or are overtaken by the bandwagon effect and increasingly follow the actions of other investors which can translate into a period of sustained momentum. The slow absorption and assimilation of new information and news also gives rise to positive autocorrelation (Barberis, Shleifer and Vishny, 1998). The positive autocorrelation is supportive of the trending nature of stock prices for instance, a positive news report will result in positive returns over the given near future.

The conservatism bias is complemented by an array of noisy rational expectations theories, which posit that prices do not instantly reflect all available information. The noisy rational expectation models attribute the slow reaction of the market to information asymmetry and cost of information, rather than investor psychology (Park and Irwin, 2007). The models are based on the assumption that the informed traders are willing to pay for new information and will react quickly to information in order to capture profits or restrict losses. In contrast, the ill-informed will take longer to react to information and will go with the market in the following periods which results in prices trending in a particular direction over sustained periods. This implies that investors can utilise technical tools and techniques to identify the systematic gradual adjustment of trends and profit from the subsequent overreaction.

Financial time series data is also susceptible to the presence of long memory or the biased random walk. Similar to the conservatism bias which posits that overtime investors response to new information increases as they assimilate the news, long market memory can be construed as the decaying effect that a past event has on future outcomes (Aye, Balcilar, Gupta, Kilimani, Nakumuryango and Redford, 2012). Long market memory is characterised by persistent temporal dependence or the presence of positive serial correlation between stock prices which decreases overtime before disappearing. The entry of new information is not immediately absorbed; however, it is expected to influence the stock price in subsequent periods which results in trending stock prices. The presence of long market memory directly challenges the random walk hypothesis which states that stock prices have no correlation from one term to the next and prices reflect all information immediately. In essence, if the Random Walk Hypothesis is to be valid, the market should not have any memory.

A series that exhibits long memory is also characterised by distant but non-periodic cyclical patterns that tend to repeat themselves (Barkoulas and Baum, 1996). Therefore, price series with long memory provide technical analysts with an opportunity to use trading techniques that explicitly depend on identifying representative and repetitive patterns. These patterns ideally provide technical analysts with cues regarding potentially repetitive trend behaviour or market cycles that can be exploited to maximise returns beyond a buy and hold strategy.

Aye, *et al.* (2012) test the long market memory in stock returns in Brazil, Russia, India, China and South Africa (BRICS countries) from 1995 to 2012. The results support the presence of long market memory in all five stock exchanges which contradicts the weak form EMH. Similarly, Skaperda (2014) finds statistically significant evidence of long market memory over the period 2000 to 2013, in 22 international stock markets from Asia, Europe and North America. The presence of long memory provides an opportunity for technical analysts to predict and exploit trends with greater certainty given the slow assimilation of new information and the existence of correlation in time series data.

Majority of the behavioural theories predominantly relate the irrational stock market fluctuations to the arrival of new information in the market. However, according to Shiller (1990) stock price variability is not necessarily due to new information or changes in economic variables. Instead, variability in stock prices can be attributed to herd behaviour or psychology of the masses whereby many investors follow or copy the decisions of other investors. According to the behavioural finance proponents, investors' irrationality contributes to the resemblance of decisions and opinions that guide their actions. Herd behaviour of groups can be attributed to the social pressure of belonging, the rationale that a group cannot be wrong or from trying to mimic profits of other investors. Herding behaviour has been documented by Lao and Singh (2011) in the Chinese and Indian stock market and by Almeida, Costa and da Costa (2012) in the United States, Chilean, Argentinean and Mexican markets. Similarly, Ouarda, El Bouri and Bernard (2013) find evidence of herding within majority of the sectors in the European stock markets.

The presence of herding in financial markets can influence prices by affecting the demand and supply equilibrium conditions. Schmidt (2002) uses agent based models to indicate that the actions of multiple traders can affect market liquidity. The combined actions of many investors can either lead to excess demand which causes prices to rise or an excess supply resulting in a downward spiral in prices over the short term. The imbalance in supply and demand conditions may persist and take time to clear. Therefore, the potential disequilibrium in markets provides an opportunity to identify trends and profit using positive feedback trading (Hershleifer, 2001). Feedback traders buy into trends, thus exaggerating them and leading to systematic overshooting of prices and trend formation that can be identified by and exploited using technical trading tools.

The literature on pricing anomalies, investor psychology and market memory contradicts the Random Walk Hypothesis and EMH, as past prices could provide insight into future trends and cycles. A slow response of the market and a farsighted, astute understanding of trends could theoretically allow technical analysts to time the market.

2.8. Conclusion

The Modern Portfolio Theory pioneered by Markowitz (1952) introduces the concept of mean-variance efficiency which is graphically depicted in the efficient frontier of risky assets. The efficient frontier denotes portfolios that provide the highest possible return for given levels of risk or lowest risk for given level of returns. Tobin (1958) developed on the MPT and suggested the two step separation theorem. The first step involves identifying the market portfolio which occurs at the point of tangency between the efficient frontier and the highest attainable capital allocation line known as the capital market line. Secondly, investors allocate their capital between the market portfolio and the risk-free asset in order to match the investment characteristics to the investors risk profile. Both the MPT and separation theorem are underpinned by the Efficient Market Hypothesis (EMH) proposed by Fama (1970, 1991), which states that investors are rational and would therefore have homogenous expectations in terms of mean-variance optimisation goals.

Market efficiency entails that market prices fully and fairly reflect all available information instantaneously and thus, rules out the potential to consistently outperform the market. The Random Walk Hypothesis posits that price trends cannot be anticipated as price changes are unsystematic. The EMH proposes three forms of market efficiency namely the weak, semi-strong and strong form, with each form introducing a more sparse and restrictive type of information that is already incorporated into the market quotation of a security. The three forms of the EMH sequentially rule out the ability of successfully using a particular forecasting tool to consistently outperform the market. Therefore in an informationally efficient market, the EMH promulgates a simple passive investment strategy for instance by buying and holding mutual funds or exchange traded funds (ETF's).

On the contrary, detractors from the EMH state that the concept of efficient markets is a theoretical ideal based on unrealistically restrictive assumptions for example rationality of all investors. However, in reality markets could experience cycles of mispricing arising from sources such as information asymmetry and investor irrationality promulgated by the behavioural finance school of thought. According to behavioural finance, investors are irrational and their decision making is affected by psychological biases and cognitive errors.

The prospect theory promulgated by Kahneman and Tversky (1979) provides support for behavioural finance by elaborating on the behaviour of investors in the presence of risk. The prospect theory introduces loss aversion which states that investors experience greater disutility from losses than the utility realized from equal gains. Furthermore, the prospect theory posits that investors are risk-averse in the positive domain and risk-seeking in the negative domain. Hirshleifer (2001) summarizes sources of behavioural biases into three categories namely, emotions, heuristic simplification and self-deception. The probable presence of investors psychological biases suggests that stock price could deviate from or overshoot their true intrinsic values.

According to Siegel (2006), in the presence of noise in the market, the cap-weighted market portfolio ceases to be mean-variance efficient. The cap-drag on performance inherent in cap-weighted indices can be avoided by employing alternative indexing strategies such as equal-weighted, fundamental-weighted and optimised asset allocation techniques. Asset allocation employing the static portfolio optimisation approach provides investors with a low cost strategy that identifies constant optimal constituent weights, in order to maximise the mean-variance efficiency of the portfolio.

Alternatively, investors can implement dynamic market timing techniques in the form of technical analysis. Technical analysis involves the use of past price and volume data to identify future market trends. It is built on the basic tenets that prices move in trends and trends adjust slowly which contradicts the Random Walk Hypothesis and EMH. The presence of anomalies, dependencies in prices and investors psychological biases also challenges the EMH and lends a justification for payoffs to technical analysis.

3

A Review of Prior Literature

3.1. Introduction

According to the Efficient Market Hypothesis (EMH), investor's attempts to engage in active portfolio management and timing strategies are bound to be futile, as all known information is already incorporated in the asset price. With the three forms of the EMH sequentially ruling out the profitability of active management using progressive information, the EMH implicitly promulgates a passive buy and hold strategy that aims to track rather than outperform a specified benchmark. The implementation of passive investment strategies has largely been assisted by the advent and growth of tracking instruments such as depository notes, exchange traded funds (ETF) and passive mutual funds. In particular, the underlying mechanism of the ETF's provides investors with an instrument that represents a basket of investable securities that can be purchased in the same manner that a stock is traded on an exchange. Therefore, investors can easily implement passive cap-weighted strategies at minimal cost with the added advantage of liquidity (Gastineau, 2008). However, empirical literature suggests that in real world markets, investors deviate from the academic ideal of rationality. According to behavioural finance, investors are subject to cognitive and systematic errors driven by irrationality, which culminate into market inefficiencies such as overreaction and subsequent reversals documented by De Bondt and Thaler (1985, 1987). Consequently, irrationality in financial markets challenges the mean-variance efficiency of the optimal cap-weighted market portfolio proposed by the Modern Portfolio Theory (MPT).

Motivated by the potential existence of market inefficiencies and performance drag of cap-weighted portfolios, investors and portfolio managers are likely to engage in alternative active management strategies in order to outperform rather than simply track a benchmark. Active managers commonly use stock picking or alternative portfolio weighting methods that differentiate the portfolio composition and performance from the benchmark. Yu (2008) and Hsieh (2010) document the use of active extension and optimised asset allocation strategies. The studies test various strategies that differ in terms of portfolio constraints such as short selling and leverage, in order to identify optimal weightings aimed at achieving a particular investment objective, such as mean-variance optimality.

On the other hand, dynamic market timing strategies involve timing market or sector trends. Dynamic timing involves the use of a technique that identifies the optimal turning points or best portfolio constituents based on rolling time-series performance. Investors can attempt to time markets by implementing technical strategies based on prior momentum of stocks or industries. Momentum strategies can assist in identifying sectors in which to take long and short positions based on the direction of persistence, as suggested by Moskowitz and Grinblatt (1999). Alternatively, more conventional quantitative tools such as moving averages employed by Faber (2007) and Hsieh (2010) could be used to identify and profit from trends. This chapter also discusses the use of charting based techniques that could be used to identify buy or sell signals directly from price and volume charts. The aim of using these technical tools is to buy into an asset or sector as promptly as possible following a return trough in order to profit from bull markets and sell straight after its peak to avoid losses during bear markets. The use of these technical strategies that extrapolate trade signals from past price and volume data are essentially tests of the weak form EMH, which states that technical analysis is fruitless in outperforming the market.

3.2. Price Efficiency of Passive Exchange Traded Funds (ETF's)

Passive ETF's are investment instruments that are designed to track the performance of a particular index or asset class. Unlike mutual funds, the ETF's are priced and traded throughout the day like securities on a stock exchange. The value of an ETF is determined by a basket of securities that are held in proportion to their representation on a benchmark or underlying index, whose returns the ETF aims to replicate (Charteris, 2013). ETF's can be purchased on the secondary market by investors. Authorised participants who act as market makers can also create and redeem ETF shares in kind in the primary market, by depositing or selling the constituent shares with the ETF trust or custodian.

Though passive ETF's are designed to track an index, market frictions such as information asymmetry, dividends, benchmark volatility, management costs and transaction costs are likely to result in ETF's that do not perfectly track the underlying index (Frino and Gallagher, 2001). Tracking error refers to a quantified measure of the deviation between a fund and its benchmarks returns. It is used as measure of efficiency and performance of a passive index tracking instrument. Furthermore, the tracking error of a fund is also affected by the type of replication strategy adopted by the ETF manager. Replication strategies can be full replication, stratified sampling or optimisation techniques (Gallagher and Segara, 2005). In theory, full replication strategies should be able to minimise tracking error by holding all underlying index constituents in the exact proportions. However, the probable higher cost of full replication could exaggerate the tracking error, as the fund has to hold all securities in the exact proportions as the underlying index. Stratified sampling and optimisation techniques may also be prone to high tracking errors as these funds only hold a representative subset from the entire list of index constituents, in an attempt to mimic the risk and return attributes of an underlying index. The tracking accuracy of replication strategies such as stratified sampling can also be affected by the managers' skill or decision making with regard to selecting the appropriate assets.

Gallagher and Segara (2005) examine the performance of ETF's in the Australian market over the period January 2002 to December 2003. The study tests the ability of passive ETF's to track the underlying indices on the Australian Stock Exchange (ASX). The study focuses on 4 ETF's that track various S&P/ASX equity indices and employs two different tracking error performance measures. The first measure simply takes the average of the absolute deviations between the fund and its benchmark, whereas the second measure looks at the standard deviation of the differences between the fund and benchmark returns. Although the findings demonstrate the presence of tracking errors using both computational approaches, the findings are not significant. Analysis of the results also demonstrates that there is no significant bias, and the mean average differences between the ETF and index returns are negligible. Furthermore, as per the objective of the ETF's none of them outperform or underperform their respective benchmark indices. Therefore, in the long run investors will achieve returns similar to the underlying index.

Svetina and Wahal (2008) study a wider sample of 584 ETF's which include domestic United States (U.S.) equity, international equity and fixed income ETF's from 1993 to 2007. The study assesses the efficiency in terms of the excess compound annual returns as well as the tracking error between the ETF and its respective underlying index. Unlike the findings of Gallagher and Segara (2005), the results show that in terms of returns, passive tracking ETF's generally underperform their benchmarks over the study period as suggested by the persistent negative tracking errors. Furthermore, the tracking errors are higher for international equity ETF's in comparison to the U.S. ETF's. The general deviations of ETF returns and tracking error are attributed to the presence of transaction costs incurred upon index reconstitutions.

Blitz and Huij (2011) also evaluate the performance of Global Emerging Market (GEM) ETF's over a 7 year period from 2003 to 2010. The study focuses on emerging market ETF's listed in the U.S. and European ETF markets. The findings of the study show that the tracking errors over the short term are highly overstated due to the price fluctuations and deviations from the net asset value (NAV). However, over longer evaluation periods the tracking errors reduce substantially to levels computed using the NAV. Passive emerging market ETF's possess substantially higher tracking errors than passive ETF's that track developed market indices. The results also show that ETF's that employ statistical or stratified sampling techniques possess higher tracking errors than ETF's that rely on full replication techniques. However, it is important to note that the authors assert that full replication strategies are not guaranteed to have better index tracking abilities than statistical techniques. Statistical sampling techniques may achieve better tracking performance and lower tracking errors;

however, that is dependent on the ETF management team's ability to make optimal trading choices in order to match the characteristics of the underlying index.

Although tracking error is a widely used metric for performance evaluation of passive ETF's and index tracking instruments, prior literature does not restrict the application of performance evaluation metrics that are more widely used in assessing actively managed investment tools. However, the assessment and interpretation of results need to be handled in the context of the objectives of passive investment vehicles. Garyn-Tal (2013) assesses the alpha which provides an indication of underperformance or outperformance of an ETF relative to the underlying index from 2000 to 2012. The study employs data on 88 ETF's that track Russell and S&P indices in the U.S. stock markets. The main objective of the study is to compare the ETF alpha computed based on regressing the ETF and index excess returns to the ETF alpha computed using risk-adjusted excess returns. The risk-adjusted excess returns account for risks by adjusting the underlying index returns for direction in the case of inverse ETF's and for leverage in the case of leveraged ETF or both for inverse leveraged ETF's. The findings of the study show that there is a high correlation and agreement in alphas computed using excess return and risk-adjusted excess returns, thus the two methods can be used interchangeably without a significant bearing on validity of results.

Investors can also assess the performance of ETF's based on price efficiency. Price efficiency of ETF's is concerned with deviations of prices from the NAV and how quickly this deviation disappears, as authorised participants create and redeem units. Ackert and Tian (2000) are amongst the first to assess the price efficiency of Spider ETF's that track the S&P 500 in the United States (U.S.). The examination period of the study was from January 1993 to December 1997. The study indicates that the Spiders do not trade at an economically significant discount or premium over time even though the fund experiences reasonable premiums and discounts over the short-term. In a subsequent study, Elton, Gruber, Comer and Li (2002) also examine the performance of the S&P 500 Spider ETF from 1993 to 1998. The results show that on average the Spider ETF trades at 0.018% discount to its NAV and the deviation disappears within one day. The effective elimination of the discount through the creation and redemption process keeps the market price close to the NAV and suggests that the Spider ETF's are price efficient.

Price efficiency of ETF's has also been studied in emerging markets. Lin, Chan and Hsu (2005) test for the price efficiency of Taiwan's only ETF at the time of writing, namely the Taiwan Top 50 Tracker fund (TTT) over the period 2003 to 2004. The findings of the study show that the TTT ETF does not trade at a significant premium or discount. Although the ETF trades a premium for long periods, the price deviations from the NAV are noted to be minimal and insignificant, thus ruling the potential arbitrage opportunities. The almost perfect correlation between the TTT ETF and the Taiwan Top 50 Index suggests that the ETF is price efficient and provides a convenient vehicle to replicate the index performance.

Charteris (2013) evaluates the price efficiency of South African Listed ETF's over the period June 2008 to December 2012. The sample consists of 4 domestic and 3 global ETF's listed on the JSE Limited. The findings of the study show that 5 of the funds trade at a premium and 2 funds trade at a discount to their NAV. Furthermore, similar to the findings of Elton, *et al*. (2002), the price deviations from the NAV do not persist for more than 2 trading days, thus limiting the potential arbitrage opportunities. However, the fact that current day deviations can provide incremental information regarding the next day's returns is stated to be in violation of the weak form EMH. In addition, Charteris (2013) also proposes a method of assessing price efficiency using volatility. The volatility of an ETF's return in theory should not exceed that of the underlying index in a market in which rational investors base their valuation on fundamental metrics. Overall, the study concludes that the South African ETF market is fairly efficiently priced, thus ruling out prolonged arbitrage opportunities.

In a more recent study, Bas and Sarioglu (2015) evaluate the price efficiency of ETF's from the Turkish market. The study examines 16 ETF's over the period 2005 to 2013. The findings of the study are congruent with prior studies and show that the ETF prices are close to their NAV's. Furthermore, the study concludes that there are no economically significant arbitrage opportunities in the Turkish market. Similarly, Swathy (2015) investigates the price efficiency of 5 ETF's listed on the National Stock Exchange of India (NSE). The study period spans from 2010 to 2015. The results show that ETF's are price efficient with 4 of the ETF's trading at the NAV. Furthermore, any deviations from the NAV do not persist for more than one day. Thus, empirical literature largely supports the use of ETF's as efficient tools to implement passive index tracking strategies promulgated by the EMH.

3.3. Portfolio Optimisation in Active Management

In an investment industry plagued by competition and multiple investment options, portfolio managers and investors constantly envy of outperforming rather than passively tracking specified benchmarks. This can be done by systematically placing the portfolio out of sync of the general market or the pre-specified benchmark. However, in many cases investors are bound by certain portfolio constraints and regulations that limit their investment actions.

Clarke, De Silva and Sapra (2004) investigate the effect that portfolio constraints have on limiting investors abilities to fully make use of available information. The study employs the S&P 500 data. In order to determine the effect of different constraints the study utilises the information ratio which is an indication of the managers' skill, in order to determine how effectively the information is transferred into portfolio weights. The results show that the most significant constraint that limits the investors' use of information is the long-only constraint as it restricts investors from attractive hedging opportunities. In addition, the long-only constraint limits the ability to make profits from short selling unattractive securities. Furthermore, simply allowing a limited amount of short positions in a portfolio can significantly improve the portfolio performance and efficiency of information usage. For instance, short selling 20% and investing the proceeds on the long side (120/20 strategy) retains 100% market exposure and could be advantageous in terms of improved portfolio performance. Sorensen, Ma, Hua and Qian (2007) support the findings of Clarke, *et al.* (2004) by using a simulation technique under a variety of real world conditions, which show that relaxing the long-only constraint on portfolios can deliver higher alphas and risk-adjusted returns. Sorensen, *et al.* (2007) also explore the costs of long-short strategies and find that the benefits of taking moderate short positions outweigh the additional costs associated with leverage or borrowing shares as well as higher turnover.

In the light of increased application of long-short or active extension investment strategies, substantial research has surrounded the question of optimal level of short positions. Alford (2006) shows that alpha increases more by increasing short positions from long-only to 20% than increasing short positions from 20% to 40%. Therefore, the rate of performance improvement is not a linear function of the level of short positions taken and that beyond a certain point additional short positions may erode performance. Similarly, Sorensen, *et al.*

(2007) conduct a simulation analysis of various shorting ratios and the results show that there is no single optimal ratio. The study concludes that the optimal level of shorting is influenced by various factors such as the investment mandate and the costs of implementation.

According to Johnson, Ericson and Srimurthy (2007) although investors are exposed to varying choices of active extension strategies, the 130/30 strategy that shorts 30% and goes long 130% is one of the most widely used strategies. The study conducted over a 13 year period from 1994 to 2006 employs the Russell 1000 and MSCI EAFE indices sorted based on the Global Industry Classification Standard (GICS). The results show that the 130/30 adds significant value over long-only strategies with both long and short positions contributing to the outperformance of the traditional long-only constrained strategy. Géhin (2007) compares the 130/30 strategy to alternative less restrictive levels of shorting strategies. The study explores simulated short positions between 10% and 50% which is in line with the US Regulation-T (Reg-T)[1] and European Union Regulations of maximum 200% gross market exposure. The study concludes that due to the mass of variables affecting the performance of active extension strategies such as managers' skill, market conditions, transaction costs and turnover costs, the supremacy of a single level of shorting cannot be established. Consequently, certain 130/30 funds such as the New York Life Investment Management Mainstay 130/30, have adopted flexible shorting varying between 20% and 40% with long positions between 120% and 140%, respectively (Géhin, 2007).

Portfolio constraints play a significant role in determining optimal asset allocation. Yu (2008) investigates style based static portfolio optimisation on South Africa's JSE Limited from 1998 to 2006. The study performs portfolio optimisation for four investment strategies namely; long-only mean-variance optimised strategy with no leverage, long-only tracking error optimised strategy with no leverage, long-short mean-variance optimised strategy with leverage and the market neutral strategy with leverage. The study leverages portfolios up to 200% by allocating the long portfolio amongst the local style indices with short positions in the JSE/FTSE All Share Top 40 index. Cash is used as a balancing item if the long positions exceed or fall short of 100%. The results of the study show that the long-short and market

[1] United States Federal Reserve Board regulation governing the amount of short positions or credit that a brokerage firm or dealer can extend to customers for the purchase of securities. Reg-T limits maximum borrowing to 50% of the initial purchase price, which is equivalent to a 150/50 active extension strategy.

neutral strategies generate higher returns with same level of risk as the long-only strategy. Furthermore, the Sharpe ratio of long-short and market neutral strategies increases continuously as the leverage increases to 200%. The results support earlier studies that document the drag created by the long-only constraint and improvement in performance resulting from taking short positions.

Hsieh (2010) extends upon the study by Yu (2008), by applying the methodology to a wider universe of international style proxies developed from the Dow Jones Sector Titans Composite Index over the period 1991 to 2008. The study tests the four strategies investigated by Yu (2008) in a global market context with short sales permitted in the MSCI World Index which is employed as the market proxy. The static optimisation process incorporating short sales and leverage ensures that the portfolio performance is distinguishable from constituent style indices. The results of the study show a drastic improvement in risk-adjusted performance for strategies which undertake short sales and leverage in comparison to the traditional long-only strategies. Analysis of the results indicates that the improvement in risk-adjusted performance of short-sale enabled strategies is largely attributable to the risk reduction benefits rather than improved returns. The standard deviation is almost half for short-sale enabled strategies in comparison to long-only strategies, and beta which is a measure of systematic risk is close to zero for both short-sale enabled strategies. Henceforth, the optimised long-short and market neutral strategies achieve higher risk-adjusted returns than the MSCI World Index, the constituent style indices and the long-only strategies as measured by the Sharpe ratio and Treynor measure. The findings of Yu (2008) and Hsieh (2010) also indicate that static optimisation models can profitably be used to allocate resources in order to outperform pre-specified benchmarks.

3.4. Market Timing Using Technical Analysis

Investors could also improve portfolio performance beyond a passive strategy by employing timing strategies. Timing of attractive industries could be achieved through the use of conventional technical trading rules. One of the objectives of using technical strategies is to assist with optimal timing in order to maximise returns. Furthermore, technical tools have the added advantage of providing risk management benefits during market downturns even though most technical indicators tend to be lagged in nature (Hsieh, 2010). For instance, during downturns such as the 2002 dotcom bubble and 2008 financial crisis, the majority of the sectors tend to be highly correlated (Hsieh, Hodnett and van Rensburg, 2012). The correlation between sectors reduces the effectiveness of sector driven strategies that rely on the imperfect sector correlation. However, by employing technical indicators investors could reduce drawdown and losses during market downturns by systematically hedging the exposure to the market, following trigger signals from conditioned trading rules.

Grauer, Hakansson and Shen (1990) conduct one of the first studies that examines the sector rotation strategy. The study focuses on the U.S. equity market which consists of 12 equally weighted and value weighted indices over the period of 1934 to 1986. Three forms of sector rotation strategies are tested namely, passive, semi-active and active strategies. The passive strategy adopts a buy and hold approach and holds the value weighted sector index. The semi-active strategy holds equally weighted sector indices and requires rebalancing. The active strategy employs a multi-period portfolio selection approach based on historical data between the value and equally weighted sector indices. Grauer, *et al.* (1990) conclude that semi-active and active strategies perform well and earn abnormal returns. According to Ammann and Verhofen (2008), the fact that the study does not incorporate predictive variables suggests that it is essentially based on market momentum and mean reversion.

Beller, Kling and Levinson (1998) explore the potential tools to predict sector performance. The study period spans from 1973 to 1995 and covers 55 sector groupings in the U.S. equity market. The study develops six portfolios each quarter, namely a benchmark market portfolio, three portfolios based on predicted returns and two mean-variance optimised portfolios. The three portfolios based on predicted return include a portfolio with the highest return sectors (momentum based approach), the lowest return sectors (contrarian style approach) and a portfolio which takes a long and short position in the highest and lowest ex-post return sectors, respectively. Although these portfolios provide mixed results with regard to outperformance of the benchmark, the mean-variance optimised portfolios provide the strongest predictive strength. Both mean-variance optimised portfolios provide statistically significant positive alpha of 3.00%. Thus, Beller, *et al.* (1998) conclude that past sector performance can be used to predict future trends.

3.4.1. Sector Momentum Effect and Investment Strategies

As suggested by prior literature, momentum in stocks is well documented in both U.S. and international markets by Jegadeesh and Titman (1993), Rouwenhorst (1998), Conrad and Kaul (1998) and Schiereck, De Bondt and Weber (1999). Furthermore, sector based research has substantially focused on the presence of momentum within sectors. Moskowitz and Grinblatt (1999) test for the presence of the momentum effect in sector components of stock returns. The study tests for persistence in returns mainly over the intermediate-term from 1963 to 1995. The study employs the two-digit Standard Industrial Classification (SIC) codes to classify New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and National Association of Securities Dealers Automated Quotations (NASDAQ) stocks into sectors. The authors find that sector momentum is persistent as well as a significant contributing factor to individual stock momentum.

Moskowitz and Grinblatt (1999) show that in a given period, a basket of winner or loser stocks are largely concentrated in a few sectors. Henceforth, the study explores a momentum investment strategy in order to exploit sector momentum. The methodology involves developing 2 portfolios, namely the winner and loser portfolios based on past returns, using the overlapping holding periods technique suggested by Jagadeesh and Titman (1993). The winner portfolio is constructed by equally weighting the 3 best performing sectors and the loser portfolio is based on equally weighting the 3 lowest ranked sectors. The strategy takes a long position in the winner portfolio and shorts the loser portfolio, thus creating a self-financing strategy. The study tests 1, 6 and 12 months formation periods and 1, 6, 12, 24, and 36 month holding periods. The strategy is rebalanced at the end of each holding period based on the preceding formation periods winner and loser industries. The analysis of the results mainly focus on the 6 month formation and holding periods, which provides 0.43% monthly average returns while other formation and holding periods provide similar results. The study also shows that the majority of the monthly returns are attributable to the winners continuing to outperform whereas the gains from shorting loser sectors was proportionately less. Moskowitz and Grinblatt (1999) conclude that a sector or industry momentum strategies are able to achieve significantly higher returns than a traditional stock momentum strategy.

In a subsequent study, Bacmann, Dubois and Isakov (2001) investigate the profitability of momentum strategies in the G-7 countries (U.S.A., United Kingdom, Canada, France, Japan, Germany and Italy). The study explores the role played by sectors in explaining momentum over the period 1973 to 2000 and employs the level 6 Financial Times Stock Exchange (FTSE) international industry classification. The results of employing a zero cost self-financing strategy and normalised long-short weightings indicate that the 6 month formation and holding strategy provides significantly positive results at a 5% confidence level for all G-7 countries, except Japan.

Swinkels (2002) furthers the study of Moskowitz and Grinblatt (1999) by examining the profitability of sector momentum strategies in an international context by employing the U.S., Europe and Japanese stock market data. The study period spans from 1973 to 2000 and employs the Datastream sector classification. The study adopts the same methodology employed by Moskowitz and Griblatt (1993). However, Swinkels (2002) selects a fixed number of 4 sectors within winner and loser portfolios. The finding of the study shows that stock level momentum patterns are widely observed at sector level for all regions studied. In the U.S. market, sector momentum is absent at a 3 month formation period, however it is positive and significant for 6 and 9 month formation periods. The results for 12 month formation periods are not significant in the U.S., thus suggesting that sector momentum is a medium or intermediate-term effect in the U.S. The sector momentum results from the European market suggest that sector momentum is generally more pronounced in European markets than in the U.S. market. For instance, a 6 month formation and holding strategy provides 0.19% higher excess return in Europe than in the U.S. and the results are significant at a 10% level. The Japanese market shows no indication of the presence of sector momentum, which is not surprising as individual stock momentum is also absent in Japan.

Swinkels (2002) also tests momentum strategies with a one month skip between formation and holding periods. The results show that the skip significantly reduces excess returns and the difference is largest at short horizons. This is congruent with Moskowitz and Grinblatt's (1999) findings, as a delay in trading wipes out profits. Swinkels (2002) also addresses the concern that momentum profits are attributable to compensation for bearing higher risks. However, the factor loadings on the Fama-French (1993) three factor model indicate that the momentum effect is not a compensation for bearing risk on market, value and size factors.

In a subsequent study, Giannikos and Ji (2007) revisit the profitability of sector momentum strategies and its link to individual stock momentum in the U.S. and 37 international countries. The study employs the two-digit SIC code over the period 1962 to 2000. The selected methodology is based on Jegadeesh and Titman's (1993) study and focuses on a 6 month formation and holding period. The findings of the study reiterate that sector momentum strategies provide economically meaningful and statistically significant profits around the world. Sector momentum strategies are found to be profitable on each continent tested with average statistically significant monthly profits of 0.63%, 0.41% and 0.53% in the Americas, Asia and Europe, respectively. Sector momentum strategies also provide abnormal returns in both developed and emerging economies. However, the sector momentum effect is stronger in developed markets, which is congruent with individual stock momentum findings as suggested by Rouwenhorst (1998). Furthermore, the average world excess return using the sector momentum strategy is 0.49% and is statistically significant at a 1% significance level.

Giannikos and Ji (2007) find that winner portfolios from 89.5% of the countries studied significantly outperform their respective local markets. Thus, long positions in winner portfolios largely contribute to the momentum returns, which is congruent with the study by Moskowitz and Grinblatt (1999). Furthermore, Giannikos and Ji (2007) also find no evidence of sector momentum effect in Japan which is in line with the earlier studies by Bacmann, *et al.* (2001) and Swinkels (2002). However, the concern with regard to Giannikos and Ji's (2007) study is that it does not account for transaction costs. The findings are supported by the assertion that transaction costs do not eliminate momentum profits as stated by Jegadeesh and Titman (1993) and Korjczky and Sadka (2004). However, the presence of transaction costs cannot be ignored for short horizon, frequent trading. This is supported by the findings of Pan, Liano and Huang (2004), which show that the sector momentum effect is significantly reduced after considering real world trading costs.

Fu and Kang (2009) investigate the sector momentum effect in the Taiwanese market from 1995 to 2007. The study adopts the methodology promulgated by Lo and Mackinlay (1990) which is applied to 19 Taiwanese sector groupings. Unlike Jegadeesh and Titman's (1993) methodology which ranks the stocks and selects top and bottom deciles, Lo and Mackinlay's (1990) approach divides all sectors into two groups. The group of sectors with returns greater than the average are taken as the winner portfolio and the group with returns less than the average are part of the loser portfolio. Furthermore, instead of assigning equal weighting to winner and loser portfolios, the strategy assigns weights based on the difference between sector returns and the average return of all sectors. The advantage of Lo and Mackinlay's (1990) approach is that all industries are included in the winner and loser portfolios, which is important if the sectors are not sufficient. The results of the study show that out of all the holding and formation period permutations, only one strategy provides statistically significant positive returns at a 5% level. Therefore, the sector momentum effect is minimal in Taiwan and the findings are reaffirmed by applying Jegadeesh and Titman's (1993) methodology. Fu and Kang's (2009) findings are congruent with the study by Liu and Fu (2011) on the Taiwanese market over the period 1995 to 2009. Liu and Fu (2011) find that the sector momentum effect is very small in Taiwan and non-existent after considering trading costs.

Empirical literature presented provides evidence in support of the presence of the sector momentum phenomenon; however, the majority of the studies have focused on assets that are not easily tradable. For instance, Moskowitz and Grinblatt (1999) successfully document the existence of sector momentum and resultant profits; however, an investment strategy looking to exploit these gains would have to invest in as many as 230 stocks for certain sectors. Henceforth, studies have explored the opportunity to benefit from sector momentum through tradable sector tracking instruments such as mutual funds or ETF's.

O'Neal (2000) examines the potential to exploit sector momentum using actively traded sector mutual funds. The examination period spans over a 10 year period from 1989 to 1999 and the study employs Fidelity Select Portfolios sector funds. The advantage of using mutual funds over individual stocks is that the transaction costs are known in advance. Furthermore, investors can track a sector through a single investment vehicles rather than purchasing multiple stocks. O'Neal (2000) tests 3, 6 and 12 month formation and holding period strategies. The results suggest that the sector momentum strategy using mutual funds provides statistically significant excess returns of 7.50% per annum and the momentum effect is strongest for the 12 month holding period. Over the 10 year examination period, the majority of the momentum portfolios outperform the S&P 500, Wilshire 5000 and Russell 2000 index in terms of total returns. Momentum portfolios also fare better than the benchmark derived from the mutual fund universe. However, the higher total risk of the 12 month momentum portfolios entails that only one out of the four portfolio's match the S&P 500 in terms of risk-adjusted performance, as measured by the Sharpe ratio. In addition, three out of four portfolios achieve higher Treynor measures than the S&P 500, which denotes excess returns per unit of systematic risk. According to O'Neal (2000) systematic risk should be prioritised when incorporating the momentum strategy in a well diversified portfolio.

Although O'Neal (2000) successfully documents and promulgates the use of sector mutual funds to profit from sector momentum, the study has been criticised with respect to the choice of investment vehicle used. By using actively managed mutual funds, there is uncertainty regarding whether the outperformance can be attributable to sector momentum or to the skill of the mutual fund portfolio manager. Consequently, Andreu Swinkels and Tjong-A-Tjoe (2013) address the problem of non-investability in prior studies by analysing the profitability of sector momentum strategies using passive sector ETF's. ETF's are similar to mutual funds in that they represent a stake of ownership on a pool of assets. However, the advantage of trading ETF's over mutual funds is that they are priced and traded throughout the day and ETF's can be sold short, which may not be the case for mutual funds.

Andreu, *et al.* (2013) employ ETF's that are designed to track the S&P Select Sector Indices which include all stocks from the S&P 500 index over the period 1998 to 2009. The study employs the methodology used by Jegadeesh and Titman (1993) and the results show that a 6 month formation and holding strategy provides 0.84% excess return per month. The returns and risk-adjusted performance from using ETF's are in line with studies based on non-tradable indices with shorter and longer holding periods providing lower returns. The findings also reiterate the lack of statistical significance of the results which is attributed to the short horizon period over which the instruments have been available. The study also explores the impact of transaction costs in order to ascertain profitability with main focus on the bid-ask spreads, as commission and market impact costs are fairly low for online and individual traders. The results show that a long-short 6 month sector momentum strategy employing ETF's incurs average 0.17% bid-ask spread costs, which are well below the break-even transaction costs of 0.65%. Furthermore, Andreu, *et al.* (2013; 144) provide support for sector momentum strategies by concluding that, *"Over the past decade, average returns from industry momentum trading have not decreased, whereas trading costs have."*

3.4.2. Applications of Quantitative Moving Averages (MA's)

Although moving average's (MA's) are amongst the most widely used technical tools, MA's are criticised by opponents of technical analysis as highlighted by Miccolis and Goodman (2012; 37), *"some investors may view MA strategies with great suspicion, as they are closely associated with ultra-short-term technical analysis, market timing, and everything that is anathema to pure, strategic, long-term investing."* Regardless of the views against MA's, several studies have successfully documented the applications of MA strategies.

Brock, Lakonishok and LeBaron (1992) test two simple trading rules based on moving averages and the trading range break-out. The study employs the Dow Jones Industrial Average (DJIA) Index over the period 1897 to 1986. The moving average strategy employed by the study utilises two moving averages with crossover trading rules. The crossover rules generate buy (sell) signals when the short-term MA exceeds (falls below) the long-term MA. The MA's are used in the study as they help smooth out the volatilities within the price series. The study employs short MA's ranging from 1 to 5 days and long MA's between 50 and 200 days. The second set of trading rules employ the trading range break-out indicator, with buy (sell) signals when the price penetrates the resistance (support) levels. The resistance and support levels refer to the local maximum and minimum price levels, respectively over the past 50, 150 or 200 day price windows. The findings of the study show that simple technical trading rules can be used to earn statistically significant abnormal returns. Furthermore, buy signals provide higher returns than sell signals using all trading rules. Overall, the study concludes that simple technical trading rules possess trend predictive power, however transaction costs should be considered carefully when implementing any trading rule strategy.

In a subsequent study, Bessenbinder and Chan (1997) evaluate 26 technical trading rules out of which 20 rules are purely based on MA's. The first 10 rules are variable MA rules which generate buy and sell signals based on MA crossovers. The remaining 10 MA rules are fixed MA rules and differ from variable MA rules in that the buy or sell signals generated from the crossover are assumed to be issued for a fixed number of days after being initiated. The study employs DJIA index data over the period 1926 to 1991. The findings support the study by Brock, Lakonishok and LeBaron (1992) and show that simple trading rules have significant forecasting power. Furthermore, trading rules employing Variable MA's possess higher breakeven returns than the average transaction costs over the entire study period.

Faber (2007, 2013) develops a Tactical Asset Allocation (TAA) model which uses the simple average crossover filters to determine market entry and hedge signals. The TAA model is back-tested on S&P 500 returns data over the period 1900 to 2005. The model performs especially well by profiting during bull markets and hedging with cash during bear markets, thus avoiding significant drawdown. The model is able to significantly outperform the benchmark S&P 500 index; however, it is noted that the models primary value adding can only be understood when applied to an entire business cycle. Faber (2007) also adapts the TAA model to multiple asset classes which include the US and foreign stocks, US bonds, commodities and real estate over the period 1972 to 2005. Adapting the TAA model to multiple asset classes allows investors to benefit from diversification and market timing. The strategy assigns equal weightings to each asset class and subsequently shifts the exposure between the asset class and cash, based on crossover MA indicators. The results show that the model is able to outperform a buy and hold strategy on a risk-adjusted basis as suggested by higher Sharpe ratios. The TAA strategy also reduces maximum drawdown to 9.51% in comparison to the constituent asset classes, which possess maximum drawdowns of 40% to 60% except for US bonds. The findings support the assertion that MA's allow investors to be on the right side of the market at all times, as prices cannot rise significantly without generating a buy signal, nor can they fall considerably without generating a sell signal. In terms of practical application, the study highlights the low commission and management cost burden given the low turnover of only 3 or 4 round-trip trades per year with less than one round-trip trade per asset class per year. Therefore, Faber (2007) concludes that the TAA model can assist investors in earning, *"equity-like returns with bond-like volatility."*

In an updated study, Faber (2013) extends the number of asset classes by including global style indices such as small and large-cap value and momentum indices, as well as increased number of bond indices. The study also tests alternating asset class weightings to reflect conservative, moderate and aggressive portfolio allocations. In an aggressive study, the asset classes with high return potential receive higher weighting with the extension of added leverage, whereas a conservative model assigns higher weighting to low volatility asset classes such as bonds. The results of the study from 1973 to 2012 show that as the portfolio becomes more aggressive, the returns from the MA driven TAA model increases. In addition, all strategies outperform the buy and hold strategy in terms of risk-adjusted performance as measured by the Sharpe ratio, while simultaneously providing lower maximum drawdown.

Hsieh (2010) and Hsieh, Hodnett and van Rensburg (2012) test the application of exponential moving averages (EMA's) as part of a cash protection strategy. The trend following MA strategy is applied to a global momentum and value proxy developed from constituents of the Dow Jones Sector Titans Composite index over the period 1991 to 2008. The MA strategy is also applied to the MSCI World index from 1970 to 2008. The MA strategy employs two moving averages, namely the fast moving average (FMA) and the slow moving average (SMA). A buy (sell) signal is generated when the FMA cuts through the SMA from below (above). The trend following models are applied to two cash protection mechanisms, namely a 100% cash protection mechanism that converts the entire market exposure into cash and a 50% cash protection mechanism that converts only half of the exposure into cash during bear markets. The study tests permutations of slow and fast moving average rates from 0% to 100% at 10% intervals before selecting and assessing the best combinations. Hsieh, Hodnett and van Rensburg (2012) highlight that the optimal rates for SMA and FMA vary based on the dataset. For instance, in the case of the MSCI World Index, the Sharpe ratio is maximised at 30% FMA and 20% SMA, whereas the Sharpe ratio for the global momentum proxy is maximised at 80% FMA and 20% SMA. In the case of the value proxy, the Sharpe ratio is maximised at 100% FMA and 50% SMA.

The findings of the study show that trend following models employing hedging mechanisms can help improve risk-adjusted performance as measured by the Sharpe ratio. In the case of the MSCI World Index, the implementation of the EMA strategies result in doubling of the Sharpe ratio in comparison to unprotected MSCI World Index, as well as a significant reduction in risk as measured by standard deviation, 5 percent VaR and maximum drawdown. Furthermore, the 100% cash protection mechanisms provide higher geometric returns and Sharpe ratios than corresponding 50% cash protection strategies for all three indices on which the MA models are applied. The MA model also reduces downside risk, regardless of whether 100% or 50% cash protection is employed.

Miccolis and Goodman (2012) explore the use of single MA's, crossover MA's and MA gradients as indicators of buy and sell signals. The MA gradient strategy takes the first derivative of the MA to determine the slope. The positive slope indicates market entry and changeover to negative slope denotes an exit signal. The study employs the S&P 500 data and 10 equity sectors that constitute it from 1991 to 2011. The results of the study are widely congruent with earlier studies by Faber (2007, 2013), Hsieh (2010) and Hsieh, Hodnett and van Rensburg (2012), with the MA crossovers providing higher returns and significantly lower drawdown than the S&P 500 index. The findings highlight the strategies participation in the market during bull market phases and successful hedging using cash during bear markets. The study also documents a combination strategy of all three MA techniques (single, crossover and gradient techniques) and finds that the combined trading rules provide better results than using each tool individually. The study also applies the combined MA strategy to the S&P equity sectors. In the sector rotation strategy, exit signals from any of the sectors entail reallocating the proceeds into the sectors experiencing gains. The back tested results show that the sector rotation strategy significantly helps improve returns and minimise drawdown in both the in-sample and out-of-sample periods. The study also emphasises that MA indicators are reactive or lagged and should therefore be conditioned to identify market turning points as promptly as possible.

In a more recent study, Chong, Ng and Liew (2014) test the performance of Moving Average Convergence and Divergence (MACD) and Relative Strength Index (RSI) rules. The study employs five indices which include the Milan Comit General, S&P/TSX Composite, DAX 30, Dow Jones and Nikkei 225, over the period 1976 to 2002. The results show that both tools consistently generate significant abnormal returns in the Italian and Canadian markets. The trading rules also perform well when applied to the Dow Jones index. The findings from these three indices are in line with earlier findings of Chong and Ng (2008), from applying the MACD and RSI rules on the London Stock Exchange from 1935 to 1994. However, a combined analysis of the results shows that investors ought to ascertain the profitability of technical rules in different markets, as the rules are not robust to the choice of market.

3.4.3. Performance of Technical Charting Heuristics

Technical analysts have widely employed quantitative tools such as MA's; however the use of charting techniques remains comparatively sparse. Neftci (1991) demonstrates that charting techniques that account for the non-linearity of asset prices can be used to predict future market trends. The study formalised the head and shoulder and triangle patterns into local maxima and minima. However, the formal identification of local maxima and minima corresponding to recognisable patterns is noted to be extremely tedious. Lo, Mamaysky and Wang (2000) address the difficulties encountered by Neftci (1991), by developing an automatic approach to non-linear pattern recognition in past stock price data. The findings provide incremental information for NASDAQ stocks, even though the results do not guarantee significant excess profits. The findings of Lo, *et al.* (2000) provoke further research into charting based expert systems. Consequently, Leigh, Purvis and Regusa (2002c) explored and furthered the application of charting by introducing technical charting heuristics.

Charting heuristics use pattern recognition techniques, by implementing the template matching methodology employed in photographic character identification. The template matching technique juxtaposes past price or volume data with representative patterns in order to predict future trends. The notion behind the success of technical charting is the belief that certain price patterns are indicative of future price trends. In order to operationalize the charting heuristic, the pattern matching technique is linked with technical trading rules. The trading rules stipulate that if the representative pattern is identified over the previous specified trading window period, the investor should buy the stock, and hold it for a specified number of trading days or holding period.

Leigh, *et al.* (2002c) were the first to implement a charting heuristic using the template matching technique. Leigh, *et al.* (2002c) test the charting heuristic using the NYSE Composite Index daily closing prices from January 1st, 1981 to December 31st, 1996. The template matching technique makes use of archetypal 10x10 template grids, which consist of weights of the representative patterns. The study employed a sloping bull flag pattern template. The closing prices of the NYSE are also translated into 10x10 windows which allow for the computation of the cross multiplication between archetypal template grids and past price windows, the sum of which is used as a measure of pattern fit. Leigh, *et al* (2002c) select a 60 trading day window and utilise a fit threshold of 90th percentile or better, of the previous days fit values on a running basis. All tests are conducted using a 20 day holding period following a buy signal. The findings show that stock price trends can be predicted as the charting technique provides a higher return than a random investment strategy and the results are statistically significant at a 1% level. Although Leigh, *et al.* (2002c) test the bull flag's predictive power, the study does not rigorously test alternative trading rules.

Consequently, Leigh, Modani, Purvis, and Roberts (2002a) conduct the first study that made use of alternative charting heuristic trading rules. The study evaluates two variations of the bull flag template, namely the sloping and horizontal flag. The charting heuristic is applied to the NYSE Composite Index daily closing prices from 1980 to 1999, in order to identify which template is more effective in predicting trends. Unlike Leigh, *et al's* (2002c) 60 day past price windows, both template variations are tested using a 120 day trailing price window, and a match or fit threshold of greater than 80th, 90th and 95th percentile of the fit values of the previous days. A longer 100 day holding period is selected. The results show that both bull flag template variations outperform a buying at random strategy. Furthermore, the horizontal flag pattern provided statistically significant positive risk-adjusted returns at a 1% significance level for all trading rule fit thresholds. The findings also support Leigh, *et al's* (2002c) initial premise, which asserts that higher template match variables provide a more accurate prediction of future market trends. However, according to Wang and Chan (2007) the sloping flag pattern adopted by Leigh, *et al.* (2002a) is susceptible to inaccurate fit values. This is the case, as a trend that closely follows the borders of the consolidation and subsequent breakout will provide a lower fit value, than a trend that exactly follows the consolidation phase and is followed by a price decline.

A subsequent study by Leigh, Paz and Purvis (2002b) examines a wider range of trading rule variables on the NYSE Composite Index from 1980 to 1999. Unlike Leigh, *et al.* (2002a, 2002c), the study employs a fixed fit threshold. The fit thresholds vary from 0 to 8 with higher thresholds indicating more accurate pattern fit. The constant thresholds are less conservative and increase the number of buy signals. The study also incorporates the scaled window height variable which is a measure of the depth of the window (Pring, 2002). In theory, a larger height variable is more likely to indicate a change in the price trend. The findings show that trading rules with positive fit values provide higher returns than a random buying strategy. Longer holding periods lead to higher excess returns with an 80 day holding period trading rules resulting in average excess returns of 2.33% per 80 day holding period and the findings are statistically significant at 1% level. The incorporation of the height variable increases the accuracy of the charting heuristic. Increase in the height while holding the fit threshold constant, leads to higher excess returns across all holding periods with the 80 day holding period trading rules providing statistically significant average excess returns of 7.30% per 80 day holding period.

The evidence from the NYSE supports the use of technical charting heuristics as an investment assistive tool to determine the timing of trades. The paramount shortfall of the studies conducted by Leigh, *et al.* (2002a, 2002b, 2002c) is that the results are reported gross of transaction costs, thus the implications of a practical investment strategy cannot be asserted with surety. This is the case as technical analysis studies by Fama and Blume (1966), Jensen (1978), Bessembinder and Chan (1998) as well as Bajgrowicz and Scaillet (2012), prove that even if technical analysis is profitable, adjusting for transaction costs is likely to nullify any risk-adjusted returns in developed markets. In contrast, technical analysis studies in emerging markets, for instance by Ratner and Leal (1999), as well as Marwala (2010) and Campbell (2011) on the JSE Limited show that technical trading rules can be profitable even after taking transaction costs into consideration.

The evidence from emerging economies is congruent with the findings on the NYSE. Bo, Linyan and Mweene (2005) employed the bull flag pattern to develop trading rules on the Shanghai Stock Exchange Composite Index in China. The study spanned a total of 2,808 days from January 4th, 1993 to June 30th, 2004. The study tests two bull flag variations which differ in terms of the length of the consolidation phase. The dynamics of emerging stock markets are also accounted for in the shorter holding periods to capture the abrupt fluctuations experienced in emerging stock markets. The overall findings of the study show that the higher fit variables and 40 day holding periods result in higher returns than a random selection strategy. The findings also display a positive relationship between the height variable and trading rule profits. However, a striking difference from the study conducted by Leigh, *et al.* (2002b) is that the addition of the height variable led to higher *p*-values signifying that the difference between trading rule and market average returns are not significant. However, it is important to note that the *p*-value is higher for higher standard deviation of variables. The trading rule incorporating height variables result in higher profits which translate into higher standard deviation and thus higher *p*-values, even though upside volatility is desirable. Therefore, the strength of the height variable in improving trading rule predictive ability cannot be rejected.

Wang and Chan (2007) conduct a comparative study between the NASDAQ in the U.S. and the Taiwanese stock market. The daily closing prices of the NASDAQ Composite Index from March 4th, 1985 to March 20th, 2004 and Taiwan Weighted Index (TWI) from June 1st, 1971 to March 20th, 2004 is used. The bull flag variation adopted for the study is characterised by upward sloping masts on either side of a horizontal consolidation. The results show that the charting heuristic provides significant forecasting power and higher returns than a random selection strategy in both markets. However, the annualised excess profit is higher and more significant in the Taiwanese market as suggested by the lower *p*-values. An increase in the price history window size beyond 40 days also resulted in negative excess returns on the NASDAQ. The finding is supported by Pring (2002), who states that flags develop over 5 days to 5 weeks as investors engage in controlled profit taking during this period. Wang and Chan (2007) demonstrate that charting is effective and holds practical value on both the Taiwanese stock market and the NASDAQ.

In a subsequent study, Wang and Chan (2009) test the predictive ability of the saucer and rounding tops pattern across technology stocks in the U.S. from 1971 to 2007. However, unlike previous studies, the study combines the charting heuristic and simple MA's to implement a counter trend trading system. Brabazon and O'Neal (2006) state that a counter trend trading system ensures that a buy signal is only generated if the stock is trading below its average trend level and is expected to encounter a reversal that can be captured by the charting pattern. The findings show that the charting heuristic has statistically significant forecasting power, as depicted by the positive annualised returns ranging from 3.69% to 51.05%, which are significant at the 1% significance level. Furthermore, in order to ascertain the practical relevance of using charting heuristics, the study only selects trading rules that provide significant annualised returns greater than 20% after adjusting for 1% round-trip transaction costs. The positive findings after accounting for transaction costs support the use of charting based trading rules as an assistive tool as well as a practical investment strategy.

3.5. Conclusion

Empirical literature largely supports ETF's as effective and efficient index tracking instruments. Majority of the ETF's from both developed and emerging markets possess low tracking errors and mimic the performance of their respective benchmarks. Price inefficiencies or deviations from underlying values are also observed to be minimal and noted to correct rapidly. Therefore, ETF's provide investors with a low cost, efficient, easily investable and liquid investment vehicle that can be adopted as part of a passive investment strategy. However, the systematic overshooting of stock prices leads to momentum and subsequent reversals in markets. Motivated by the presence of anomalies and potential inefficiencies driven by market irrationality, investors are likely to resort to active management strategies in order to earn abnormal returns.

Active extension portfolios that relax the restrictive long-only constraint and incorporate leverage are found to be more profitable and increase the efficiency of information usage over their long-only counterparts. Yu (2008) and Hsieh (2010) highlight the potential benefits of implementing portfolio optimisation techniques within stated constraints in comparison to long-only portfolios. Alternatively, dynamic asset allocation strategies promulgate rolling time-series portfolio adjustments that could allow investors to exploit market inefficiencies and sector cycles. Moskowitz and Grinblatt (1999) find that the sector momentum effect is fairly strong with the stocks experiencing momentum at a particular point in time being concentrated in a few sectors. Thus, investors can earn abnormal returns by investing in winner and taking short positions in loser sector portfolios. The presence of the sector momentum effect is also documented within passive investment vehicles such as sector mutual funds and sector ETF's.

The systematic overshooting of prices and presence of overreactions in markets culminate into the trending nature of prices purported by the Dow Theory. Therefore, investors could potentially time markets by employing quantitative and charting based technical tools such as moving averages and technical charting heuristics. The moving average model suggested by Faber (2007) and Hsieh (2010) uses quantified trend averages, whereas charting heuristics introduced by Leigh, *et al.* (2002a, 2002b, 2002c) identify trade signals directly from patterns within the price or volume charts. Both these technical tools are internal signal generators, as they determine buy and sell signals directly from the price and volume data of the asset or security that they are applied to. The use of these technical tools also provides the added benefit of being able to hedge market exposure during downturns, thus protecting the value of the investment and minimising downside risks. Although, both strategies are lagged in nature, they aim to identify market turning points and generate trade signals as promptly as possible, with the objective of accumulating equity like returns with bond like volatility as suggested by Faber (2007).

4

Data and Methodology

4.1. Introduction

This research is motivated by the empirical arguments between two distinct schools of investment analysts, namely active investment strategists and passive investment managers. The focus of the study is on the increasingly popular and growing exchange traded fund (ETF) market in the global investment environment. This research undertakes to test the performance of global ETF's, as well as how these instruments can be incorporated into various sector based investment strategies.

The study assesses the performance of global passive ETF's by investigating their tracking ability and pricing efficiency. Motivated by the potential inefficiencies of cap-weighted investing the study subsequently tests the mean-variance efficiency of the cap-weighted S&P Global 1200 index. This is achieved by constructing a statistically optimised portfolio using the constituent sector indices, and comparing and contrasting the sector allocation of the S&P Global 1200 index to that of the optimised portfolio. In addition, the study tests the practicality of applying active management strategies such as portfolio optimisation under real-life portfolio constraints and developing market timing strategies using the sector constituents of the S&P Global 1200 index. The aim of testing alternative allocation and timing strategies is to improve the performance of actively managed sector based portfolios beyond a passive buy and hold approach.

This chapter provides an overview of the research problem, the objectives to be undertaken to answer the research problem and the methodology employed in order to achieve the objectives. The rationale for the selected research database and the sample selection is presented. The potential biases in the research and the solutions to mitigate their effects are also outlined.

4.2. Problem Statement and Research Objectives

This research attempts to explore the application and performance of sector ETF's as part of passive and active investment strategies. The question that will be answered is whether global sector ETF's effectively and efficiently capture and track the performance of their respective underlying indices. If so, the study undertakes to determine whether investors can achieve higher risk-adjusted performance relative to the buy and hold approach, by applying sector-based alternative asset allocation or market timing strategies. The paramount aim of this research is to identify an investment technique that will allow investors to achieve the highest return while minimising risk, within stated portfolio constraints such as short positions and leverage. In order to understand the global equity market and to develop optimal sector based investment strategies, tests of the following objectives are conducted:

1. Analyse the trading characteristics and evaluate the price efficiency of passive global sector Exchange Traded Funds (ETF's).

2. Analyse the price efficiency and pricing patterns of sector ETF's and subsequently develop a rule based arbitrage trading model.

3. Compare and contrast the sector allocation and performance of the S&P Global 1200 index to that of the historical optimised sector compositions.

4. Develop and assess the performance of sector based optimised portfolios based on various optimisation objectives and real-life portfolio constraints such as restrictions on short selling and portfolio leverage.

5. Develop and assess the performance of three technical trading strategies; namely a sector momentum based rotation strategy, a trend timing model employing exponential moving averages (EMA) and an alternative trend timing strategy based on technical charting heuristics.

In its contribution to the body of knowledge, the study attempts to highlight the performance and pricing efficiency of global sector ETF's. The results of the study are expected to draw attention to the extent of mispricing and degree of price efficiency in global ETF markets.

The study also tests for asset allocation as well as timing strategies within global equity markets using tradable sector indices and investment vehicles in the form of global sector ETF's, in order to retain practical relevance and investability. The results from alternative asset allocation strategies will speak to the extent and attractiveness of the relative correlation between global industries, and the potential deviations from the purportedly less efficient cap-weighted indices. The findings from the static optimised model will also provide a comparison in global equities between sector based portfolios constructed in this research and style based portfolios tested by Hsieh (2010). Application and results from technical trading strategies provide insights into the asset allocation and risk management decisions across different phases of the economic cycle, especially during market downturns.

4.3. Data and Sample Selection

In order to evaluate the performance of sector based strategies in the global equity market, the research database should ideally be characterised by sufficient sector and country representativeness. Substantial literature on international investing has focused on country-based portfolio investing. Traditional country based investing attempts to benefit from potential imperfect correlations between countries, as different countries have structurally different economies and may be at different stages of the economic cycle. However, studies by Weiss (1998), Cavaglia and Moroz (2002) and Cavaglia, Diermeier, Moroz and De Zordo (2004) have shown that sector based factors have a stronger bearing on the investment returns than country based factors, which are largely correlated due to globalisation.

Emiris (2004) explores the benefits of country and sector based investing in a global context. The study is conducted over 24 countries and 10 global industries over a 713 week period from January 1990 to September 2003. The results of the study show that there is an increase in the correlation between country indices which reduces diversification and market timing opportunities, whereas there has been a decline in the correlation between global industry indices. Similarly, LaBarge (2008) shows that over the period from 2004 to 2008, sector based investment strategies are able to achieve much greater diversification benefits than country based strategies. This in turn has provided support for sector based portfolio allocation strategies as market sectors are expected to be in favour at different points of the economic cycle. Various studies have also explored the performance of relative sector performance and have found that sectors do not necessarily move in lockstep movements. To an extent sectors tend to lead or lag one another as suggested by Hou (2007). According to Hou (2007), new economic information diffuses at varying rates and has different effects on sectors in the United States, thus leading to non-synchronised industry movements.

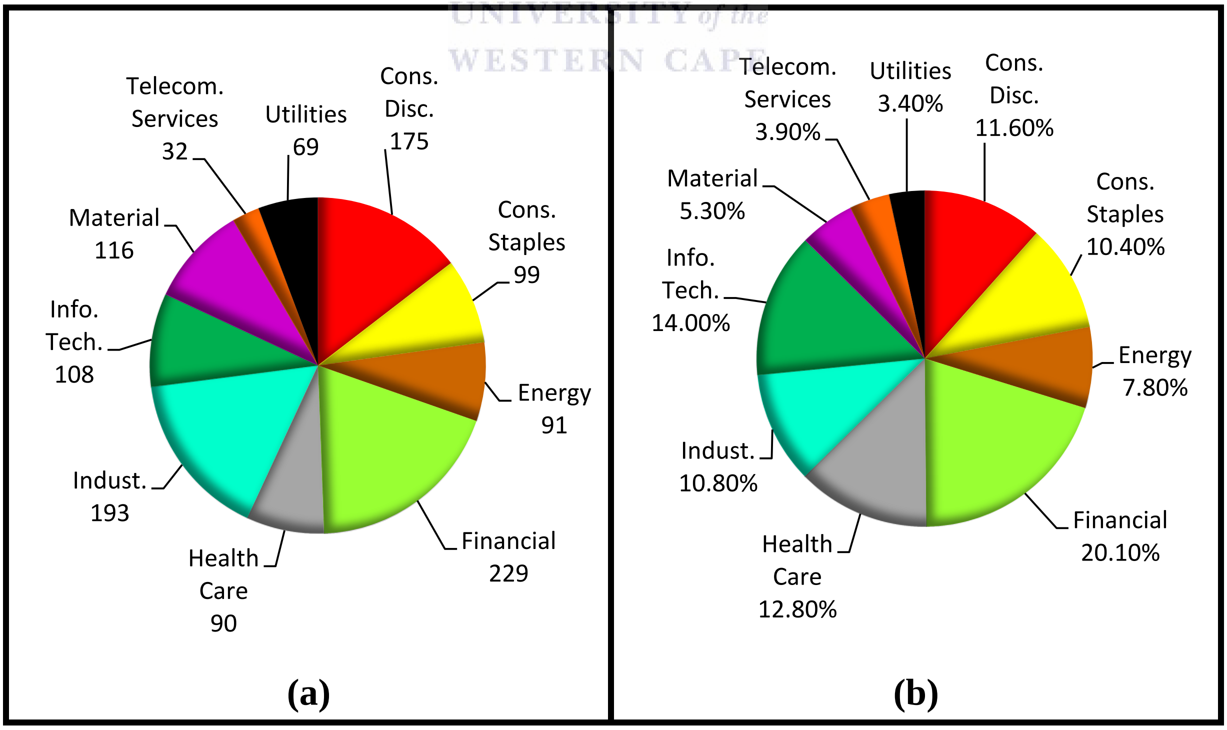
Furthermore, according to Weiss (1998), sector based diversification and asset allocation strategies in local or single country markets are bound to be fruitless. Cavaglia, *et al.* (2004) also purport that within-country sector based investing is a less effective investment approach. This is the case as all sectors are exposed to certain country specific risk factors which could reduce the benefits from domestic market sector based investing. The extent of correlation between domestic market sectors also eliminates the gains from market timing between sectors. However, according to Weiss (1998) and Solnik and McLeavey (2014) certain factors that are systematic at a domestic or country level, become diversifiable when viewed in an international market context. Therefore, the failure of sector based diversification in a single country's market can be attributed to the correlation and systematic country specific factors that affect all sectors. On the other hand, global sector indices are expected to be more imperfectly correlated, which could provide potential diversification and timing opportunities. Thus, empirical literature suggests that this research requires a global equity database which has sufficient sector as well as country representation. Therefore, the study employs the Standard and Poor's (S&P) Global 1200 Index, as it is characterised by a substantial 70% coverage of the global equity market capitalisation and provides both geographic and economic sector balance.

The S&P Global 1200 Index is a market capitalisation weighted index that includes securities from 29 countries, and represents a composite of 7 headline indices from North America, Europe, Asia, Australia and Latin America. The 1,202 index constituents represent the blue-chip, liquid, profitable and sector-representative stocks from each selected region. The index classifies stocks into 10 sectors based on the Global Industry Classification Standard (GICS). The sectors include financials, information technology, healthcare, consumer discretionary, industrials, consumer staples, energy, materials, telecommunication services and utilities. Furthermore, unlike the Morgan Stanley Capital International (MSCI) World Index, the S&P Global 1200 Index does not constrain selection to developed financial markets (MSCI, 2015). Instead, the market representativeness criterion in the index methodology ensures that stocks from both developed and emerging markets are included within the index. The S&P Global 1200 Index also has the benefit of being investable, which refers to the extent to which investors can buy into the index or its constituents at minimal cost in order to replicate its returns. In addition, iShares S&P Global by Blackrock Investments provide sector ETF's on all 10 S&P Global 1200 sector indices. The presence of the sector ETF's could allow investors to easily replicate sector returns through a single investment vehicle. Henceforth, the documented characteristics support the use of the S&P Global 1200 Index as the research database for evaluating global sector ETF investment strategies.

The study is conducted over a 13 year examination period which spans from July 5th, 2002 to February 6th, 2015. The study employs secondary data in the form of price and volume statistics of the S&P Global 1200 Index and sector indices, which is downloaded from Bloomberg databases. All backtesting and data analysis is done using the Microsoft Excel spreadsheet tool and its incorporated VBA function.

The sector breakdown of the S&P Global 1200 Index as at January 30th, 2015 is depicted in Figure 4.1. The index does not have equal number of constituents in each sector as depicted in Figure 4.1 (a). The financial sector is the least concentrated with 229 securities, followed by industrials and consumer discretionary with 193 and 175 securities, respectively. Telecommunications sector is the most concentrated with 32 securities. However, the index weights each sector based on the market capitalisation and therefore, the sector breakdown differs in comparison to number of constituents. The pie chart in Figure 4.1 (b) depicts the relative proportion of each sector based on market capitalisation. Sector weightings range from 3.4% of the utilities sector to 20.1% of the financial sector.

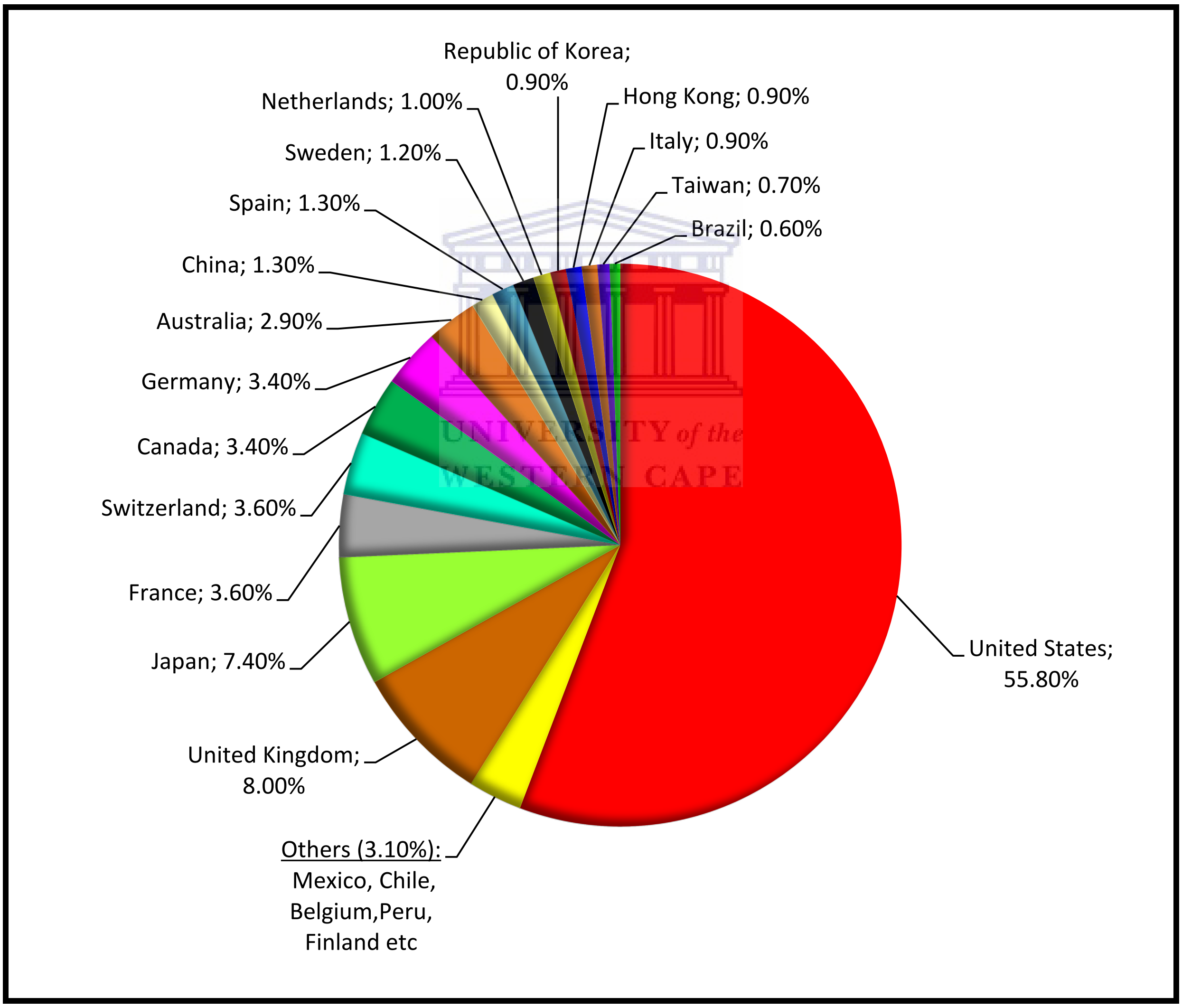
Figure 4.1: S&P Global 1200 Index Sector Breakdown



Source: S&P Dow Jones Indices (2015)

Figure 4.2 illustrates the country composition of the S&P Global 1200 Index as at January 30th, 2015. Although the index incorporates both developing and emerging markets, the emerging markets have a significantly lower representation. The index is mainly dominated by the United States, United Kingdom and Japan with 55.8%, 8.0% and 7.4% index weights, respectively. From all the emerging markets included in the sample, China accounts for the highest weighting of 1.3%. Austria, Portugal and Colombia receive the lowest index weights based on their market capitalisation, with each country having less than 0.1% representation.

Figure 4.2: S&P Global 1200 Index Country Breakdown



Source: S&P Dow Jones Indices (2015)

The price, net asset value (NAV) and volume data of the S&P Global sector ETF's is also downloaded from Bloomberg databases. All 10 sector ETF's are passive funds with the objective to track rather than to outperform the underlying sector indices. Table 4.1 provides a summary of the basic trading characteristics of the ETF's tracking each sector which includes the ETF name, trading code, total average monthly bid/ask spread, total expense ratio (TER) and the ETF replication strategy.

Table 4.1: Trading Characteristics of S&P Global 1200 Sector ETF's

ETF Name	ETF Ticker Code	TER	Average Bid/Ask Spread	Replication Strategy
iShares S&P Global Healthcare Sector	IXJ	0.48%	0.15%	Representative Sampling
iShares S&P Global Energy Sector	IXC	0.48%	0.16%	
iShares S&P Global Industrials Sector	EXI	0.48%	0.29%	
iShares S&P Global Telecom. Serv. Sector	IXP	0.48%	0.13%	
iShares S&P Global Cons. Staples Sector	KXI	0.48%	0.32%	
iShares S&P Global Financials Sector	IXG	0.48%	0.21%	
iShares S&P Global Materials Sector	MXI	0.48%	0.19%	
iShares S&P Global Cons. Disc. Sector	RXI	0.48%	0.28%	
iShares S&P Global Technology Sector	IXN	0.48%	0.20%	
iShares S&P Global Utilities Sector	JXI	0.48%	0.24%	

Source: Fidelity (2015)

All S&P Global ETF's are listed on the New York Stock Exchange Archipelago (NYSE Arca) and employ a representative sampling strategy to manage the fund. A representative or stratified sampling technique selects a representative sample of securities that collectively has an investment profile similar to the underlying index, thus replicating its performance.

4.4. Methodology

The paramount empirical studies employed in this research include the research of Gallagher and Segara (2005) for trading characteristics and tracking ability of ETF's; Jares and Lavin (2004), Kayali (2007) and Charteris (2013) for the research design of testing price efficiency of ETF's and potential arbitrage trading strategies; Sharpe (1992) for the factor model to decompose the benchmarks sector allocation; Yu (2008) and Hsieh (2010) for the design of optimising and assessing various sector based asset allocation strategies; Jegadeesh and Titman (1993) and Andreu, Swinkels and Tjong-A-Joe (2013) for the methodology for testing the sector momentum strategy; Faber (2007) and Hsieh (2010) for the method of developing moving average based trend timing models; and Leigh, Frohlich, Hornik, Purvis and Roberts (2008) for the method of implementing technical charting heuristics using the template matching technique to time market trends.

4.4.1. Performance of Global Exchange Traded Funds

The research starts by testing the performance of the 10 passive S&P Global 1200 sector ETF's in Chapter 5. The performance of a passive ETF is assessed based on its ability to track the underlying index and pricing efficiency. The study employs three distinct measures to evaluate the tracking ability of the ETF's, namely two tracking error measures and the annual tracking difference. The two tracking error measures compute the mean absolute deviation and standard deviation of the differences between the ETF and its underlying index returns, respectively. On the other hand, the annual tracking difference provides a measure of the difference in returns between the ETF and its underlying index over a one year period.

Subsequently, the study tests the pricing efficiency of the ETF's, which assesses how far an ETF's market price deviates from its Net Asset Value (NAV). This is achieved by computing the arithmetic difference between the ETF price and NAV as well as assessing the length of the price deviation from the NAV using an autoregressive approach (Kayali, 2007). The approach regresses past price deviations against current day deviations in order to ascertain whether the price deviations disappear within a stated period or are persistent over subsequent days, which could signal potential arbitrage opportunities.

The study also evaluates the relationship between returns and price deviations from the NAV in order to identify whether past price deviations can be used as predictors of future ETF returns. An autoregressive test is employed for this purpose and the current day and lagged deviations are regressed against the ETF returns. The relationship between the deviations and the returns is then used to develop a trading rule based strategy that generates buy and sell signals based on current day price deviations (Jares and Lavin, 2004).

4.4.2. Benchmark Sector Allocation and Portfolio Optimisation

Chapter 6 of the research focuses on sector allocation strategies. The first test uses the Sharpe (1992) factor model to identify the sector allocation of the benchmark on an annual basis. In order to identify the weight of each sector in the benchmark, the objective of the test is set to minimise the variance of the time-series error term of the regression. The decomposed benchmark weights are then juxtaposed against the Sharpe ratio optimised allocations for each year. The Sharpe ratio optimised allocations refer to the sector weightings in each year that maximise the Sharpe ratio of the portfolio.

In line with the work of Yu (2008) and Hsieh (2010), the study also tests four static optimisation strategies under different portfolio constraints namely, the mean-variance efficient long-only strategy with no leverage, mean-tracking error long-only strategy with no leverage, mean-variance efficient long-short strategy with leverage, and mean-variance efficient market neutral strategy with leverage. The optimal portfolio from each strategy is selected on the basis of the highest risk-adjusted return as measured by the Sharpe ratio, and the optimal portfolios are juxtaposed against the cap-weighted benchmark S&P Global 1200 index and assessed relative to global style based optimised portfolios tested by Hsieh (2010).

4.4.3. Market Timing Using Technical Analysis

The last part of the research tests three distinct technical analysis tools, namely the momentum strategy, exponential moving averages (EMA) and technical charting heuristics. All three strategies use trends and signals deciphered from past price and volume data to predict optimal trading points. The momentum strategy adopted for this research is based on the seminal works of Jegadeesh and Titman (1993) and Moskowitz and Grinblatt (1999). The winner and loser portfolios are constructed on an overlapping basis using different combinations of J formation and K investment periods. The study employs a self-financing strategy in which the long positions are taken in the winner portfolios and the loser portfolios are sold short. The return is therefore computed as the spread between the returns of the winner and loser portfolios, and the methodology is detailed in Chapter 7.

Secondly, in accordance with the methodology proposed by Hsieh (2010) the study tests the EMA trend timing model which uses moving average crossovers to determine buy and sell signals. Unlike simple moving averages, the EMA's have the benefit of utilising all historical data to date and are quicker in reacting to changes as higher weighting is apportioned to more recent data (Achelis, 2001). The strategy is implemented using the fast exponential moving average (FEMA) and slow exponential moving average (SEMA). The FEMA follows the index trends more closely, whereas the SEMA is a relatively more smoothed average. The trading strategy applies trading rules that are conditioned to generate buy signals when the FEMA cuts through the SEMA from the bottom, and the sell or hedge signal is generated when the FEMA cuts through the SEMA from above. The study tests various SEMA and FEMA smoothing constant permutations for each global sector index in the in-sample period in order to identify optimal permutations that can be tested for robustness in the out-of-sample period. The optimal permutations are also tested over the entire examination period and the results from the EMA strategy are assessed relative to a passive buy and hold approach. In addition, the results are reported both gross and net of the assumed 2% transaction costs incurred by individual investors on average, in order to assert practical and economic significance (Hsieh, 2010).

Thirdly, the study tests the application of a technical charting trend timing strategy as an alternative to the EMA timing strategy promulgated by Hsieh (2010). The charting based timing strategy identifies buy and sell signals directly from past and/or volume charts using the template matching technique (Leigh, Purvis and Regusa, 2002c). The technique computes how well the archetypal flag pattern fits the past price data and a buy signal is generated when the bull flag pattern fit value is greater than the trading rule fit threshold. Similarly, a sell or hedge signal is generated when the past price data resembles a bear flag pattern and generates a pattern fit value greater than the trading rule threshold. Therefore, the pattern matching technique is based on the assumption that certain past price formations provide indications of expected future returns. The pattern fit value is computed by translating the actual price or volume data into a 10x10 matrix and computing the sum-product of the actual data matrix and archetypal pattern matrix. The study tests multiple bull and bear flag fit permutations during the in-sample period and the best performing permutations are extracted and tested for robustness in the out-of-sample period. The in-sample optimal permutations are also tested for robustness over the entire study period. The trading rule performance is assessed relative to the buy and hold strategy.

Lastly, the study assess the performance of an equal weighted portfolio strategy that allocates 10% of the total capital to each sector and subsequently tests the performance of the in-sample optimal permutations in the context of a portfolio. Thus, when a buy signal is generated in one of the sectors, 10% of the capital is invested in that sector and when a sell signal is triggered the position is hedged by shifting the exposure into risk-free treasury bills. The study tests both an EMA and technical charting based portfolio strategy over the overall examination period.

4.5. Possible Biases in the Research and Their Remedies

The potential biases that could influence the findings of the research include data mining bias, time period bias, look-ahead bias and outliers. The data mining bias or data snooping refers to extensive analysis and testing of the same data set in order to identify statistically significant patterns or develop a model that works (DeFusco, McLeavey, Pinto and Runkle, 2007). All tests that include the conditioning of trading rules, will be conducted using an in-sample period during which trading rule permutations can be tested and optimal trading rules can be identified. The optimal trading rules will be applied in the non-overlapping out-of-sample period in order to test for robustness. In addition, the trading rules are also applied to the overall examination period to test for robustness and to avoid obtaining results that are time period specific. Furthermore, in line with the work of Hsieh (2010), the study will avoid data mining bias by presenting all EMA and technical charting trading rule permutations tested in the Appendix regardless of test outcomes.

Time period bias exists if the study is conducted over a period that makes the findings unique to that time period. As a result, the findings are attributable to specific market conditions during the study period (DeFusco, *et al*, 2007). In order to address time period bias, the study period is characterised by multiple economic cycles and encapsulates the 2002, 2008 and post-2009 economic downturns following the U.S. technology bubble, the 2008 global financial crisis and debt crisis that affected multiple European countries, respectively. Although the source of the economic downturns is concentrated in a few countries, the majority of the global markets included in the S&P Global 1200 indices are affected due to the contagion effect resulting from the growing economic and financial linkages between international economies.

Look-ahead bias exists when a test incorporates data that would not have been available during the time period being tested. The methodologies for all tests conducted avoid look-ahead bias by imposing a one period lag before trading following any trade signal. Furthermore, trading rules are developed based on past data or data that would have been available at any given point in the research.

In the case of charting heuristics, outliers or extreme large or small values can distort the translation of template grid weights as well as overstate the height variable of the templates. Therefore, every price history window's data points are winsorised. Any values that fall beyond the 95th percentile or are less than the 5th percentile are replaced with the respective boundary values, however the representativeness of the trend pattern is retained. Furthermore, weekly closing prices are used for both trend timing models, as it provides a better simulation of market conditions and eliminates excessive noise inherent in daily data. The use of weekly data in technical trend timing models also ensures that the models do not become susceptible to excessive short-term trading induced by anomalous daily price fluctuations.

5

Performance of Global Exchange Traded Funds

5.1. Introduction

Driven by the comparatively lower efficiency of international ETF's documented in prior literature, this chapter evaluates and analyses the performance of the S&P Global 1200 sector ETF's. The performance of passive ETF's is assessed based on how closely the ETF is able to replicate its underlying asset class's performance and whether it is priced efficiently. The goal of this chapter is to test the trading characteristics and pricing efficiency of the 10 S&P Global 1200 sector ETF's over a total of 3,165 trading days from July 5th, 2002 to February 6th, 2015. The methodologies of the tests conducted in this chapter are discussed in Section 5.2. The study starts out by computing basic risk-return statistics of the global sector indices in Section 5.3. Section 5.4 discusses the trading characteristics and tracking ability performance of the S&P Global 1200 sector ETF's. The tracking error performance measures employed by Gallagher and Segara (2005) are employed for this purpose. Three different measures of tracking ability are assessed in order to ascertain the ETF's ability to replicate their respective underlying indices performance. Successful passive ETF's should not possess significant tracking errors and should enable investors to mimic the performance and earn returns similar to the underlying indices.

Section 5.5 assesses the pricing efficiency of the sample ETF's. Pricing efficiency is concerned with how closely the market price of an ETF corresponds with or follows the fund's net asset value (NAV), which is the value of its constituent assets. In order to test the pricing efficiency of an ETF, the study computes the basic summary statistics of the price deviations from the NAV in order to establish whether an ETF trades at a premium or discount. The persistence of an ETF's price deviations from its NAV is assessed using an autoregressive approach suggested by Kayali (2007). As long as any price deviations do not persist over consecutive days, the ETF's are fairly price efficient. On the other hand, persistent ETF price deviations from the NAV indicate pricing inefficiency and probable arbitrage opportunities.

Based on the findings from the price efficiency tests, Section 5.6 looks at the identification of any significant patterns within the ETF's price deviation from the NAV that could provide a signal for future returns. The study adopts an autoregressive test employed by Jares and Lavin (2004). The approach decomposes the relationship between past price deviations from the NAV and the ETF returns. The relationship is subsequently used to develop trading rules in order to implement a rule-based trading strategy that should ideally provide higher risk-adjusted returns than a passive buy and hold approach. The details of the trading rule strategy are discussed in Section 5.2.

5.2. Descriptive Statistics and Methodology

The tests are conducted on a total of 10 S&P Global 1200 sector ETF's. All tests are conducted from the date of inception of the ETF's, with 5 of the ETF's being launched in 2002 and the remainder in 2006. The study starts by computing the basic risk-return characteristics of each sector, which includes the annual return, cumulative return and standard deviation which is a measure of total risk. The maximum drawdown which reflects the maximum peak to trough loss is also computed and the risk-adjusted performance is measured using the Sharpe ratio. The Sharpe ratio, initially referred to as the reward to variability ratio, provides a measure of the excess return or reward per unit of total risk as measured by standard deviation (Sharpe, 1966). The annualised Sharpe ratio for each sector is computed using Equation 5.1 (Hsieh and Hodnett, 2013).

$$Sharpe\ Ratio_{\ p.a.} = \frac{R_{p.a.} - R_{f\ p.a.}}{\sigma_{p.a.}} \tag{5.1}$$

where

$R_{p.a.}$	the annualised return for the sector;
$R_{f\ p.a.}$	the annualised return for the risk-free asset (Treasury bills); and
$\sigma_{p.a.}$	the annualised standard deviation for the sector.

5.2.1. ETF Tracking Ability Measures

The trading characteristics of each ETF are mainly assessed using the tracking error measures. Tracking error provides a quantified measure of the extent to which the ETF returns stray from the underlying index returns. Two different tracking error computational approaches are employed in this chapter. The first measure of tracking error (TE_1) is taken as the average of the absolute differences between the ETF returns and the underlying benchmark or index returns, as depicted in Equation 5.2.

$$TE_1 = \frac{\sum |R_{pt} - R_{bt}|}{n} \tag{5.2}$$

where

R_{pt}	the return of the ETF in period t;
R_{bt}	the return on the underlying index in period t; and
n	the number of observations over the study period.

The second computational method for measuring tracking error (TE_2) is the more common and widely used measure. The approach takes the standard deviation of the difference in returns between the sector ETF and the underlying index or asset class, as depicted in Equation 5.3. However, according to Roll (1992) the use of this approach should be treated with caution as a consistent underperformance or outperformance by a fixed percentage per day, results in a zero sum in the numerator thus incorrectly translating into an insignificant or zero tracking error.

$$TE_2 = \sqrt{\frac{\Sigma(e_{pt} - \bar{e}_p)^2}{n-1}} \tag{5.3}$$

where

e_{pt} R_{pt} - R_{bt};
$\bar{e}_p$ the mean deviation of ETF returns from index returns; and
n the number of observations over the study period.

In order to assert the level of significance of the tracking errors, the study computes a Student's *t*-statistic of the mean deviation for each ETF, using Equation 5.4 (DeFusco, McLeavey, Pinto and Runkle, 2007).

$$t - statistic = \frac{\bar{e}_p}{\sigma_{\bar{e}_p} / \sqrt{n}} \tag{5.4}$$

where

$\bar{e}_p$ the mean deviation of ETF returns from index returns;
$\sigma_{\bar{e}_p}$ the standard deviation of the deviation of ETF returns from index returns; and
n the number of observations over the study period.

The trading characteristics are also assessed using the tracking difference measure, which is computed by taking the difference between the annualised ETF returns and the annualised underlying index returns, as depicted in Equation 5.5.

$$Tracking\ Difference_{p.a.} = R_{p.pa} - R_{b.pa} \tag{5.5}$$

where

$R_{p.pa}$ the annualised return of the ETF; and
$R_{b.pa}$ the annualised return of the underlying index.

5.2.2. ETF Price Efficiency

Section 5.5 of the chapter looks at the pricing efficiency of ETF's. In order to assess the pricing efficiency of ETF's, the study first computes the ETF price deviations from the NAV. The monetary (U.S. dollar amount) and percentage price deviations are computed using Equation 5.6 and 5.7, respectively (Charteris, 2013).

$$D_t = P_t - NAV_t \tag{5.6}$$

$$PD_t = \frac{D_t}{NAV_t} x\ 100 \tag{5.7}$$

where

D_t	the ETF price deviation from the NAV on day *t*;
P_t	the ETF price on day *t*;
NAV_t	the Net Asset Value on day *t*; and
PD_t	the percentage price deviation on day *t*.

Based on the price deviation data, the study computes basic statistics which include the average percentage price deviation, standard deviation and *t*-statistics to infer statistical significance. The average absolute deviation is also computed using Equation 5.8.

$$Average\ Absolute\ Deviation = \frac{|PD_t|}{n} \tag{5.8}$$

where

PD_t	the percentage price deviation on day *t*; and
n	the number of observations over the study period.

The study subsequently tests for the persistence in deviations of prices from the NAV. This is achieved by determining the influence of lagged or past period price deviations on the current period deviation. Thus the persistence is examined by running a regression of the price deviation on day *t*, with the deviations of the previous 2 days as depicted in Equation 5.9.

$$D_t = \Omega_o + \Omega_1 D_{t-1} + \Omega_2 D_{t-2} + \varepsilon_t \tag{5.9}$$

where

D_t	the price deviation on day *t*;
D_{t-1}, D_{t-2}	the price deviation 1 and 2 days before day *t*, respectively;
Ω_0	the regression intercept;
Ω_1, Ω_2	the coefficient of the 1 and 2 day lagged deviations, respectively;
ε_t	the regression error term.

If the coefficients of the one or two day lagged prices, Ω_1 or Ω_2, are insignificant it indicates that the price deviations disappear within 1 or 2 trading days, respectively. However, if the coefficients are significant it is indicative of persistent deviations for 1 or 2 trading days, respectively. The study selects a 2 day cut off, as any deviation persisting for longer than 2 days provides an indication of pricing inefficiency (Charteris, 2013).

Section 5.6 of the chapter assesses whether price deviations can provide signals for future ETF returns, thereby allowing investors to profitably trade ETF's. The relationship between the price deviations from the NAV and the returns of the ETF is identified by means of a regression analysis, depicted in Equation 5.10 (Jares and Lavin, 2004; Chateris, 2013).

$$R_t = \text{ƀ}_o + \text{ƀ}PD_t + \text{ƀ}_2 PD_{t-1} + \varepsilon_t \tag{5.10}$$

where

R_t	the returns of the ETF in period *t*;
PD_t	the percentage price deviation on day *t*;
PD_{t-1}	the percentage price deviation 1 day before day *t*;
ƀ_0	the regression intercept;
ƀ_1	the coefficient of the deviation on day *t*;
ƀ_2	the coefficient of the 1 day lagged deviation; and
ε_t	the regression error term.

The signs and significance of the coefficients (ƀ_1 and ƀ_2) are used as indicators of the relation between the day to day returns. For instance, a positive coefficient, ƀ_1, coupled with a negative coefficient, ƀ_2, suggests that a positive deviation at the end of the day, provides an indication of a negative return on the following day and vice versa.

The relationship between the deviations and the returns are subsequently used to develop a trading rule based arbitrage trading model, in order to take advantage of future expected prices based on current prices. A two-step trading rule is used to determine the buy and sell signals. In order to avoid excessive trading based on the signals triggered by the trading rule, a trading filter is incorporated into the rule to ensure that trading only takes place if the ETF price deviates from the NAV by more than '*X'* amount. The trading rule triggers a long position *"if the price is less than the NAV by X"*. On the other hand, *"if the price is greater than the NAV by X"* a short position in the ETF is triggered.

The cut off value or '*X*' that is incorporated into the trading rule varies between ETF's and is determined by the average absolute deviation over the examination period as suggested by Cherry (2004). Consequently the study avoids subjectivity as it does not select an arbitrary minimum cut off point.

The price deviation from the NAV is computed at the end of each trading day, and in the case of rule triggered trading days, it is assumed that the ETF is acquired at the next day's opening price (P_0) and the trade is closed out at the closing price (P_1) on the same day. The returns for long (Rt_l) and short (Rts) positions on rule indicated days are computed based on Equation 5.11 and 5.12, respectively.

$$R_{tl} = \frac{P_1 - P_0}{P_0} \tag{5.11}$$

$$R_{ts} = \frac{P_0 - P_1}{P_1} \tag{5.12}$$

The trading rule based strategy is juxtaposed against and compared to the passive buy and hold strategy. In addition, to assert economic and practical significance the study computes the maximum transaction cost that can be incurred before the trading rule strategy would become unprofitable. This maximum cost value is then compared against the actual industry ETF transaction costs to assert whether the trading strategy would be profitable in practice. The maximum or breakeven transaction cost is computed using Equation 5.13 (Charteris, 2013).

$$Max.Transaction\ Cost = \frac{TR_{TR} - TR_{B\&H}}{PS} \tag{5.13}$$

where

TR_{TR}	the total cumulative return for the trading rule strategy over the period;
$TR_{B\&H}$	the total cumulative return for the buy and hold strategy over the period; and
PS	the number of position changes over the study period.

5.3. Results: Global Sector Risk-Return Characteristics

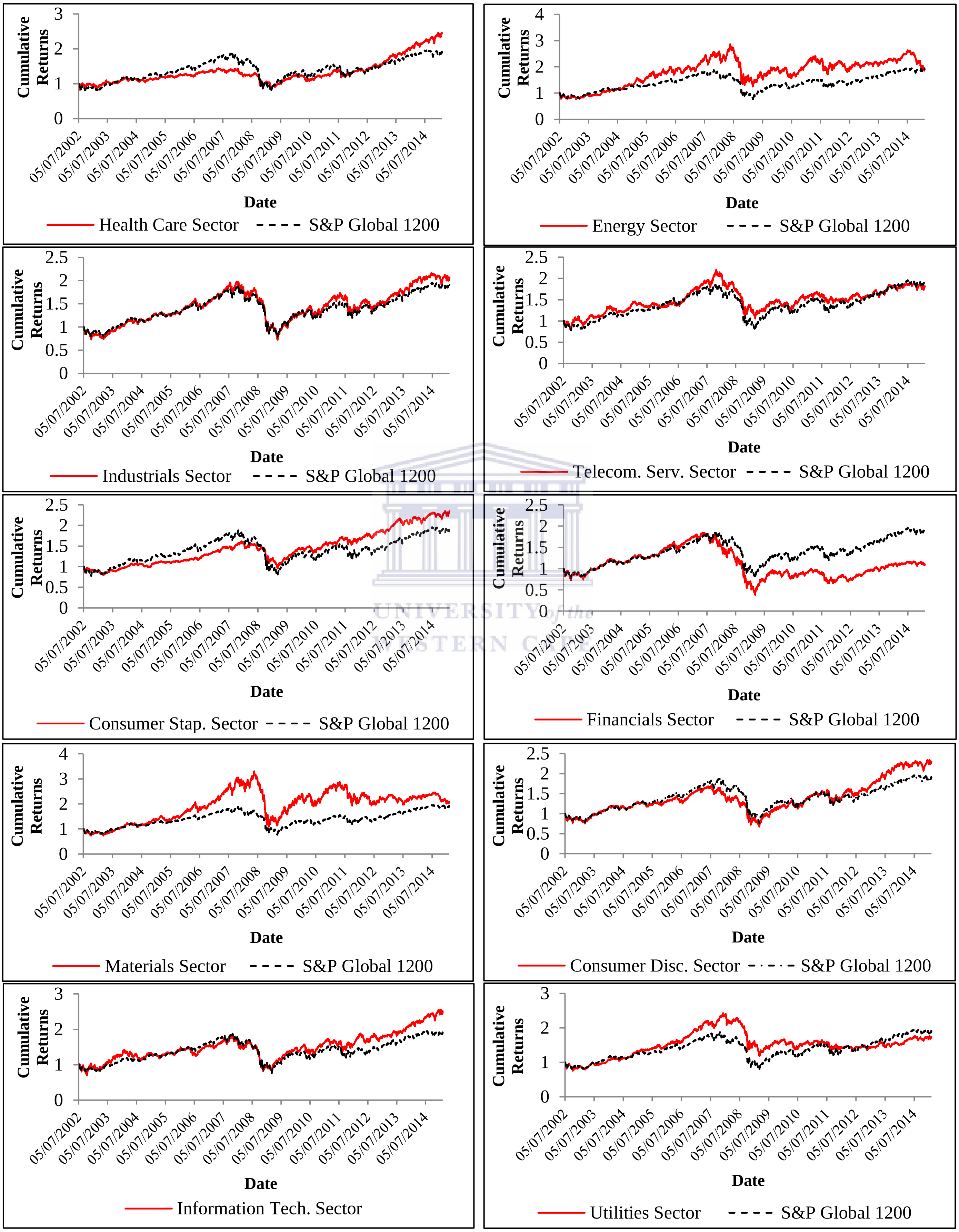
The risk-return characteristics of each global sector over the study period are displayed in Table 5.1. The summarised results reflect the performance of each sector over multiple economic cycles, with the information technology and materials sectors displaying the highest returns. The financials and utilities sectors experience the lowest returns as well as worst risk-adjusted performance, with the utility sector being characterised as a sideward's moving market for a large proportion of the examination period, as depicted in Figure 5.1.

The consumer staples and healthcare sectors provide the highest risk-adjusted performance as measured by the Sharpe ratio. This can be attributed to the resilient and defensive profile of the sectors across different economic cycles, which is depicted in the significantly lower volatility as measured by standard deviation and reaffirmed by the lowest maximum drawdown. Furthermore, Figure 5.1 highlights that the consumer staples and healthcare sectors also experience lower drawdowns and losses during the 2008 financial crisis and the 2011 European debt crisis in comparison to other sectors and the benchmark S&P Global 1200 index. The financials and materials sectors show high cyclicality and correlation with economic phases. The two sectors possess the highest volatility and maximum drawdown measures. In addition, the two sectors experience significantly higher losses than the benchmark S&P Global 1200 index during phases of economic turmoil, as depicted by the drop in cumulative returns during periods corresponding with the 2008 global financial crisis and the 2011 European debt crisis in Figure 5.1.

Table 5.1: Global Sector Risk-Return Characteristics

S&P Global 1200 Sector	Annual Return	Cumulative Return	Standard Deviation	Max. Drawdown	Sharpe Ratio
Healthcare	8.39%	2.41	14.97%	-42.06%	47.04%
Energy	8.86%	2.02	22.77%	-56.48%	32.96%
Industrials	7.71%	2.07	18.39%	-63.40%	34.60%
Telecommunication Services	6.44%	1.84	16.93%	-52.09%	30.07%
Consumer Staples	7.74%	2.33	12.70%	-40.70%	50.33%
Financials	3.78%	1.11	24.03%	-79.28%	10.10%
Materials	9.15%	2.16	23.17%	-67.40%	33.68%
Consumer Discretionary	8.71%	2.36	17.95%	-60.08%	40.99%
Information Technology	9.63%	2.48	20.16%	-56.08%	41.03%
Utilities	5.48%	1.68	15.97%	-51.36%	25.88%

Figure 5.1: Sector versus Benchmark S&P Global 1200 Index Cumulative Returns



5.4. Results: Trading Characteristics and Tracking Ability of Global ETF's

The performance of the passive sector ETF's is assessed based on its ability to replicate the underlying index returns. The daily tracking errors as well as the annual tracking difference for each of the 10 passive sector ETF's are depicted in Table 5.2. Examination of the daily tracking error, TE_1, shows that the average absolute tracking error differs between the ETF's and ranges from a minimum of 0.298% for the consumer staples sector ETF to 0.558% for the information technology sector ETF. The second tracking error measure, TE_2, provides congruent results with tracking errors ranging between 0.495% and 1.129%. The tracking errors can be attributed to transaction costs, cash drags during rebalancing as a result of illiquidity, time zone differences affecting global securities trading, exclusion of dividends in computing index returns, lags in accounting for the ETF's dividend returns, annual management costs as well as the replication strategy which may not perfectly replicate the underlying index returns due to management errors (Hill, Nadig, Hougan and Fuhr, 2015). The results also reiterate the presence of varying tracking errors between ETF's even though they are constructed using the same replication strategy.

The annual tracking difference is a more useful measure for investors as it provides a quantified difference between the ETF and underlying index returns over a stated holding period. The annual tracking differences are positive for all 10 ETF's and ranges between 0.274% and 1.633%, which suggests that the ETF's provide higher returns on an annualised basis in comparison to their respective underlying indices. However, the tracking error and annual tracking difference measures are not statistically significant as the *t*-statistics displayed in square brackets in Table 5.2 are substantially lower than the critical values for all 10 sector ETF's. Thus, there is no significant difference in the sector ETF's return and underlying index returns over the study period. The results also show that the high volatility sectors such as the materials and financials sectors depicted in Table 5.1, generally appear to have higher tracking errors and annual tracking differences. This is supported by Hill, *et al.* (2015), as higher market or sector volatility translates into higher bid-ask spreads and uncertain changes in market direction, thus making it more difficult to rebalance the fund.

Table 5.2 also highlights that all 10 ETF's experience positive mean deviations from the underlying index returns, with the highest average deviations of 0.006% experienced by the financials and materials sector ETF's. The most probable source of the positive deviations and tracking errors over the study period is the inclusion of dividend returns in computing the ETF returns, whereas the dividends are excluded from the computation of the underlying index prices thereby resulting in higher ETF returns. However, the deviations between the ETF and Index returns for all 10 ETF's are insignificant and not statistically significantly different from zero. The findings therefore suggest that there is no significant bias in performance and the S&P Global 1200 sector ETF's neither significantly underperform nor outperform their underlying indices over the examination period, as per their fund objective. Furthermore, analysis of the results show that over the examination period, the majority of the ETF's provide similar cumulative returns as the underlying indices and the positive deviations from the index returns would be nullified when adjusted for transaction costs. Henceforth, the S&P Global 1200 sector ETF's allow investors to closely replicate the performance of their respective underlying sector indices.

Table 5.2: ETF Tracking Performance and Deviations from Index Price

iShares S&P Global ETF	Mean Deviation from Index	Median Deviation from Index	Tracking Error 1 (TE_1)	Tracking Error 2 (TE_2)	Annual Tracking Difference
Healthcare Sector	0.002% [0.2257]	0.001%	0.315%	0.495%	0.539%
Energy Sector	0.004% [0.4069]	-0.001%	0.338%	0.518%	1.023%
Industrials Sector	0.003% [0.1574]	-0.007%	0.396%	0.599%	0.821%
Tele. Services Sector	0.002% [0.1489]	-0.001%	0.452%	0.743%	0.525%
Consumer Staples Sector	0.002% [0.2090]	-0.006%	0.298%	0.538%	0.530%
Financials Sector	0.006% [0.4570]	-0.007%	0.480%	0.768%	1.633%
Materials Sector	0.006% [0.2466]	0.007%	0.518%	0.814%	1.514%
Cons. Discretionary Sector	0.003% [0.0950]	0.006%	0.442%	0.742%	0.832%
Info. Technology Sector	0.001% [0.0498]	-0.007%	0.558%	1.129%	0.274%
Utilities Sector	0.002% [0.2883]	0.005%	0.390%	0.637%	0.513%

Test t-statistics for each sector are depicted in parentheses.

5.5. Results: Percentage Deviations from NAV and Persistence of Deviations

Table 5.3 displays the summary statistics of the percentage ETF price deviations from the NAV over the examination period. The results show that all 10 sector ETF's trade at a premium to the NAV and the premiums are statistically significant at a 1% significance level for all sector ETF's. The telecommunications sector ETF incurs the highest average daily premium of 0.20%, whereas the lowest premium is attributable to the industrials sector ETF with an average of 0.06%. The results also show that ETF prices fluctuate both above and below the NAV, with all 10 ETF's incurring a higher proportion of positive deviations. The proportionately higher frequency of positive deviations reaffirms the positive premiums for all ETF's, with higher proportions of positive deviations translating into higher average deviations from the NAV. The higher absolute average price deviation in comparison to the mean deviation confirms the presence of short-term positive and negative price deviations.

The daily average price deviations of the S&P Global 1200 sector ETF's are lower than deviations on international ETF's recorded in earlier studies by Ackert and Tian (2000) and Jares and Lavin (2004). Accordingly, the findings suggest a potential improvement in ETF pricing efficiency over time. However, the price deviations on the majority of the S&P Global 1200 ETF's are higher than most domestic ETF's documented in earlier research by Gallagher and Segara (2005), Lin, *et al.* (2005), Charteris (2013) as well as Bas and Sarioglu (2015). The higher price deviations on international ETF's are consistent with prior literature and are mainly attributable to the holdings across different countries and time zones. As a result, the trading hours of the stock exchange on which the ETF and underlying securities are traded may differ. For instance, market sentiment, news and events may affect the ETF prices through changes in demand and supply conditions, however, the NAV may only be adjusted the following day once the exchange on which the underlying asset is listed opens. The higher price deviations on international ETF's may also be attributable to the lack of liquidity of the underlying assets. The lack of liquidity, especially inherent in emerging markets, may prevent authorised participants from creating or redeeming shares timeously, as well as restricts arbitrageurs' ability to trade the underlying assets and wipe away any mispricing (Condon and Collins, 2013). Short term premiums or discounts may also be a result of aggressive buying or selling of the ETF relative to the underlying security, which may cause the ETF price to stray from the NAV.

Table 5.3: Percentage ETF Price Deviation from NAV

iShares S&P Global ETF	Average Price Deviation	Standard Deviation	*t*-statistic	No. of Positive	No. of Negative	Zeros	Absolute Average
Healthcare	0.12%	0.51%	12.964***	1866	1248	51	0.34%
Energy	0.10%	0.45%	11.776***	1833	1311	21	0.32%
Industrials	0.06%	0.54%	4.992***	1269	836	1	0.38%
Tele. Service	0.20%	0.59%	19.255***	2185	946	34	0.43%
Con. Staples	0.10%	0.45%	10.615***	1341	762	3	0.30%
Financials	0.12%	0.66%	10.592***	1969	1183	13	0.45%
Materials	0.07%	0.69%	4.504***	1261	843	2	0.48%
Cons. Disc.	0.07%	0.57%	5.363***	1262	840	4	0.37%
Info. Tech.	0.17%	0.52%	17.900***	2042	1107	16	0.36%
Utilities	0.09%	0.50%	8.402***	1275	827	4	0.35%

*Statistical Significance is denoted by ***, ** and * for 1%, 5% and 10% levels, respectively.*

The presence of significant premia across all ETF's sampled does not necessarily entail that the ETF's are price inefficient. The price efficiency of the ETF's is dependent upon the persistence of the price deviation documented in Table 5.3, and whether it allows investors sufficient time to profit from the mispricing. The results from analysing the persistence in deviations are displayed in Table 5.4. The intercepts of the regression, Ω_0, approximates the average deviations between the price and NAV over the study period. Congruent with the results presented in Table 5.3, all the ETF's trade at a premium to the NAV as reflected by the positive intercept estimates. Furthermore, the premiums are statistically significant at a 1% level for all funds that were sampled.

The coefficients of the one and two period lagged deviations are also significant at a 1% level for all 10 funds, thus indicating that the premiums do not disappear within two trading days. The persistence of the price deviations beyond two trading days suggests that the ETF's are not price efficient over the short term. Consequently, the inefficiency can provide opportunities for arbitrageurs to exploit the mispricing and earn profits through the ETF creation and redemption process. The findings are congruent with an earlier study by Engle and Sarkar (2006), which shows that the price deviations on the majority of the international ETF's persist for several trading days. However, the findings are in contrast to the study by Charteris (2013), which shows that the deviations for the 3 international ETF's sampled disappear within two trading days.

Table 5.4: Persistence in Price Deviations

iShares S&P Global ETF	Ω_0	*t*-statistic	Ω_1	*t*-statistic	Ω_2	*t*-statistic
Healthcare	0.028	6.804***	0.276	16.053***	0.259	15.094***
Energy	0.011	5.183***	0.243	14.010***	0.228	13.176***
Industrials	0.021	3.992***	0.021	13.602***	0.230	10.853***
Tele. Services	0.074	10.849***	0.083	4.721***	0.110	6.224***
Consumer Staples	0.043	7.450***	0.219	10.087***	0.113	5.203***
Financials	0.046	8.116***	0.230	13.172***	0.189	10.941***
Materials	0.031	3.759***	0.165	7.659***	0.151	7.013***
Cons. Discretionary	0.028	5.117***	0.144	6.682***	0.167	7.781***
Info. Technology	0.143	8.595***	0.176	4.584***	0.195	5.090***
Utilities	0.033	6.200***	0.128	5.966***	0.195	9.129***

*Statistical Significance is denoted by ***, ** and * for 1%, 5% and 10% levels, respectively.*

Although most studies show that domestic ETF's are fairly price efficient with deviations disappearing within one or two trading days, the evidence on international ETF is mixed and comparatively sparse. One of the main reasons for the higher persistence in deviations in international ETF markets is the non-synchronous trading hours between the ETF and underlying index markets. With most global ETF's consisting of securities from different time-zones, the repetitive and constant difficulty of acquiring the underlying assets for the purpose of creating and redeeming ETF's on a daily basis, can result in the NAV lagging behind the funds market price for several consecutive days.

As noted earlier, liquidity is one of the causes for the deviations in prices and is also a contributing factor to the persistence of deviations on American Depository Receipts (ADR's), which are similar in nature to international ETF's. ADR's are stocks that trade on the U.S. market and represent a specified number of shares in a foreign market. The Indian ADR market has been subject to persistent premiums partly due to liquidity constraints that prevent investors from engaging in arbitrage and driving away deviations for lengthened periods (Saxena, 2006; Stigler, Shah and Patnaik, 2010). Similarly, the lack of liquidity can result in the persistence of deviations for international ETF's, as it may take several days to trade the underlying securities. Engle and Sarkar (2006) attribute part of the pricing inefficiency of global ETF's to the higher cost and risks associated with international trading such as currency risks. In addition, the increased complexity of the creation and redemption process for international ETF's could also contribute to the persistence in deviations.

5.6. Results: Price Deviations as Predictors of Future Returns

Based on the evidence that the S&P Global 1200 sector ETF's are not entirely price efficient, the study examines whether the deviations can provide signals for future returns that can be used to guide investors ETF trading strategies. The results from the regression between the ETF returns and price deviations are displayed in Table 5.5. The coefficients of the same period deviations are positive, whereas the coefficients of the one period lagged deviations are negative for all ETF's. Furthermore, all the coefficients for both the synchronous deviations as well as the one day lagged deviations are statistically significant at a 1% significance level. The findings suggest that a positive deviation at the end of the trading day provides an indication of a negative return the following day. The nature of the relationship between the deviations and the returns conform to an overreaction in the ETF market which is followed by subsequent reversal or correction to eliminate or reduce the deviation. The findings are also in line with earlier studies by Jares and Lavin (2004) and Charteris (2013).

Table 5.5: ETF Return Analysis

iShares S&P Global ETF	β_0	*t*-Statistic	β_1	*t*-Statistic	β_2	*t*-Statistic
Healthcare	0.000	0.135	1.134	30.923***	-0.860	-23.457***
Energy	0.002	20.265***	0.045	8.610***	-1.045	-19.847***
Industrials	0.000	-1.092	1.911	37.460***	-0.947	-18.557***
Tele. Services	-0.001	-4.860***	1.408	43.526***	-0.786	-24.341***
Consumer Staples	0.000	-1.547*	1.432	34.367***	-0.824	-19.770***
Financials	-0.001	-3.635***	1.764	43.960***	-0.845	-21.221***
Materials	-0.001	-2.430***	2.005	43.274***	-0.459	-9.898***
Cons. Discretionary	0.000	-0.729	1.484	32.870***	-0.666	-14.754***
Info. Technology	0.000	1.035	1.007	21.051***	-0.936	-19.572***
Utilities	-0.001	-3.332***	1.613	34.935***	-0.678	-14.678***

*Statistical Significance is denoted by ***, ** and * for 1%, 5% and 10% levels, respectively.*

In order to exploit the identified relationship between the deviations and returns, the study employs a two-step trading rule strategy promulgated by Jares and Lavin (2004). The results from the trading rule based strategy and comparative buy and hold approach are presented in Table 5.6. All the trading rule strategies provide higher average daily returns than the buy and hold strategies over the study period. The trading rule strategies also provide substantially higher cumulative returns in comparison to the buy and hold approach, with the highest cumulative returns of 47.238 and 40.170 accruing to the trading strategies employing the information technology and telecommunications sector ETF's, respectively. The two sectors on which the trading strategy provides the highest returns are also characterised by the highest price deviations and thus, higher pricing inefficiency as depicted in Table 5.3 and Table 5.4. The cumulative returns on the 5 ETF's that were listed in 2006 (denoted by the symbols, ″, in Table 5.6) are also generally lower than the other 5 ETF's that were listed in 2002. This is the case as they have a lower time period over which to accumulate returns, however the validity of the results is maintained as they are assessed relative to the buy and hold strategy over an equal study period. From the 5 trading strategies on the ETF's that were listed in 2006, the strategy employing the utilities sector generates the highest cumulative return of 13.53 in comparison to 0.95 earned by the corresponding buy and hold strategy.

The rule based ETF trading strategies also provide lower total risk as measured by the standard deviation in comparison to the buy and hold strategies for all ETF's, and the results are congruent with the findings from the Japanese and Hong-Kong iShares ETF's tested by Jares and Lavin (2004). Furthermore, the results show that the absolute deviation trading filter incorporated within the trading rules successfully curbs the problem of excessive trading by restricting trading to approximately 35% of the study period. The trading frequency closely conforms to the strategy of Jares and Lavin (2004) and Chateris (2013), both of which trade for approximately 30% of the study period.

In order to assert practical relevance of the trading strategy, the study computes the maximum breakeven transaction costs. The breakeven costs are juxtaposed against the actual average transaction costs on the iShares S&P Global 1200 sector ETF's. The actual transaction costs consist of the average bid-ask spread and the total expense ratio or management cost incurred when trading the ETF, as these two components are the main costs that affect returns when trading ETF's (Hill, *et al.*, 2015). The findings displayed in Table 5.6 show that 7 of the ETF's have higher breakeven transaction costs than the actual average costs of 0.70% applicable to the sampled ETF's, suggesting that investors can profitably trade using the trading rules even after taking transaction costs into consideration. The highest breakeven transaction costs are attributable to the information technology and telecommunications sector ETF's, with the maximum costs of 4.15% and 3.27%, respectively before the strategy would become unprofitable. However, 3 of the ETF's, namely industrials, consumer staples and materials sector ETF's, have lower breakeven costs than the actual average costs. Thus, the costs of trading these 3 ETF's would be too high and the strategy would be unprofitable. Furthermore, the inferior performance of these 3 sector ETF strategies cannot be attributed to the relatively shorter period over which the ETF's have been in the market, as the number of position changes adjusts the breakeven costs for trading frequency and time frame.

The results from the trading rule strategy depicted in Table 5.6 illustrate that the strategy is profitable and provides higher returns with lower risks, even after taking into consideration the market downturns that are encapsulated within the sample period, such as the 2008 financial crisis and the 2011 European debt crisis. In addition, the positive performance and profitability of the trading rule strategy also contradicts the notion of weak-form efficiency of the efficient market hypothesis (EMH), as the strategy uses data and trends extrapolated from past prices to successfully predict future returns.

Table 5.6: Daily Return Descriptives of Trading Rule and Buy and Hold Strategies

iShares S&P Global ETF	Strategy	Average Returns	Standard Deviation	Maximum Daily Return	Minimum Daily Return	Cumulative Return	Position Changes	Average Trading Cost†	Breakeven Trading Cost
Healthcare Sector	Buy and Hold	0.035%	1.125%	11.626%	-9.480%	2.444	0	0.70%	
	Trading Rule	0.111%	0.807%	11.626%	-7.185%	30.279	1110		2.51%
Energy Sector	Buy and Hold	0.038%	1.689%	15.417%	-13.151%	2.105	0	0.70%	
	Trading Rule	0.081%	1.233%	15.417%	-13.151%	10.128	1104		0.73%
Industrials Sector″	Buy and Hold	0.027%	1.527%	11.089%	-8.867%	1.395	0	0.70%	
	Trading Rule	0.084%	1.162%	11.089%	-8.462%	5.086	824		0.45%
Tele. Serv. Sector	Buy and Hold	0.027%	1.359%	13.568%	-9.605%	1.732	0	0.70%	
	Trading Rule	0.122%	0.986%	12.151%	-7.635%	40.170	1174		3.27%
Con. Staples Sector″	Buy and Hold	0.034%	1.067%	8.580%	-7.694%	1.807	0	0.70%	
	Trading Rule	0.082%	0.807%	8.335%	-7.694%	5.239	794		0.43%
Financials Sector	Buy and Hold	0.020%	1.830%	14.099%	-14.397%	1.102	0	0.70%	
	Trading Rule	0.094%	1.395%	14.099%	-11.333%	14.391	1130		1.18%
Materials Sector″	Buy and Hold	0.023%	1.974%	14.249%	-13.113%	1.180	0	0.70%	
	Trading Rule	0.025%	1.530%	14.249%	-13.113%	1.334	774		0.02%
Con. Disc. Sector″	Buy and Hold	0.035%	1.459%	9.709%	-11.116%	1.668	0	0.70%	
	Trading Rule	0.123%	1.116%	9.706%	-9.176%	11.750	716		1.41%
Info. Tech. Sector	Buy and Hold	0.039%	1.444%	9.005%	-8.756%	2.467	0	0.70%	
	Trading Rule	0.127%	1.038%	9.005%	-7.900%	47.239	1080		4.15%
Utilities Sector″	Buy and Hold	0.007%	1.347%	12.214%	-9.548%	0.954	0	0.70%	
	Trading Rule	0.129%	1.023%	10.938%	-9.548%	13.527	769		1.63%

ETF's that are by the asterisk, ″, denotes funds that were launched on 22/09/2006. The remainder of the ETF's were launched on 05/07/2002.
† Average iShares Global Transaction costs (Management cost: 0.48%; and Bid-Ask Spread: 0.22%) (Source: Fidelity, 2015)

5.7. Conclusion

The tracking performance of the S&P Global 1200 sector ETF's is assessed based on three index tracking measures, two of which are the tracking errors and the third one is a tracking difference measure which quantifies the deviations over a stated period. The results from all three measures indicate that the ETF's are subject to non-zero or more specifically positive tracking errors, however the findings are not statistically significant. The tracking measure results are consistent with the analysis of the cumulative and geometric return as well as maximum drawdown statistics over the entire examination period, which highlight that the ETF's provide similar performance to the underlying index with no significant evidence of over or under-performance. As a result, investors can employ the sector ETF's as part of investment strategies in order to replicate or earn the performance of the sector indices.

The ETF price deviations from their respective NAV's were found to be positive which suggests the ETF's trade at a premium. Furthermore, the premiums are statistically significant for all iShares S&P Global 1200 sector ETF's. The ETF price deviations from the NAV are also persistent for more than two trading days for all ETF's sampled, which is consistent with prior literature on international ETF's as documented by Engle and Sarkar (2006). The evidence therefore points to the funds being price inefficient over the examination period. The persistence of the price deviations can be attributed to the international holdings of the global ETF's which result in non-synchronous trading hours, potential lack of liquidity of underlying assets coupled with aggressive ETF trading, transaction costs as well as risks associated with foreign securities trading amongst other factors. Consequently, the authorised participants or arbitrageurs ability to eliminate the price deviations timeously through the ETF creation and redemption process is restricted.

The results from the ETF return analysis highlight a significant negative relationship between the ETF price deviations and the following period returns, thereby suggesting that a positive (negative) deviation at the end of the day provides an indication of probable negative (positive) returns the following day. Based on the identified relationship, the study tests a trading rule based strategy that uses past deviations to determine market entry signals. The trading strategy performs exceptionally well relative to the buy and hold strategy, with the information technology and telecommunications sector ETF's providing the highest cumulative returns. The trading rule strategy also provides lower total risk relative to the buy and hold strategy. The findings also reiterate a positive relationship between ETF price deviations and success of the trading rule strategy. In addition, the majority of the trading rule strategies provide positive returns after accounting for higher transaction costs and spreads experienced when trading global ETF's. Overall, the trading rule strategy outperforms the buy and hold approach and the findings contradict the weak form of the EMH, as information contained in or extrapolated from past data is used to predict future ETF returns.

6

Benchmark Sector Allocation and Portfolio Optimisation

6.1. Introduction

The focus of this chapter shifts from testing the performance of passive global ETF's to active asset allocation and optimisation strategies, over the period from July 5th, 2002 to February 6th, 2015. The objective of this chapter is to assess the sector allocation of the cap-weighted benchmark S&P Global 1200 index. The chapter also develops and evaluates the potential benefits of sector based optimised portfolios relative to passive cap-weighted investment strategies.

The sector exposures of the cap-weighted S&P Global 1200 index are identified using the Sharpe (1992) factor model and the decomposition procedure is detailed in Section 6.2. The changes in sector allocation are subsequently evaluated in light of the economic events or phases during corresponding periods. The findings are also juxtaposed against the Sharpe ratio optimised weights over the examination period in order to identify whether cap-weighting over or under-weights certain sectors especially during major economic events such as economic downturns. The differences in sector exposures between the two allocation methods are also assessed in order to identify probable sources of disparities in performance. The test results are demonstrated in Section 6.3.

Section 6.4 presents the results of the static portfolio optimisation strategies with different constraints. The chapter adopts the optimisation methodology and format employed by Yu (2008) and Hsieh (2010), however the focus of this study is on sector based optimisation rather than investment styles. The study identifies optimised sector based portfolios for 4 distinct investment strategies, namely the mean-variance efficient long-only strategy with no leverage, mean-tracking error long-only strategy with no leverage, mean-variance efficient long-short strategy with leverage and the mean-variance efficient market neutral strategy with leverage (Hsieh, 2010). All 4 optimisation strategies are based on real-life portfolio constraints. Section 6.5 extracts and summarises the performance statistics of the 4 global sector based optimised portfolios from each investment strategy and evaluates them against their respective benchmarks.

6.2. Methodology and Descriptive Statistics

This chapter employs the same set of S&P Global 1200 sector indices tested in the previous chapter and all tests are conducted using weekly sector index returns.

6.2.1. Estimating Deviations from Optimal Sector Allocations

The study evaluates the deviations in sector exposures between the cap-weighted S&P Global 1200 index and the Sharpe ratio optimised allocations. The Sharpe (1992) factor model is adopted in order to identify and evaluate the changes in the benchmarks underlying sector exposures or weights over the examination period. The decomposition process is achieved by regressing the weekly time-series benchmark returns on the weekly time-series returns of the global sectors using Equation 6.1.

$$r_{S\&P\ Global\ 1200,t} = \left[\left(w_{s1}\ x\ r_{s1,t}\right) + \left(w_{s2}\ x\ r_{s2,t}\right) + \cdots + \left(w_{sn}\ x\ r_{sn,t}\right)\right] + \mathcal{E}_i \quad (6.1)$$

where

$r_{S\&P\ Global\ 1200,t}$	the time-series return on the S&P Global 1200 index in week t;
$r_{s1,t}, r_{s2,t}, r_{sn,t}$	the sector returns for the *1st*, *2nd* and n^{th} sector in week t;
w_{s1}, w_{s2}, w_{sn}	the sector exposures for the *1st*, *2nd* and n^{th} sector; and
$\mathcal{E}_i$	the error term which represents the market return that is not explained by the exposures to the global sector indices.

In order to determine the weights of each sector, Equation 6.1 is firstly rearranged to make the error term the subject of the formula as depicted in Equation 6.2.

$$\mathcal{E}_i = r_{S\&P\ Global\ 1200,t} - \left[\left(w_{s1}\ x\ r_{s1,t}\right) + \left(w_{s2}\ x\ r_{s2,t}\right) + \cdots + \left(w_{sn}\ x\ r_{sn,t}\right)\right] \quad (6.2)$$

Equation 6.2 is conditioned to restrict the weights of each sector between 0% and 100% and the sum of the weights of the sectors must equal 100%. The objective of the regression is set to minimise the variance of the time-series error term depicted in Equation 6.3, which is equivalent to minimising the tracking error measure.

$$\sigma_{\mathcal{E}}{}^2 = \frac{\sum\left(\mathcal{E}_{i,t} - \bar{\mathcal{E}}\right)^2}{n-1} \quad (6.3)$$

where

$\sigma_{\mathcal{E}}{}^2$	the variance of the error term;
$\mathcal{E}_i$	the time-series error term in period t;
$\bar{\mathcal{E}}$	the average of the time-series error term; and
n	the number of weeks in each year sampled.

Based on the constraints and objective of the regression, the study runs a series of 52 week regressions for each year of the study period. Once the sector exposures of the market proxy have been identified, they are juxtaposed against the Sharpe ratio optimised allocations annually. The historical optimised allocations are also computed on an annual 52 week basis and provide the sector weights in Equation 6.4 that maximise the Sharpe ratio (refer to Section 5.2) over each year.

$$r_{OP,t} = (\hat{w}_{OP,s1}\ x\ r_{s1,t}) + (\hat{w}_{OP,s2}\ x\ r_{s2,t}) + \cdots + (\hat{w}_{OP,sn}\ x\ r_{sn,t}) \tag{6.4}$$

where

$r_{OP,t}$	the returns on the optimised portfolio, O*P*, in year *t*;
$r_{s1,t}, r_{s2,t}, r_{sn,t}$	the returns on the *1*st, *2*nd and *n*th sector indices; and
$\hat{w}_{OP,s1}, \hat{w}_{OP,s2},\ \hat{w}_{OP,sn}$	the weights of the *1*st, *2*nd and *n*th sector indices in the sector based portfolio, O*P*, that maximise the Sharpe ratio.

The study subsequently computes each sectors excess allocation in the cap-weighted S&P Global 1200 index using Equation 6.5.

$$Excess\ Weight_{sn,t} = w_{sn} - \hat{w}_{OP,sn} \tag{6.5}$$

where

$Excess\ Weight_{sn,t}$	the excess weight of the *n*th sector in year *t*;
w_{sn}	the cap-weighted exposures for the *n*th sector; and
$\hat{w}_{OP,sn}$	the exposure of the *n*th sector in the optimised portfolio, O*P*.

6.2.2. Static Portfolio Optimisation

The study further conducts static portfolio optimisation based on real-life constraints. Following the methodology of Hsieh (2010), the optimisation procedure employs the mean-variance optimisation objective and identifies the sector allocations that minimise the portfolio's total risk as measured by standard deviation at each level of portfolio returns. The weighted return of the sector based portfolio, *P*, in month *t* is computed using Equation 6.6.

$$r_{P,t} = (\ddot{w}_{P,s1}\ x\ r_{s1,t}) + (\ddot{w}_{P,s2}\ x\ r_{s2,t}) + \cdots + (\ddot{w}_{P,sn}\ x\ r_{sn,t}) \tag{6.6}$$

where

$r_{P,t}$	the returns on the sector based portfolio, *P*, in month *t*;
$r_{s1,t}, r_{s2,t}, r_{sn,t}$	the returns on the *1*st, *2*nd and *n*th sector indices; and
$\ddot{w}_{P,s1}, \ddot{w}_{P,s2},\ \ddot{w}_{P,sn}$	the optimal weights of the *1*st, *2*nd and *n*th sector indices in the sector based portfolio, *P*.

The standard deviation of the sector based portfolio, P, is computed using Equation 6.7.

$$\sigma_P = \sqrt{\frac{\sum(r_{P,t} - \bar{r}_P)^2}{n-1}} \tag{6.7}$$

where

$r_{P,t}$	the return for the sector based portfolio, P, in month t;
$\bar{r}_P$	the mean return for the sector based portfolio over the study period; and
n	the number of weeks over the examination period (n = 628 weeks).

The static optimisation tests start out by testing the mean-variance efficient long-only strategy. The long-only with no leverage constraint restricts sector weightings between 0% and 100%. In addition, the sum of the portfolio weightings should always equal 100%. The test identifies the weightings that minimise the portfolio standard deviation for each level of portfolio returns (Hsieh, 2010). The portfolio returns are bound between the lowest sector return of 5.79% attributable to the financials sector and the highest return of 11.39% attributable to the materials sector. The strategy permits investment across all 10 sector indices as well as the S&P Global 1200 index.

The second optimisation strategy aims to identify the sector allocations that minimise the portfolio's mean-tracking error for each level of return. The test maintains the same long-only and no leverage constraints as the first test and constrains the total sector exposure to 100%. The tracking error of the portfolio, TE_P, provides a quantified measure of how closely the portfolio tracks the benchmark. The tracking error is the standard deviation of the sector based portfolio's returns in excess of the S&P Global 1200 index, as depicted in Equation 6.8 and resembles the second tracking error measure, TE_2, discussed in Section 5.2 (Hsieh, 2010).

$$TE_P = \sqrt{\frac{\sum(r_{ER,t} - \bar{r}_{ER})^2}{n-1}} \tag{6.8}$$

where

$r_{ER,t}$	the excess return of portfolio, P, relative to the benchmark in month t;
$\bar{r}_{ER}$	the mean excess return of portfolio, P, relative to the benchmark; and
n	the number of weeks over the examination period (n = 628 weeks).

The third optimisation procedure tests the long-short mean-variance efficient optimised strategy with leverage capped at 200%. The long-short strategy like the mean-variance efficient long-only strategy identifies the allocation that minimises the risk for each level of portfolio return, however it allows short positions in any of the sectors. This is the case, as investors can take short positions by short selling the S&P Global Sector ETF's. As per the methodology of Hsieh (2010), the strategy starts out by investing 100% of the capital in the risk-free United States 3-month treasury bills (T-bills), thus the lowest return starts from 1.35%. The strategy subsequently identifies optimal allocations at each level of return, with the initial long positions being financed by equal amount of short positions. However, unlike in prior studies by Yu (2008) and Hsieh (2010) that constrain short positions to 100%, this study only permits short positions up to 50%, after which point any additional long positions are financed by liquidating holdings in the risk-free T-bills. Therefore, at the maximum market exposure the strategy translates into a 150/50 active extension strategy with a maximum leverage of 200%, which is in line with the United States Regulation-T (Reg-T) limits on long-short strategies for individual investors (Géhin, 2007).

Lastly, the research identifies sector based optimal portfolios for the market neutral hedge fund strategy with leverage. The market neutral strategy also imposes a 200% leverage limit which is a general constraint in the hedge fund industry (Hsieh, 2010). Henceforth, the long and short positions are capped at 100% and -100%, respectively. The market neutral strategy differs from the long-short strategy as it requires that the investment in long position must be equal to the short position held, thereby resulting in zero investment portfolios. Similar to the long-short strategy, the test begins with 100% of the capital invested in the risk-free T-bills, however this investment is held constant throughout the test.

The study subsequently identifies the optimal sector portfolios from all 4 investment strategies. The best sector allocations under each set of constraints are selected based on the highest risk-adjusted return as measured by the Sharpe ratio. These optimal portfolios are juxtaposed against the S&P Global 1200 index and assessed based on return, risk and risk-adjusted measures. The summarised performances of the optimal global sector based portfolios are also assessed relative to global style based portfolios constructed by Hsieh (2010), thereby providing a comparative analysis in global equities of the optimisation techniques employing different constituent index classifications. The risk-adjusted performance measures employed in this chapter include the Sharpe ratio (refer to Section 5.2) and the Treynor Measure. The Treynor measure computes the annualised excess returns, per unit of systematic risk as measured by the CAPM beta. The CAPM beta is calculated by running a regression between the sector and market proxy (S&P Global 1200 index) excess returns. The annualised Treynor measure is calculated using Equation 6.9 (Hsieh and Hodnett, 2013).

$$Treynor\ Measure_{p.a.} = \frac{R_{p.a.} - R_{f\ p.a.}}{\beta_M} \tag{6.9}$$

where

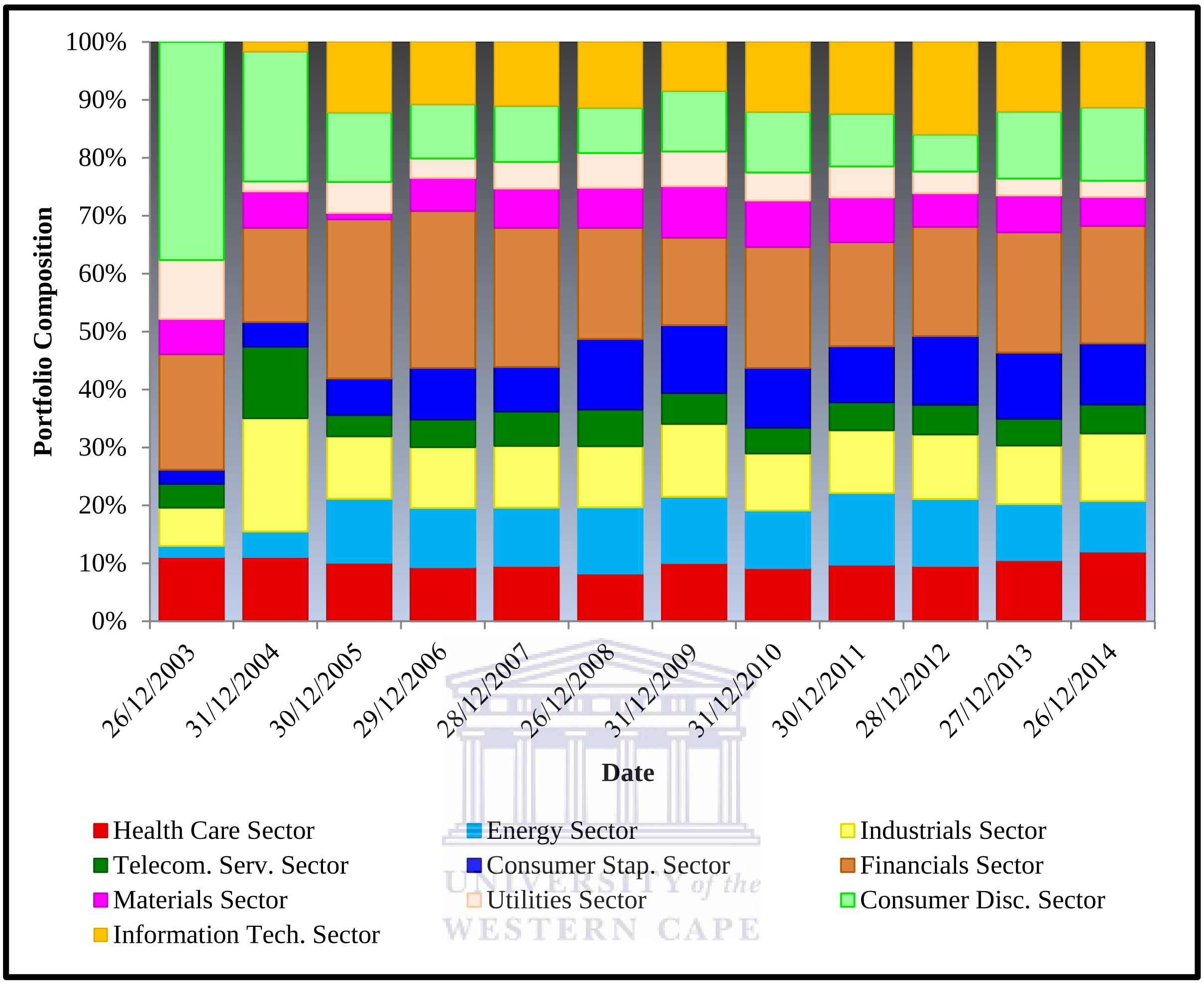
$R_{p.a.}$	the annualised return of the sector or portfolio;
$R_{f\ p.a.}$	the annualised return for the risk-free Treasury bill rate; and
β_M	the beta estimate for the sector or portfolio against market proxy, *M*.

6.3. Results: Deviations from Optimal Sector Allocation

Although the data outlined in Chapter 4 provides a static sector representation and allocation of the S&P Global 1200 index, it does not provide a time-series or annual decomposition of the sector weightings. Henceforth, the Sharpe (1992) factor model is used to identify the average annual sector exposures or weightings of the cap-weighted S&P Global 1200 index over the examination period and the results are graphically depicted in Figure 6.1. The results show that the sector exposures largely remain fairly stable and only experience gradual changes from one year to the next. The healthcare, telecommunication services, materials and utilities sector exposures are subject to minimal changes throughout the study period with only notable fluctuations between 2002 and 2004. In relative terms, only the consumer discretionary sector experiences a significant decrease in exposure between 2003 and 2004 as the weighting of the industrials, energy and information technology sectors increase. The increased exposure to these three sectors can be attributed to the industrial boom from 2002 to 2007, as the majority of the world economies experienced a significant bull market phase following the post 2002 recovery from the technology bubble (Appel, 2008).

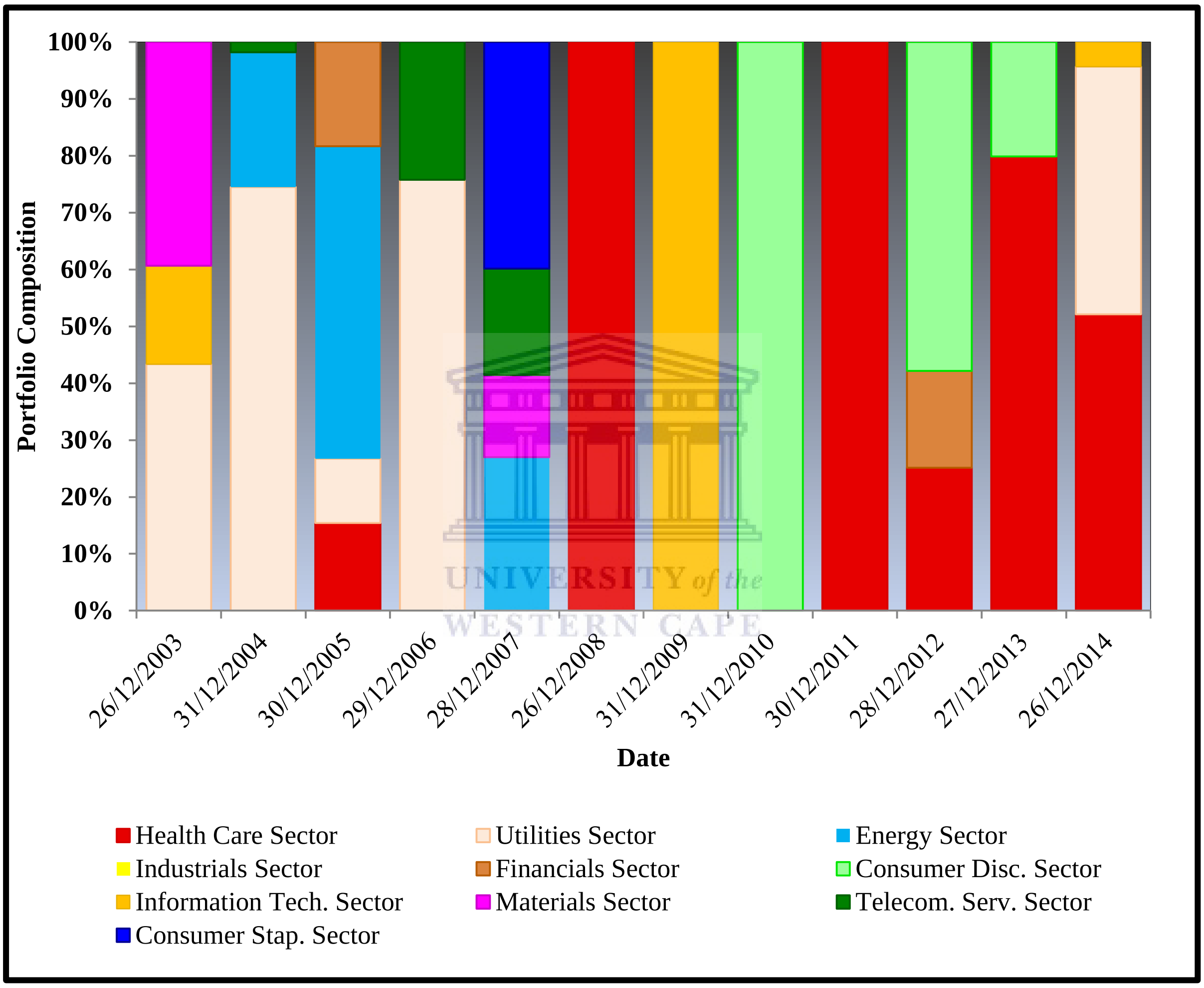
The exposure to the consumer staples sector shows an increasing trend throughout the study period, with the highest exposure recorded during the 2008 financial crisis as well as in 2012, following the European debt crisis. Consequently, the results support the assertion that the sector is comparatively more resilient than other sectors across different economic phases, as market capitalisation and thus composition in the index changes by a lower proportion than other sectors. The findings are also congruent with earlier results presented in Section 5.3. The role of the financial sector in generating the benchmark return is also interesting as the sector has the highest weighting across the majority of the years in the study period. The exposure to the financial sector is significantly reduced during the 2008 economic crisis that largely stemmed from and affected the financials sector. However, based on market capitalisation weighting the financial sector retains the highest exposure even during market downturns and quickly rebounds following the crisis which is in line with the empirical business cycle analysis of Bodie, Kane and Marcus (2008). The relatively higher exposure to the financial and energy sectors could also be a significant factor that contributes to the volatility and drawdown experienced by the S&P Global 1200 index during periods of economic turmoil, as these sectors are characterised by high cyclicality and volatility.

Figure 6.1: S&P Global 1200 Sector Decomposition



The results from the comparative optimised sector compositions over the same annualised sub-periods are depicted in Figure 6.2. In contrast to the sector allocations of the cap-weighted S&P Global 1200 index, the Sharpe ratio optimised compositions experience drastic changes from one year to the next. This supports the premise that different sectors are in favour at different points of the economic cycle as suggested by Cavaglia and Moroz (2002), Cavaglia, Diermeier, Moroz and De Zordo (2004), Hou (2007) and Bodie, Kane and Marcus (2008). The healthcare sector has the highest representation or exposure in the optimised composition from year to year throughout the study period, as it possesses attractive risk-return attributes. Other sectors that have a comparatively higher representation in the Sharpe ratio optimised composition include the energy, information technology, utilities and consumer discretionary sectors. The financial, telecommunication services and materials sectors have lower exposures, with the industrials sector having no exposure in any of the years. Interestingly, the consumer staples sector has very low exposure in the annual Sharpe ratio optimised compositions even though it has the highest Sharpe ratio over the entire examination period. This could be attributed to the sectors resilient profile which makes it relatively more attractive than other sectors when assessed over multiple economic phases rather than over short time frames.

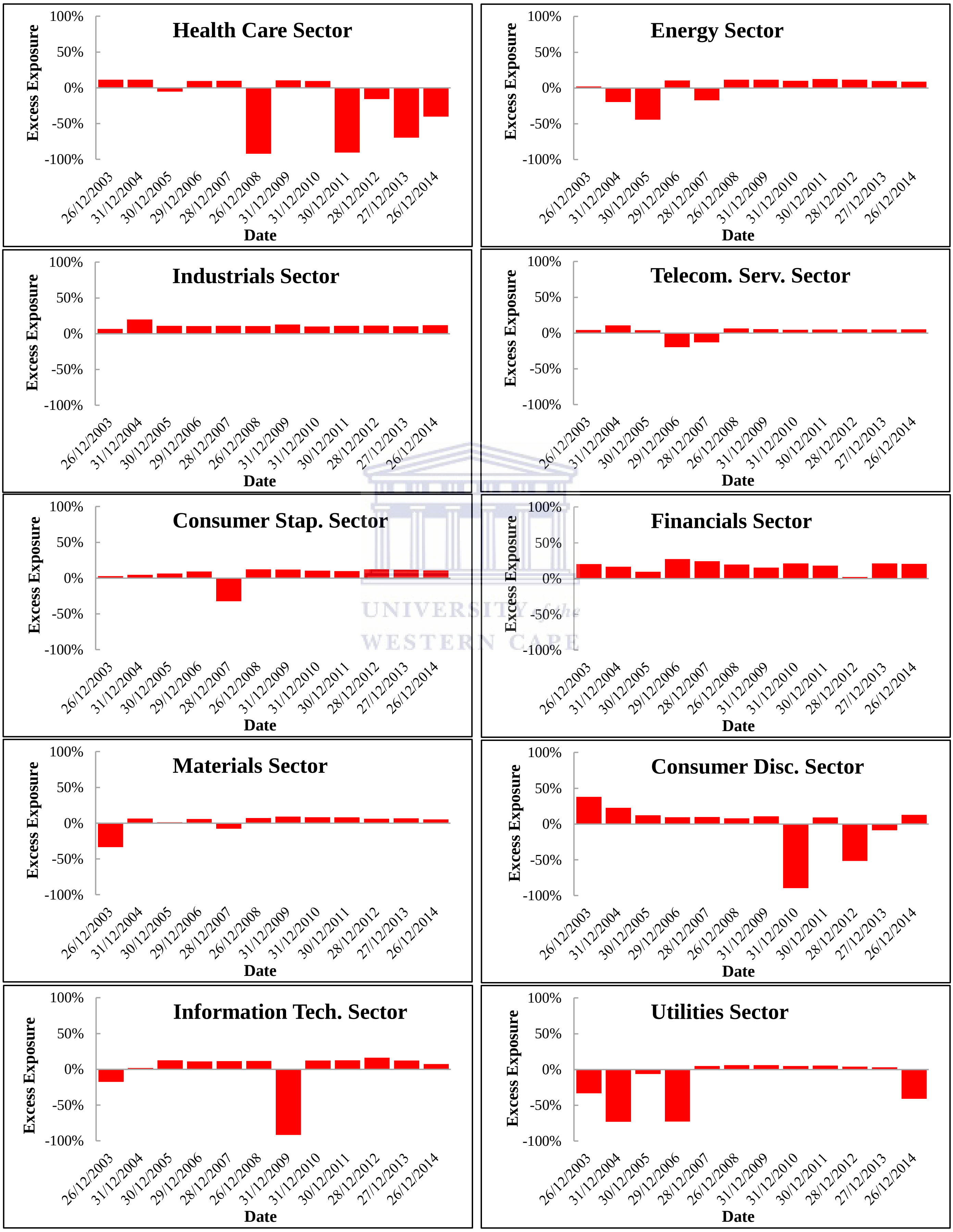
Figure 6.2: Sharpe Ratio Optimised Sector Allocation



The differences in performance of the cap-weighted S&P Global 1200 index and Sharpe ratio optimised compositions over the study period are also substantial, with the Sharpe ratio optimised compositions achieving an annualised return of 22.12% in comparison to 8.39% of the S&P Global 1200 index. Furthermore, the Sharpe ratio optimised composition accrues 9.447 cumulative returns in comparison to 2.170 earned by the S&P Global 1200 index. The variation in performance is evaluated based on the differences in sector allocation between the S&P Global 1200 index and the optimised compositions, as depicted in Figure 6.3. The positive percentages in Figure 6.3 represent the weight over allocated by the S&P Global 1200 index in excess of the weight apportioned to the respective sectors by the Sharpe ratio optimised allocation. On the other hand, the negative values reflect the weight under allocated by the S&P Global 1200 index relative to the weight allocated by the Sharpe ratio optimised composition. The findings show that the cap-weighted S&P Global 1200 index generally overweight's the financial, industrials, materials and consumer staples sectors over the examination period. Following the 2002 technology bubble, the cap-weighting methodology employed by the S&P Global 1200 index underweights the energy and utilities sectors, and overweight's the consumer discretionary sector. Furthermore, cap-weighting tends to underweight the resilient healthcare sector, especially during the 2008 global financial crisis and following the 2011 European debt crisis. The benchmark portfolio also loses out on earning attractive returns by underweighting the information technology and consumer discretionary sectors in 2009 and 2010, respectively.

The results therefore highlight that although the cap-weighting methodology provides a low cost, self-rebalancing passive approach to investing, it does not necessarily provide the optimal or highest attainable risk-adjusted returns. Consequently, Section 6.4 takes a look at 4 static optimised investment strategies under different portfolio constraints, in order to identify optimal sector exposures or allocations that can provide higher risk-adjusted returns than a passive buy and hold approach in the cap-weighted S&P Global 1200 index.

Figure 6.3: Sector Exposure in Excess of Optimal Allocation



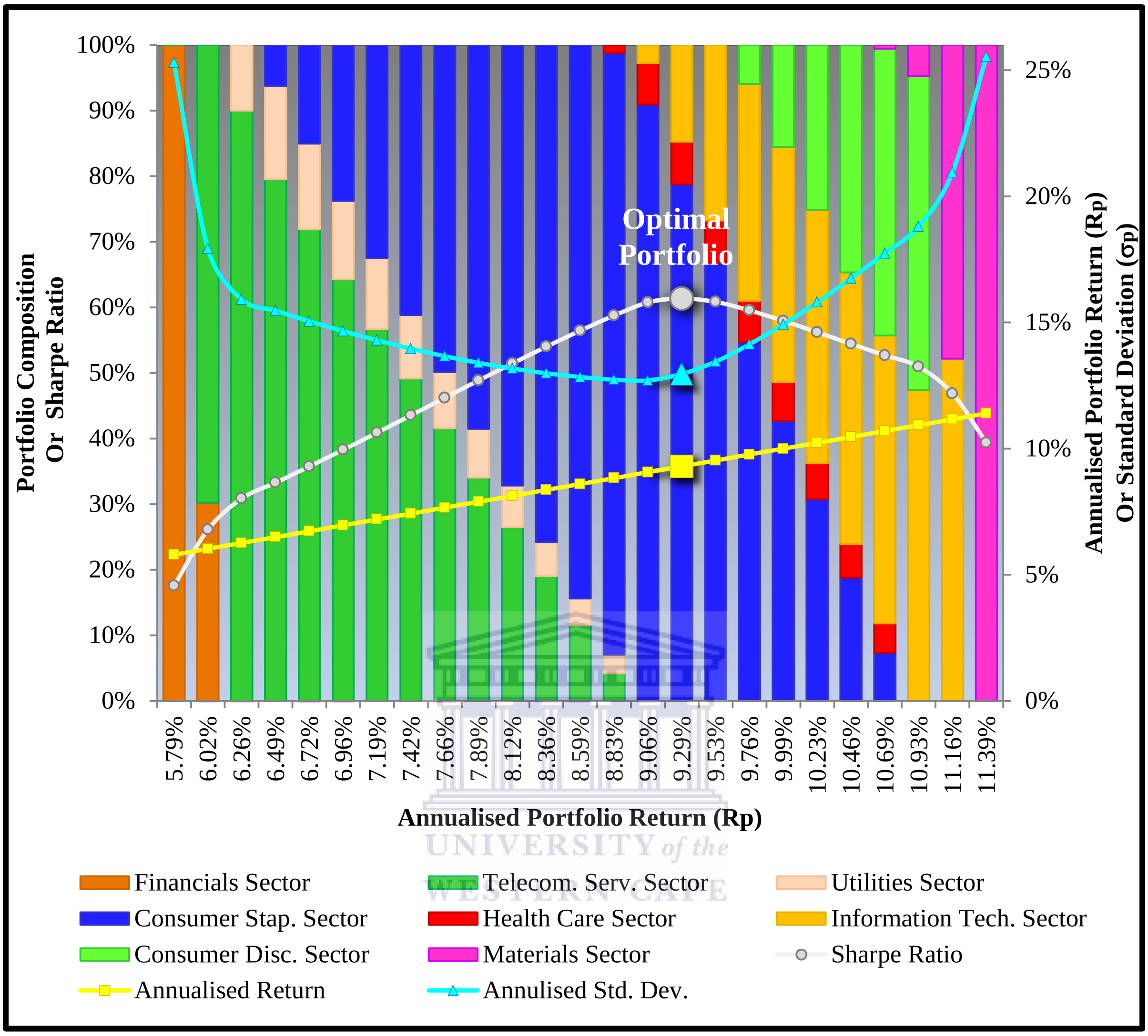
6.4. Results: Static Optimal Sector Based Portfolios

The results of the long-only mean-variance efficient optimised portfolios at each level of annualised portfolio return are graphically depicted in Figure 6.4. The histograms in the graph illustrate the portfolio composition or exposure to each global sector, whereas the yellow, blue and grey lines represent the portfolios' annualised return, standard deviation and Sharpe ratio, respectively. The long-only mean-variance efficient optimisation process starts out by allocating 100% of the capital into the financial sector as it has the lowest return of 5.79% and searches for the optimal sector allocation by replacing the exposure with more efficient sectors until 100% of the capital is invested in the materials sector, as it has the highest annualised sector return of 11.39%.

As the portfolio return gradually increases from 5.79%, the investment in the financial sector is sequentially replaced by the telecommunication services and utilities sectors, which is followed by the consumer staples sector. In order to increase the returns at a higher rate than the standard deviation, the optimisation process subsequently introduces the healthcare and information technology sectors, before investing in the consumer discretionary and materials sectors in order to further improve returns. The energy and industrials sector are redundant and not included in the optimisation process at any level of returns.

The optimal Sharpe ratio of the long-only mean-variance efficient strategy is equal to 61.34% and occurs when the annualised portfolio return and standard deviation are equal to 9.29% and 12.96%, respectively. The optimal compositions of the sector portfolio comprises of 78.30% invested in the consumer staples sector, 14.96% invested in the information technology sector and 6.34% invested in the healthcare sector over the examination period. An increase in returns beyond 9.29% causes the investment in the consumer staples sector to decrease as it is sequentially replaced by the information technology, consumer discretionary and materials sectors. Accordingly, the annualised Sharpe ratio of the portfolios decreases, as the portfolio standard deviation increases at a higher rate than portfolio returns.

Figure 6.4: Long-Only Mean-Variance Efficient Optimised Portfolios

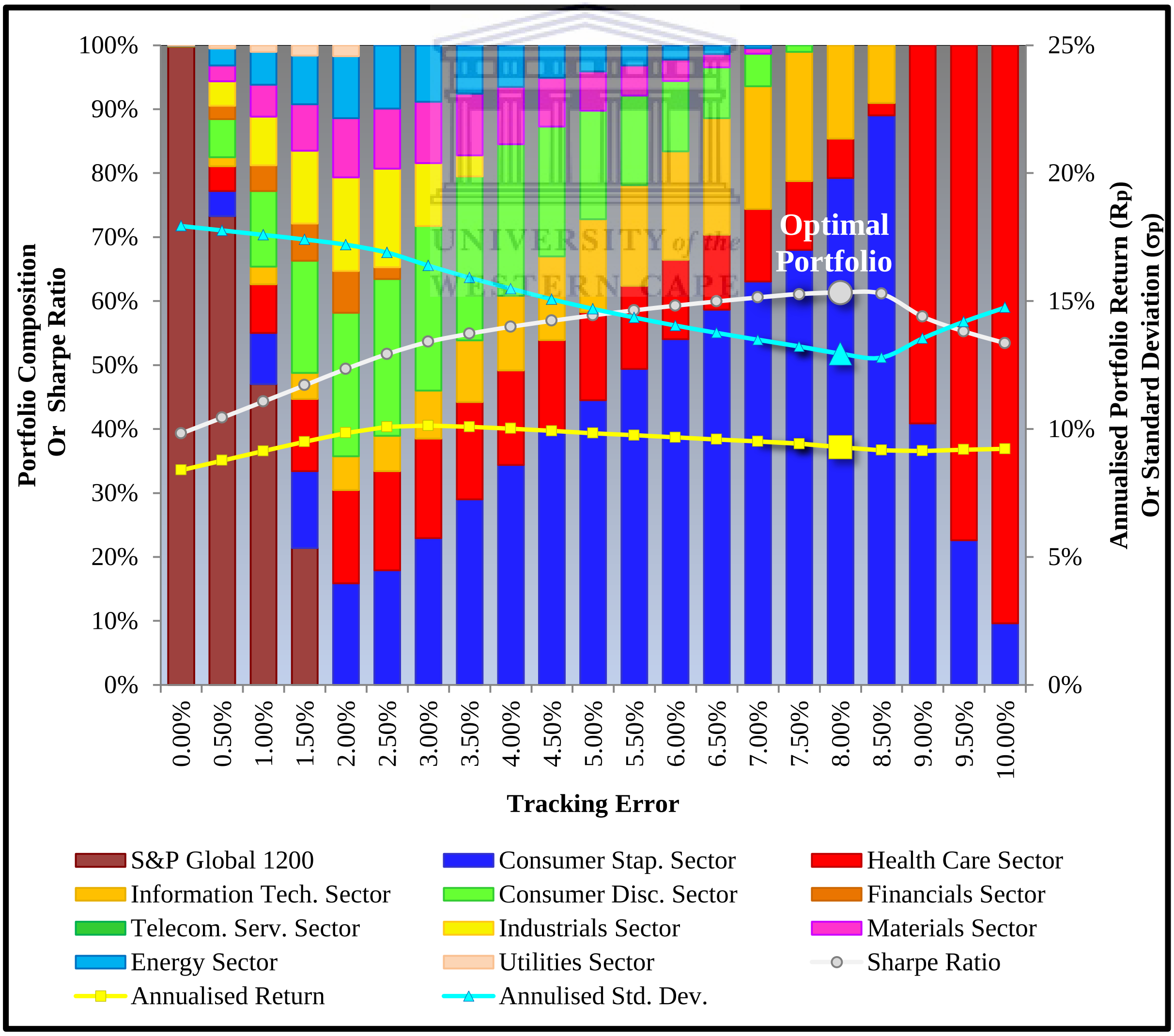


The risk-return characteristics and portfolio compositions of the mean-tracking error optimised long-only strategy are illustrated in Figure 6.5. Unlike the mean-variance efficient optimisation strategy, all 10 sectors are included in the mean-tracking error optimisation process. The optimisation process starts out by investing 100% of the capital in the S&P Global 1200 index which equates to a 0.00% tracking error. The tracking error is then gradually increased which results in a decrease of the exposure to the S&P Global 1200 index as it is replaced by the sector indices. The consumer staples, information technology and healthcare sectors gradually begin to dominate as the tracking error increases further.

The annualised Sharpe ratio of the mean-tracking error long-only strategy is optimised at 60.67% when 79.44% of the capital is invested in the consumer staples sector, 14.39% is invested in the information technology sector and 6.16% is invested in the healthcare sector. The annualised portfolio return and the standard deviation of the optimised portfolio are 9.21% and 12.96%, respectively. Furthermore, the portfolio composition and risk-return attributes of the optimal portfolio from the mean-tracking error strategy are very similar to the optimal portfolio from the mean-variance efficient optimisation strategy.

The optimal portfolio occurs when the portfolios mean-tracking error from the S&P Global 1200 index is equal to 8.00%, at which point the standard deviation decreases at a faster rate than portfolio returns. Beyond this point, the healthcare and consumer staples sectors almost entirely dominate the portfolio and the Sharpe ratio begins to decrease, as the returns continue decreasing and standard deviation starts increasing.

Figure 6.5: Long-Only Mean-Tracking Error Optimised Portfolios

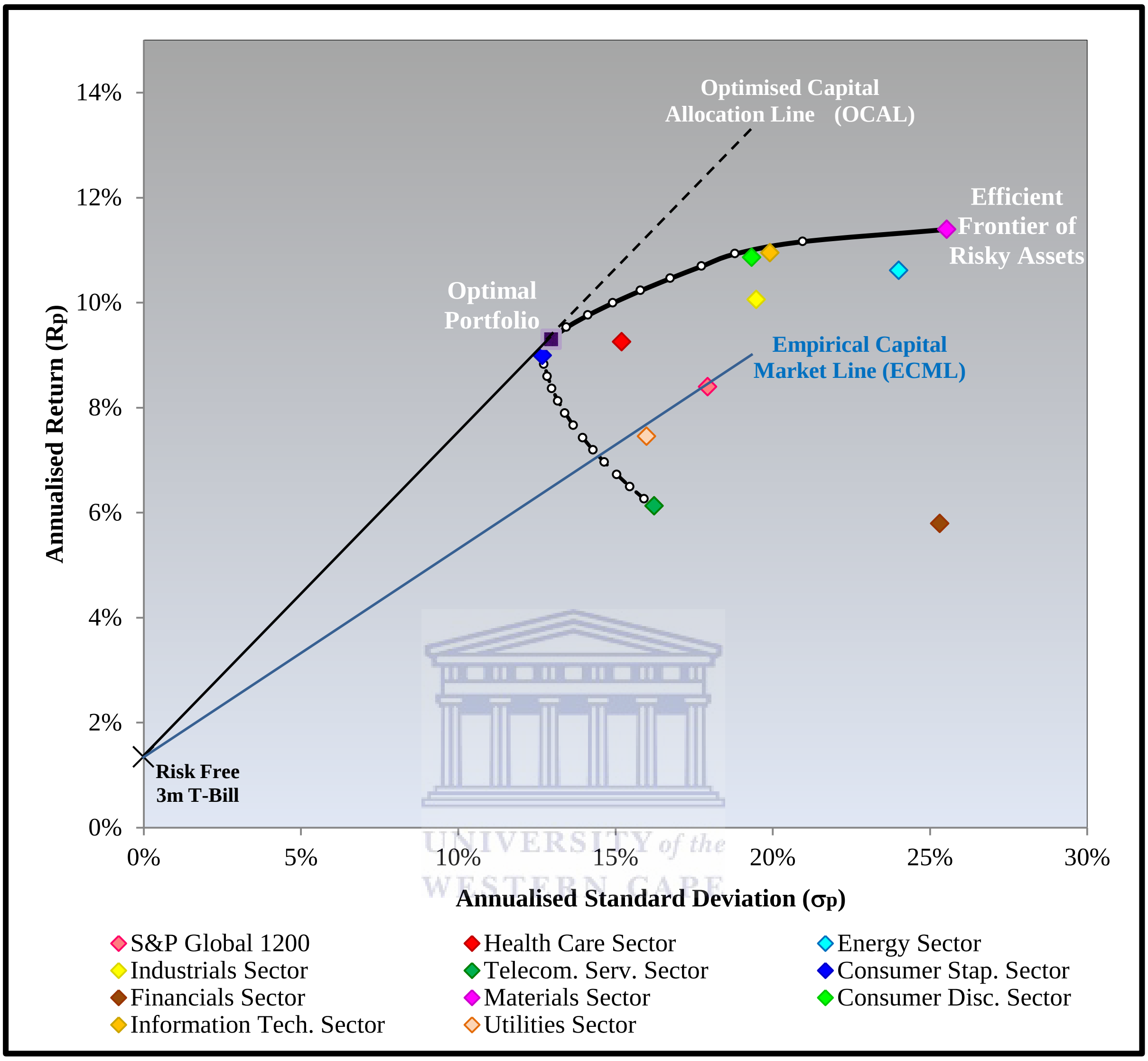


The results from the mean-variance efficient long-only optimisation strategy are used to construct the mean-variance efficient frontier illustrated in Figure 6.6. The efficient frontier represents the portfolios that provide the highest return for a given level of risk or lowest risk for a given level of return. The S&P Global 1200 index and the individual sectors that either fall on or below the efficient frontier are also plotted on the diagram. The long-only optimal portfolio also plots on the efficient frontier and is denoted by the purple square marker. The Sharpe ratio optimised portfolio represents the portfolio that provides the highest excess return per unit of total risk as measured by standard deviation.

The combination line between the risk-free asset and the optimal portfolio is termed as the optimal capital allocation line (OCAL). Portfolios that lie on the OCAL provide the highest risk premiums per unit of total risk and provide superior performance to other sector based portfolios that are developed under the equivalent long-only and no leverage constraints (Hsieh, 2010). In terms of risk-adjusted performance, the portfolios that plot on the OCAL also outperform all portfolios that lie on the empirical capital market line (ECML), which reflects the asset combinations between the risk-free asset and the S&P Global 1200 index. This is highlighted by the steeper gradient or slope of the OCAL in comparison to the ECML.

Investors can tailor their investments to match individual risk appetites, by lending at the risk-free rate and investing the remainder of the capital in the long-only optimal portfolio, thereby resulting in portfolios that plot between the risk-free asset and the optimal portfolio. However, the extended portion of the OCAL that lies beyond the long-only optimal portfolio is marked by a dashed line as it represents unattainable portfolios due to the long-only and no leverage constraints. These constraints prevent investors from short-selling or borrowing at the risk-free rate in order to invest more than the initial capital in the optimal portfolio. As a result, investors can only select portfolios that lie on the solid segment of the OCAL (Hsieh, 2010).

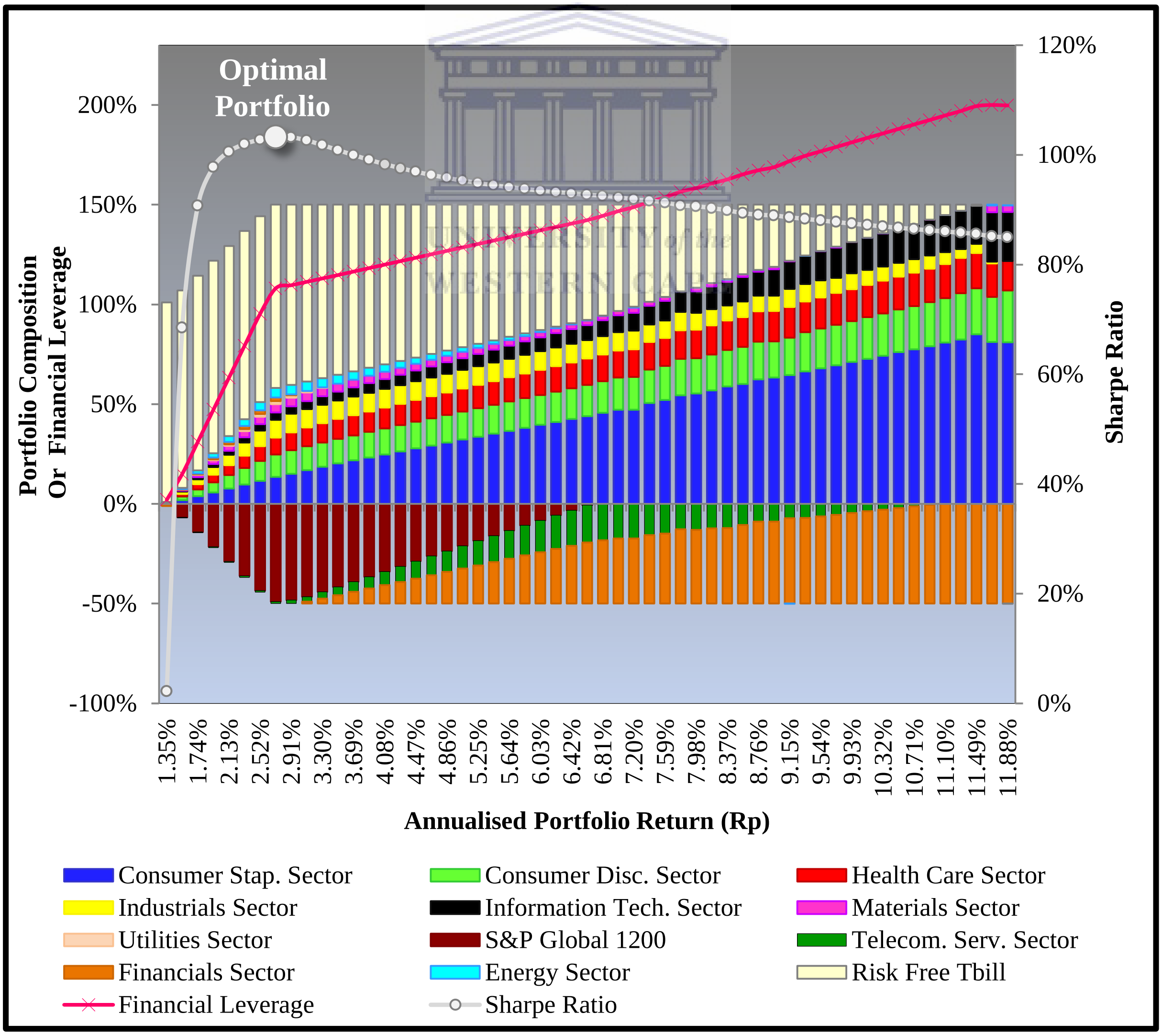
Figure 6.6: The Efficient Frontier for Long-Only Portfolios



The results from the mean-variance efficient long-short strategy with leverage are graphically depicted in Figure 6.7. The strategy starts out by investing 100% of the capital in the risk-free asset, thus the lowest return is 1.35%. The strategy subsequently short sells the less efficient sectors and takes long positions in the more efficient ones in order to improve the Sharpe ratio. After holding 50% short positions and 100% leverage as depicted by the pink line, any further long position is financed by reducing the investment in the risk-free asset. Initially, the strategy takes a short position in the S&P Global 1200 index, however beyond the 100% leverage mark, it starts short selling the telecommunication services and financial sectors. In terms of long positions, the consumer staples sector is the most dominant at all levels of returns with consumer discretionary and healthcare sectors also having a fair representation.

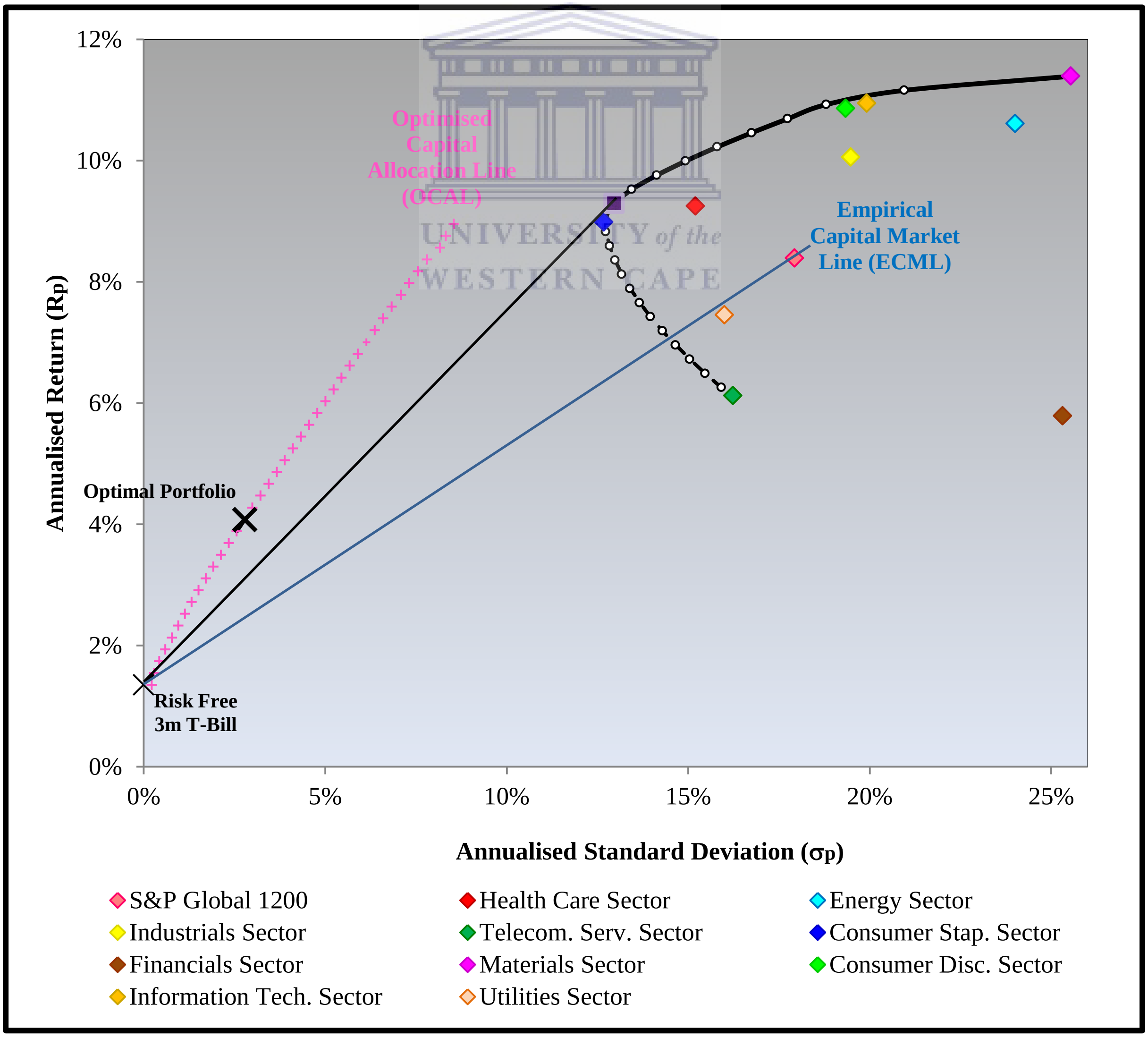
The Sharpe ratio initially increases at a decreasing rate and is maximised at 103.26%. The optimal portfolio hold short 48.97% of the capital in the S&P Global 1200 index, 92.92% is allocated to the risk-free asset, 13.50% is invested in the consumer staples sector, 11.30% in the consumer discretionary sector, 9.93% in the industrials sector and 8.48% in the healthcare sector. The remainder of the capital is spread between the other sectors. The optimal Sharpe ratio occurs when 108% leverage is used and the annualised portfolio return and standard deviation are equal to 2.72% and 1.33%, respectively. Beyond this point, increasing the exposure to the sector indices results in higher returns at the cost of standard deviation increasing at a higher rate, as investment in the stable risk-free proxy reduces. Henceforth, increasing leverage beyond 108% causes the Sharpe ratio to gradually decrease.

Figure 6.7: Long-Short Mean-Variance Efficient Portfolio Optimisation with 200% Leverage Limit



The relaxation of the long-only and no leverage constraints permit the long-short strategy to achieve higher Sharpe ratios, as the strategy can benefit from active extension which allows short selling inefficient assets and investing the proceeds in more efficient assets. Figure 6.8 illustrates the long-short optimised capital allocation line (OCAL), marked by the series of pink crosses. The long-short OCAL lies above and has a steeper slope than the long-only OCAL denoted by the solid black line. Thus, the long-short OCAL dominates all portfolios and individual sectors that lie below it, as it provides higher reward-to-risk ratios. The long-short optimal portfolio, marked by the black marker in Figure 6.8, represents the portfolio that provides the highest risk-adjusted return as measured by the Sharpe ratio. Portfolios that lie on the long-short OCAL also dominate any asset mix between the risk-free asset and the market portfolio, represented by the solid blue ECML.

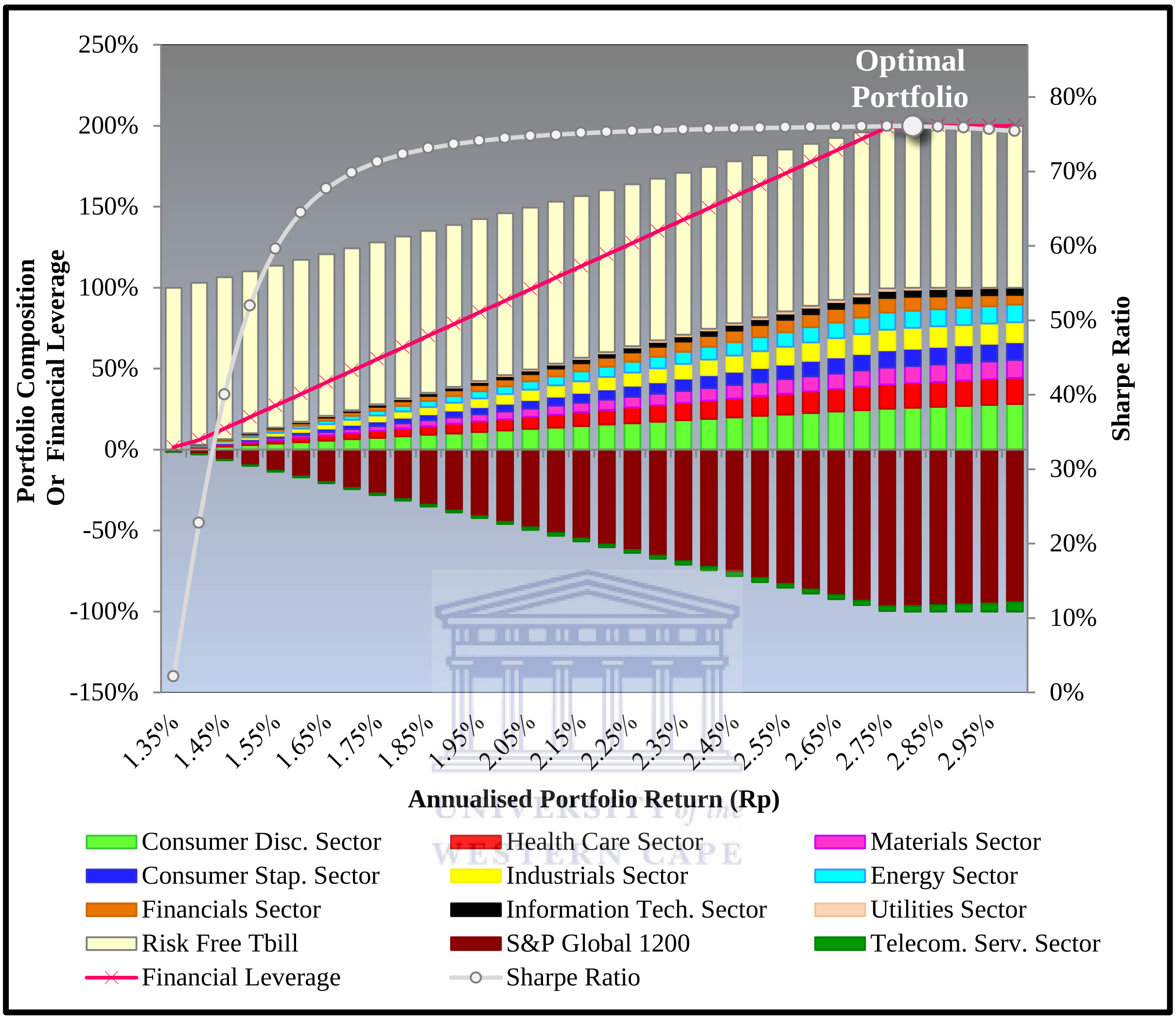
Figure 6.8: The Efficient Frontier for Long-Short Portfolios with 200% Leverage Limit



The mean-variance optimised results from the market neutral hedge fund strategy with 200% leverage cap are depicted in Figure 6.9. Unlike the long-short strategy, the investment in the risk-free asset remains constant at 100% throughout the optimisation process and the long positions in the sector indices are entirely financed by the short positions held mainly in the S&P Global 1200 index. Henceforth, the market neutral strategy results in a series self-financing portfolios that have zero net exposure to the S&P Global indices. The market neutral optimisation process minimises the variance at each level of return, starting from 1.35% as 100% of the initial capital is invested in the risk-free asset. The returns subsequently increase as the exposure to the various sector indices increases while simultaneously short selling the less efficient S&P Global 1200 index. As a result, the Sharpe ratio increases at a decreasing rate as leverage increases up to 200%. In contrast to the long-short strategy with leverage, the long positions in the market neutral strategy apportion a higher weighting to the consumer discretionary and healthcare sectors with the consumer staples sector receiving a comparatively lower exposure. The materials, industrials, financials and energy sectors also receive moderate allocation as returns increase.

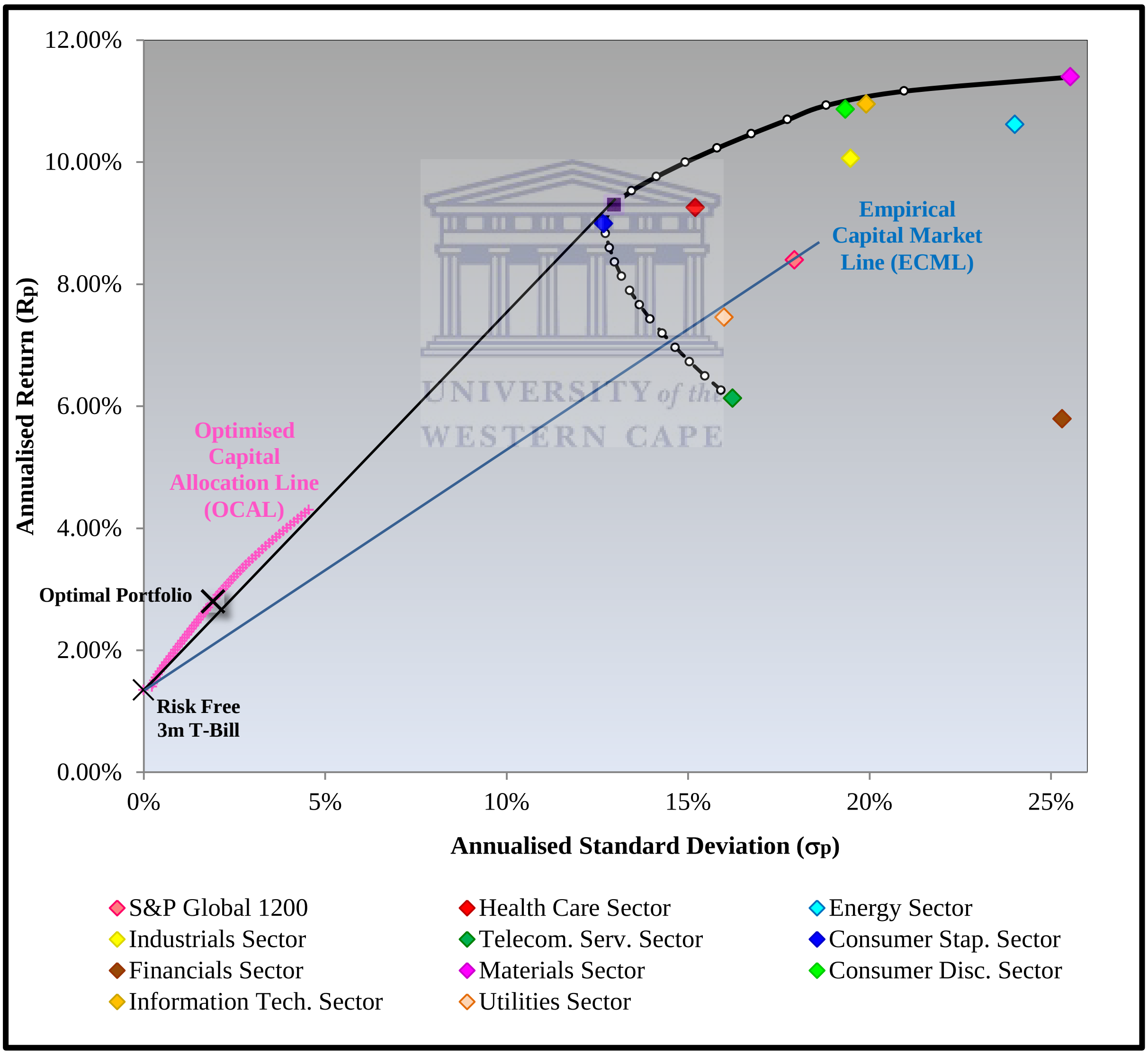
The market neutral strategy achieves its optimal portfolio when 96.67% and 3.33% of the portfolio is held short in the S&P Global 1200 index and the telecommunication services sector, respectively. At the optimal portfolio allocation, 100% is held long in the risk-free asset, 25.83% in the consumer discretionary sector, 15.25% in the healthcare sector, 12.75% in the industrials sector and approximately 11% each, in the materials, financials, consumer staples and energy sectors. The remainder of the portfolio is allocated between the information technology and utilities sectors. The optimised portfolio earns a Sharpe ratio of 76.06%, with an annualised portfolio return of 2.80% and annualised portfolio standard deviation of 1.91% when 200% leverage is used. By increasing the returns beyond this point, the Sharpe ratio starts decreasing as investment held short in the telecommunication services sector increases, thus causing the portfolio's standard deviation to increase at a higher rate than portfolio returns.

Figure 6.9: Market Neutral Mean-Variance Efficient Portfolio Optimisation with 200% Leverage Limit



The results from the optimisation process of the market neutral strategy with 200% leverage are used to construct the market neutral OCAL which is graphically illustrated in Figure 6.10. The market neutral portfolios that plot on the first portion of the OCAL between the risk-free asset and the optimal portfolio, denoted by the black marker, dominate all portfolios that lie on the long-only OCAL and the ECML denoted by the black and blue solid lines, respectively. However, similar to the findings of Hsieh (2010) and the profile of the Sharpe ratio curve in Figure 6.9, the market neutral OCAL kinks after the optimal portfolio, which indicates a decline in the reward-to-risk ratio after the 200% leverage limit is achieved. The slope of the OCAL beyond the optimal portfolio is flatter than the slope of the market neutral OCAL from the risk-free asset to the optimal portfolio, which suggests that the portfolios on the second portion of the OCAL provide lower excess returns per unit of total risk in comparison to the first portion. The gradient of the second portion of the OCAL (beyond the optimal portfolio) is also less than the long-only OCAL represented by the solid black line, which indicates that the long-only OCAL has a higher reward-to-risk ratio (Hsieh, 2010). The gradient of the second portion of the market neutral OCAL remains comparatively higher than the ECML, indicating that it continues to provide a higher reward-to-risk ratio than any asset combinations between the risk-free asset and the S&P Global 1200 index.

Figure 6.10: The Efficient Frontier for Market Neutral Portfolios with 200% Leverage Limit



6.5. Summary Statistics of the Global Optimised Sector Based Portfolios

The performance statistics and portfolio compositions of the 4 global optimal portfolios and the S&P Global 1200 index are summarised in Table 6.1. The long-only mean-variance efficient and mean-tracking error optimised portfolios provide similar returns and have identical standard deviations of 12.96%. Both strategies provide higher returns and lower total risk in comparison to the benchmark S&P Global 1200 index, thus resulting in higher risk-adjusted returns as measured by the Sharpe ratio. Furthermore, the returns of the mean-variance efficient optimised long-only strategy are significantly different from the S&P Global 1200 index at a 5% significance level, whereas the returns of the mean-tracking error optimised strategy are significant at a 10% level. Both long-only strategies also provide lower maximum drawdowns than the benchmark and have lower systematic risk, as suggested by the beta measures of 0.6623 and 0.6620. The similarities in performance statistics as well as the portfolio compositions of the two long-only portfolios also indicates that the objective of minimising the portfolio variance at each level of return is equivalent to minimising the portfolios tracking error, which is in line with the findings of Hsieh (2010).

The performance statistics of the mean-variance efficient optimised long-short and market neutral strategies highlight the benefits of permitting short positions and the use of leverage in portfolio construction. Unlike the optimised portfolios of Hsieh (2010), both optimal long-short and market neutral strategies earn significantly lower returns than the long-only portfolios and benchmark S&P Global 1200 index. However, the standard deviation of the two strategies decreases by a higher proportion, thereby resulting in higher risk-adjusted returns. The two leverage-enabled optimal portfolios provide higher Sharpe ratios than the long-only counterparts with the long-short strategy providing the highest Sharpe ratio of 103.26%. In addition, the returns of both leverage-enabled portfolios are statistically significantly different from the S&P Global 1200 index at a 1% significance level, and both portfolios have beta coefficients close to zero. The long-short and market neutral strategies also experience significantly lower maximum drawdowns in comparison to the long-only strategies and the benchmark S&P Global 1200 index. Henceforth, the advantage of including short positions in a portfolio stems from the ability to substantially lower portfolio risks. In terms of portfolio composition both strategies take short positions in the less efficient S&P Global 1200 index in order to offset the risks of the long positions in other sectors. The short positions in the less efficient market proxy are consistent with the compositions of the optimised style portfolios of Hsieh (2010), which also sell short the MSCI World index. However, in contrast to the findings of Hsieh (2010) the strategies achieve their optimal portfolios at very different leverage levels. Furthermore, the difference in risk-adjusted performance between the long-short and market neutral strategies are much larger than the findings reported by Hsieh (2010). These differences can mainly be attributed to the prevailing Reg-T requirements incorporated in the constraints of the long-short strategy in this research which prevents individual investors from short selling more than 50% of the portfolio, however this restriction does not apply to market neutral hedge fund strategies.

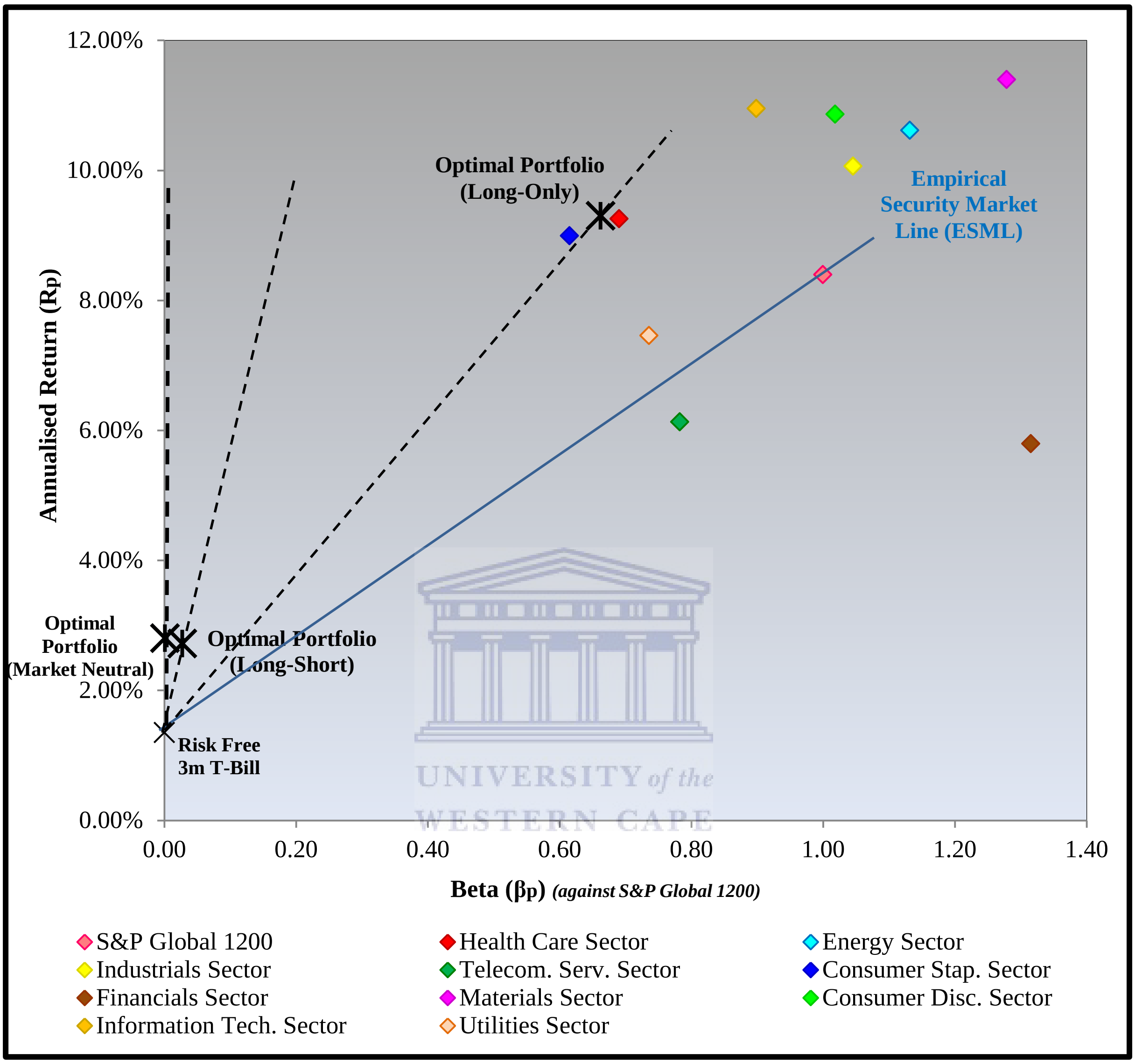
Table 6.1: Summary Statistics of the Global Optimised Portfolios

Strategy:	**Benchmark** *(S&P Global 1200)*	**Long-Only** **No Leverage**	**Long-Only** **No Leverage**	**Long- Short** **200% Leverage Cap Reg-T Limits**	**Market Neutral** **200% Leverage Cap**
Optimisation Criteria:	-	**Mean-Variance**	**Tracking Error**	**Mean-Variance**	**Mean-Variance**
<u>Performance Statistics:</u>					
Return p.a.	8.39%	9.29%	9.21%	2.72%	2.80%
***p*-value**		**[0.0352]****	**[0.0858]***	**[0.0000]*****	**[0.0000]*****
Standard Deviation p.a.	17.94%	12.96%	12.96%	1.33%	1.91%
Beta ***(against S&P Global 1200)***	1.0000	0.6623	0.6620	0.0273	0.0008
Maximum Drawdown	-58.51%	-41.56%	-41.56%	-1.96%	-1.86%
Sharpe Ratio	39.29%	61.34%	60.67%	103.26%	76.06%
Treynor Measure	7.05%	12.00%	11.88%	50.23%	1902.16%
<u>Portfolio Composition:</u>					
S&P Global 1200	100%	0%	0%	-49%	-97%
Health Care Sector	-	7%	6%	8%	15%
Energy Sector	-	0%	0%	5%	11%
Industrials Sector	-	0%	0%	9%	13%
Telecom. Serv. Sector	-	0%	0%	-1%	-3%
Consumer Staple Sector	-	78%	79%	13%	11%
Financials Sector	-	0%	0%	2%	9%
Materials Sector	-	0%	0%	4%	11%
Consumer Disc. Sector	-	0%	0%	11%	26%
Info. Tech. Sector	-	15%	15%	4%	5%
Utilities Sector	-	0%	0%	1%	1%
Risk Free T-bills	-	-	-	92%	100%
Net Exposure	100%	100%	100%	8%	0%
Leverage	N/A	N/A	N/A	108%	200%

*Statistical Significance is denoted by ***, ** and * for 1%, 5% and 10% levels, respectively.*

The risk-adjusted performance of the mean-variance optimised portfolios and the constituent sectors as measured by the Treynor measure are graphically depicted in Figure 6.11. The optimal sector based portfolios provide higher Treynor ratios than all constituent sector indices, except for the consumer staples sector which has a higher ratio than the long-only optimal portfolio. Furthermore, consistent with the findings of Hsieh (2010), all the optimised portfolios have higher Treynor measures than the benchmark portfolio as suggested by the steeper slopes of the dashed lines between the risk-free asset and optimal portfolios, relative to the slope of the empirical security market line (ESML). Therefore, the optimised portfolios provide higher excess returns per unit of systematic risk in comparison to any combination between the risk-free asset and the market proxy. The market neutral strategy provides the highest Treynor ratio followed by the long-short strategy, as they have beta coefficients close to zero and thus indicating negligible systematic risk. Consequently, the appropriate benchmark for these two strategies is the risk-free asset which provides an annualised return of 1.35%. Both the long-short and market neutral strategies therefore successfully earn positive excess returns of 1.37% and 1.45%, respectively which indicates potential arbitrage or risk-less return opportunities (Hsieh, 2010).

Figure 6.11: Relative Performances of Optimised Portfolios Measured by the Empirical Security Market Line



6.6. Conclusion

The sector decomposition of the cap-weighted S&P Global 1200 index reveals fairly stable exposures from year to year, with small changes during major economic events such as during economic downturns. On the other hand, the optimised compositions show substantial changes each year which are largely motivated by the corresponding economic phases. The changes in sector exposures each year also support the premise that different sectors are in favour at different points of the economic cycle. The disparities in performance between the cap-weighted benchmark and Sharpe ratio optimised portfolio is attributed to the sector allocation especially during major economic events. For instance, during the 2008 financial crisis the cap-weighted S&P Global 1200 index underweights resilient sectors such as the healthcare and consumer staples sectors and overweights certain sectors such as the financial and industrial sectors. Similarly, the cap-weighted S&P Global 1200 index consistently underweights the healthcare sector following the 2011 European debt crisis.

Motivated by the allocation inefficiencies of the cap-weighted market portfolio, the study develops and examines 4 Sharpe ratio optimised portfolios based on different portfolio objectives and constraints. The findings are congruent with earlier studies by Yu (2008) and Hsieh (2010) as all 4 optimal portfolios provide higher risk-adjusted returns than the cap-weighted benchmark S&P Global 1200 index, with all their OCAL's having steeper gradients than the ECML. The optimal long-only portfolios have a high exposure to the information technology sector and resilient consumer staples sector, which allows the portfolio to generate higher returns than the benchmark and simultaneously reduce standard deviation. Furthermore, in line with the findings of Hsieh (2010), the optimal long-only portfolios are characterised by similar performance with equal standard deviations, maximum drawdown and almost identical beta coefficients. The results therefore suggest that the optimisation objective of minimising the variance at each level of return is equivalent to minimising the portfolios tracking error.

More importantly, the results show that lifting the long-only constraint and allowing the use of leverage drastically improves the risk-adjusted performance of the portfolios. Both the long-short and market neutral optimised portfolios provide higher Sharpe ratios than the long-only portfolios. Portfolios with short positions and leverage benefit mainly from risk reduction rather than improvement in returns. The long-short and market neutral strategies benefit from short selling the less efficient S&P Global 1200 index in order to offset volatility of the sectors held long. As a result, the long-short mean-variance efficient optimised portfolio constructed under the Reg-T requirements provides the highest risk-adjusted performance as measured by the Sharpe ratio. Furthermore, short selling and leverage allow the optimised portfolios to have almost zero beta coefficients or systematic risk, thereby translating into significantly higher Treynor measures than the long-only counterparts. The superior Treynor measures of the optimised portfolios dominate portfolios that lie on the ESML which represents combinations between the risk-free asset and the cap-weighted S&P Global 1200 index.

The similarities between the trends in the risk-adjusted performances of the optimal global sector based portfolios identified in this research and global style based portfolios tested by Hsieh (2010), suggest that the two techniques are analogous and provide more efficient asset allocation mechanisms than the traditional cap-weighted approach. Overall, although the findings of the optimisation strategies tested in this chapter do not guarantee successful outperformance in the out-of-sample period, the results do provide substantial evidence against the mean-variance efficiency of the cap-weighted S&P Global 1200 index.

7

Market Timing Using Technical Analysis

7.1. Introduction

As an alternative to asset allocation strategies, this chapter focuses on timing market trends using technical analysis in order to outperform the relevant cap-weighted benchmarks, over the period from July 5th, 2002 to February 6th, 2015. The same set of 10 S&P Global 1200 sector indices used in prior chapters are adopted and the methodologies of the tests conducted in this research are detailed in Section 7.2. The sector based momentum strategy is the first technical trading strategy tested and the results are presented in Section 7.3. The momentum strategy is driven by the expectation that past performance is persistent and therefore a fair indication of future outcomes. The strategy buys into the best performing sectors and takes short positions in the worst performing sectors over a specified past period.

Secondly, the study tests an exponential moving average (EMA) trend timing model on the S&P Global 1200 sector indices based on the methodology promulgated by Hsieh (2010), in order to predict market trends based on crossovers of price averages. The tests are driven by the documented successful downside risk management of the moving average strategy, and the performance statistics of the EMA strategies are discussed in Section 7.4. Thirdly, the study evaluates a technical charting based trend timing model as an alternative to the EMA timing strategy developed by Hsieh (2010). Technical charting involves predicting market trends based on past price patterns. The study employs the methodology suggested by Leigh, Frohlich, Hornik, Purvis and Roberts (2008), however unlike prior technical charting studies that only test the predictive ability of charting patterns, this study tests a practical timing model using trading rules. The rules employ the bull and bear flag patterns in order to generate buy and sell signals, respectively and the results are discussed in Section 7.5.

Section 7.6 presents and discusses the performance of a global tactical sector allocation (GTSA) model in the context of an investor’s equally weighted portfolio. Two distinct GTSA models are developed, namely the EMA and technical charting based models. The results are assessed relative to the passive buy and hold strategy in the cap-weighted S&P Global 1200 index and the equally weighted sector portfolio, over the entire examination period.

7.2. Descriptive Statistics and Methodology

The technical analysis strategies tested in this chapter include a global sector momentum strategy based on the sectors return persistence over the prior specified period, an exponential moving average (EMA) strategy based on the crossover rule of the fast exponential moving average (FEMA) and slow exponential moving average (SEMA), and a technical charting strategy based on pattern recognition using the template matching technique. The study also tests a global tactical sector allocation (GTSA) model that employs the EMA and technical charting tools in the context of an equally weighted portfolio.

The EMA and technical charting strategies are implemented through the use of trading rules and both strategies employ the 100% hedging mechanism suggested by Faber (2007) and Hsieh (2010). Therefore, a sell or hedge signal indicates a shift of the entire market exposure into cash or the risk-free asset. Furthermore, the trading rules are developed and conditioned during the 339 week in-sample period from July 5th, 2002 to December 26th, 2008. The best performing trading rules from the in-sample period are subsequently extracted and tested for robustness in the 319 week out-of-sample period from January 2nd, 2009 to February 6th, 2015. The optimal trading rules from the in-sample period are also tested for robustness over the entire examination period. Furthermore, the optimal trading rule permutations from the out-of-sample and overall examination period are tested in the in-sample period, in order to assess performance and robustness of the EMA and charting strategies.

In order to avoid look-ahead bias, the study imposes a one period lag following any trade signal, which ensures that a trade for any of the 3 technical analysis strategies is only implemented in the following period. The performance of the 3 technical analysis strategies is assessed based on risk-return characteristics which include cumulative returns, annualised returns, annualised standard deviation and maximum drawdown over the examination period. The study also computes the risk-adjusted returns as measured by the Sharpe ratio both gross and net of transaction costs (refer to Section 5.2). In addition, the percentage of time the strategy is in cash is assessed for the two trading rule strategies in order to assert practicality.

7.2.1. Global Sector Momentum Strategy

This research tests for persistence in sector returns in order to determine which sectors to invest in and employs the methodology promulgated by Jegadeesh and Titman (1993) and Andreu, Swinkels and Tjong-A-Tjoe (2013). The monthly data of the 10 S&P Global 1200 sector indices is used for this purpose. The study develops and tests 20 momentum portfolios with different formation (*J*) and holding (*K*) period permutations. Formation periods of 3, 6, 9 and 12 months and holding periods of 1, 3, 6, 9 and 12 months are tested.

The study develops portfolios based on the methodology promulgated by Jegadeesh and Titman (1993) which results in a time-series of monthly returns to avoid test statistics based on overlapping returns and to increase the power of the tests (Moskowitz and Grinblatt, 1999). The study develops portfolios based on past *J* month's returns and holds for the next *K* months, however each months return is a combination of *K* ranking strategies. For example, in the case of a 6 month formation and holding period strategy also referred to as a 6,6 (*J*, *K*) strategy, each months return is a combination of six ranking strategies. At time t=0, the study ranks and takes a long position in the best performing sector, referred to as the winner portfolio and short sells the worst performing sector or loser portfolio. The study thereby allocates 1/6 of the capital or portfolio weighting in the winner which is financed by the short position, thus creating a zero cost strategy. This process continues and after 6 months 100% of the capital is allocated to the long position and financed by the short position. Furthermore, after 6 months the investment made at time t=0 is liquidated and the capital or weighting is reallocated based on the preceding 6 months. Therefore, after 100% of the capital is allocated, in every subsequent month the study reallocates $1/K$ of the capital or weight that was invested in month $t - K$. The remainder of the portfolio weighting are carried over from the previous months. The time-series returns of the winner and loser portfolios are computed by taking the sum-product of the momentum based weightings and the corresponding sector returns in month t, as illustrated in Equation 7.1.

$$r_{i,t} = (w_{s1,t}\ x\ r_{s1,t}) + (w_{s2,t}\ x\ r_{s2,t}) + \cdots + (w_{sn,t}\ x\ r_{sn,t}) \tag{7.1}$$

where

$r_{i,t}$ — the return of the winner or loser portfolio i, in month t;
$r_{s1,t}, r_{s2,t},\ r_{sn,t}$ — the returns for the 1^{st}, 2^{nd} and n^{th} sector in month t; and
$w_{s1}, w_{s2},\ w_{sn}$ — the momentum based weightings for the 1^{st}, 2^{nd} and n^{th} sector.

The returns of the momentum strategy are subsequently computed by taking the time-series excess returns of the winner portfolio relative to the loser portfolio. The momentum strategy returns are assessed in comparison to the benchmark or market portfolio, which represents the performance of the buy and hold strategy. In order to assert statistical significance of the results, the study computes the *t*-statistics for each momentum strategies returns against the market returns using a two-sample Students *t*-test.

7.2.2. Exponential Moving Average Trend Timing Model

Exponential moving average's (EMA) assign higher weightings to more recent data which allows them to react faster to changes in trends in comparison to simple moving averages. EMA's also reflect all the data from the start of the study period and avoids arbitrary cut off windows such as the 200-day simple moving averages (Achelis, 2010). The EMA trend timing model employs the moving average crossover rule to determine buy and sell signals. The study uses the fast exponential moving average (FEMA) and slow exponential moving average (SEMA) which differ based on the percentage smoothing constant applied in Equation 7.2 (Hsieh, 2010).

$$EMA_t = \left(EMA\%\ x\ p_{i,t}\right) + (1 - EMA\%) x\ EMA_{t-1} \tag{7.2}$$

where

$p_{i,t}$	the index value of index *i* in time *t*;
EMA%	the exponential moving average smoothing constant; and
EMA_{t-1}	the exponential moving average in the period *t-1*.

The *EMA%* in Equation 7.2 represents the smoothing constant or speed at which the EMA follows or tracks the actual index. Therefore, the *EMA%* for the FEMA is always higher than that of the SEMA. In addition, the EMA in a given period *t*, assigns *EMA%* of the value to the current index level and (1 - *EMA%*) of the value to the previous periods EMA value.

Following the methodology proposed by Hsieh (2010), the study implements the crossover EMA strategy by means of a trading rule which stipulates that a buy signal is generated when the FEMA cuts the SEMA from below and a sell signal is generated when the FEMA cuts through the SEMA from above. When a buy signal is generated, the strategy invests 100% of the capital into the sector thus earning the index returns, whereas a sell signal denotes that the market exposure is sold off and the position is hedged by investing in risk-free treasury bills.

In line with the study by Hsieh (2010), EMA strategies with FEMA and SEMA smoothing constants (*EMA%*) ranging from 0% to 100% at 10% intervals are tested, for each global sector index. The best performing permutations from the in-sample period are extracted and tested in the out-of-sample and overall study periods to test for robustness. The results of the EMA timing strategy are assessed relative to the buy and hold strategy in the corresponding index. In addition, the study computes the Sharpe ratio of the selected EMA strategies both gross and net of transactions costs in order to infer practical relevance of the strategy.

7.2.3. Technical Charting Heuristics Trend Timing Model

The technical charting heuristics model is implemented using the template matching technique. The template matching technique utilises quantified translation of archetypal patterns arranged in a 10x10 grid that is constituted of varying weights, in order to recognise patterns. This study employs the sloping bull flag and bear flag pattern depicted in Figure 7.1(a) and 7.1(b), respectively. The choice of the selected patterns is based on the premise that periods of consolidated returns and controlled profit taking, are followed by a trend breakout. The identification of the bull flag pattern denotes a buy signal, whereas the bear flag identification indicates a hedge signal. The highest weights represent the core patterns that are shaded in grey and the weights of the remaining cells are computed using a linear declining function moving outwards from the core. The systematic allocation of weights avoids potential data mining bias as the weights are not inferred from fitting actual test data.

Figure 7.1: Bull and Bear Flag Template Grids - *T(i,j)*

0.66	0.17	-0.43	-1.00	-1.38	-1.50	-1.41	-1.41	-0.88	0.14
1	0.58	0.05	-0.50	-0.90	-1.08	-1.07	-1.07	-0.50	0.43
1	1	0.52	0.00	-0.43	-0.67	-0.72	-0.72	-0.13	0.71
0.66	1	1	0.50	0.05	-0.25	-0.38	-0.38	0.25	1
0.31	0.58	1	1	0.52	0.17	-0.03	-0.03	0.63	1
-0.03	0.17	0.52	1	1	0.58	0.31	0.31	1	1
-0.38	-0.25	0.05	0.50	1	1	0.66	0.66	1	1
-0.72	-0.67	-0.43	0.00	0.52	1	1	1	1	0.71
-1.07	-1.08	-0.90	-0.50	0.05	0.58	1	1	0.63	-3.00
-1.41	-1.50	-1.38	-1.00	-0.43	0.17	0.66	0.66	-3.00	-3.00

(a)

-1.41	-1.50	-1.38	-1.00	-0.43	0.17	0.66	0.66	-3.00	-3.00
-1.07	-1.08	-0.90	-0.50	0.05	0.58	1	1	0.63	-3.00
-0.72	-0.67	-0.43	0.00	0.52	1	1	1	1	0.71
-0.38	-0.25	0.05	0.50	1	1	0.66	0.66	1	1
-0.03	0.17	0.52	1	1	0.58	0.31	0.31	1	1
0.31	0.58	1	1	0.52	0.17	-0.03	-0.03	0.63	1
0.66	1	1	0.50	0.05	-0.25	-0.38	-0.38	0.25	1
1	1	0.52	0.00	-0.43	-0.67	-0.72	-0.72	-0.13	0.71
1	0.58	0.05	-0.50	-0.90	-1.08	-1.07	-1.07	-0.50	0.43
0.66	0.17	-0.43	-1.00	-1.38	-1.50	-1.41	-1.41	-0.88	0.14

(b)

Source: adapted from Leigh, et al. (2008)

In order to compare the time-series price data to the representative templates grids, the index price data is translated into 10x10 index price history windows, I_t, for each week. The translation process is adaptive in that it allocates weights systematically based on the size of sliding windows being employed. To conceptualise the translation process a 20 week window is employed. The winsorised 20 week index close data is segmented into 10 chronological groups, each with 2 weekly index close values. The 10 groups are allocated to each of the 10 columns (j) of the price history window, I_t. The data allocated to each column is then assigned to the correct row (i) by computing the range for each window which is divided by 10 to determine the row width. The width is used to calculate the row interval boundaries and the 2 index closing prices pertaining to each column are mapped into the appropriate row. The weights are subsequently allocated to each cell based on what proportion of the 2 observations allocated to a column fall into each row. The sum of the weights of each column, j, equal 1 and each window, I_t, equal 10.

In order to identify the occurrence of the bull or bear flag pattern a fit value is computed. Fit is the measure of pattern match between the past price window, I_t, and the archetypal bull or bear flag grids, T (Leigh, *et al.*, 2008). Both the price history image and the archetypal bull and bear flag grids are 10x10 matrices. Therefore, the fit value in period t is the cross multiplication of the price history image, I_t, and archetypal template grid, T, as depicted in Equation 7.3.

$$Fit_{t,x} = \sum_{i=1}^{10}\sum_{j=1}^{10}\left(T_x(i,j) \;x\; I_t(i,j) \right) \tag{7.3}$$

where

$T_x(i, j)$ the template grid for archetypal pattern x (x = archetypal bull or bear flag pattern); and

$I_t\ (i, j)$ the price history window for 20 weeks preceding day t.

The study computes fit values for both the bull and bear flag archetypal template grids for each week over the examination period. In addition to the fit variable, the study incorporates a height filter using Equation 7.4 (Leigh, *et al.*, 2008). The height variable is the measure of the depth of the price history image, I_t. Therefore, in theory a higher height threshold should lead to more accurate trend predictions.

$$Height_t = \frac{max\,price_t - min\,price_t}{p_t} = \frac{range_t}{p_t} \quad (7.4)$$

where

$max\,price_t$	the maximum index price over the past 20 weeks preceding day *t*;
$min\,price_t$	the minimum index price over the past 20 weeks preceding day *t*; and
p_t	the index price on day *t*.

The technical charting strategy is implemented by means of trading rules. The strategy buys into the sector or index when the fit ($fit_{t,\ bull}$) and height ($height_{t,\ bull}$) value for the bull flag pattern in week *t*, computed using Equation 7.3 and 7.4, exceeds the bull flag fit ($\sigma_{fit,\ bull}$) and height ($\sigma_{height,\ bull}$) thresholds. When the strategy is invested in the sector it earns the sector returns. On the other hand, the strategy hedges its exposure to the sector or market by shifting into risk-free treasury bills when the bear flag fit ($fit_{t,\ bear}$) and height ($height_{t,bear}$) values exceed the bear flag fit ($\sigma_{fit,\ bear}$) and height ($\sigma_{height,\ bear}$) thresholds.

A 20 week past price window is selected which translates into approximately one-third of the number of annual trading weeks. The study tests a series of bull and bear pattern fit threshold permutations ranging from 0 to 4 in one unit increments, in order to identify the permutations that provide the best performance. The height threshold (σ_{height}) is held constant at 0 throughout the tests for both the bull and bear flag trading rules. The best combination of bull and bear flag fit thresholds for each sector index from the in-sample period are extracted and tested for robustness in the out-of-sample and overall study periods. The results from the trading rule based timing strategy are juxtaposed against the passive buy and hold strategy in the corresponding index. In line with the EMA strategy, the Sharpe ratios are presented both gross and net of transaction costs.

7.3. Results: Global Sector Momentum Strategy

The return statistics of the momentum portfolios constructed over the study period are presented in Table 7.1. Panel A of Table 7.1 depicts the average monthly returns of the momentum portfolios, whereas Panel B displays the annualised returns with *t*-statistics captured in parentheses. In line with the findings of Andreu, *et al.* (2013), the returns of all 20 sector momentum portfolios are positive. However, the portfolios developed based on the 3 month formation period provide lower returns than the buy and hold strategy in the S&P Global 1200 index, which is the market proxy. All momentum portfolios developed using 6, 9 and 12 month formation periods provide higher returns than the market portfolio. Momentum strategies that employ the 6 month formation period provide the highest returns regardless of the holding period, and the returns gradually decrease as the formation period is increased to 9 and 12 months. The effect of longer holding periods is less conclusive as suggested by the return patterns that vary for each formation period when investment period increases.

Table 7.1: Momentum Strategy Return Statistics from 05/07/2002 to 26/12/2014

J **(Formation Period)**	***K*** **(Investment Period)**					
	1	**3**	**6**	**9**	**12**	**Market**
Panel A: Raw Momentum Strategy Winner minus Loser Monthly Excess Returns						
3	0.53%	0.42%	0.08%	0.28%	0.35%	
6	0.80%	0.84%	1.04%*	1.03%*	0.96%	
9	0.77%	0.82%	0.77%	0.78%	0.87%	
12	0.64%	0.75%	0.77%	0.73%	0.74%	
Market						0.66%
Panel B: Momentum Strategy Annualised Geometric Returns with t-stats						
3	6.53%	5.15%	1.00%	3.40%	4.26%	
	[1.1271]	[1.1810]	[0.3004]	[1.1132]	[1.0609]	
6	10.10%	11.70%	13.16%*	13.15%*	12.17%	
	[0.9306]	[1.1423]	[1.3425]	[1.3120]	[1.2084]	
9	9.66%	10.42%	9.68%	9.83%	10.90%	
	[0.9233]	[1.0207]	[0.9688]	[0.9628]	[1.0485]	
12	8.01%	9.33%	9.68%	9.06%	9.28%	
	[0.7274]	[0.8359]	[0.8731]	[0.8235]	[0.8419]	
Market						8.24%

*Statistical Significance is denoted by ***, ** and * for 1%, 5% and 10% levels, respectively.*

The highest returns are achieved by the 6,6 and 6,9 momentum portfolios, with annualised returns of 13.16% and 13.15%, respectively. Furthermore, the returns of these two portfolios are significant at a 10% significance level, whereas the returns of the remaining 18 sector momentum portfolios are statistically insignificant. According to Anrdeu, *et al.* (2013) the lack of statistical significance of the majority of momentum strategy returns is largely attributable to the relatively short period over which the ETF's have been available, thus limiting the length of the examination period.

Table 7.2 illustrates the risk statistics of the momentum portfolios. Panel A of Table 7.2 shows that all momentum portfolios that provide higher returns than the market proxy in Table 7.1, are characterised by higher total risk as measured by standard deviation. Similarly, all 6, 9 and 12 month formation period strategies are characterised by substantially higher maximum drawdowns than the passive buy and hold strategy. The higher risk associated with the sector momentum strategy is also evident in Figure 7.2. The cumulative return of the representative momentum portfolios with 6, 9 and 12 month formation periods exhibit substantially higher volatility and drawdowns than the S&P Global 1200 index during periods of economic turmoil, such as the 2008 global financial crisis and 2011 European debt crisis.

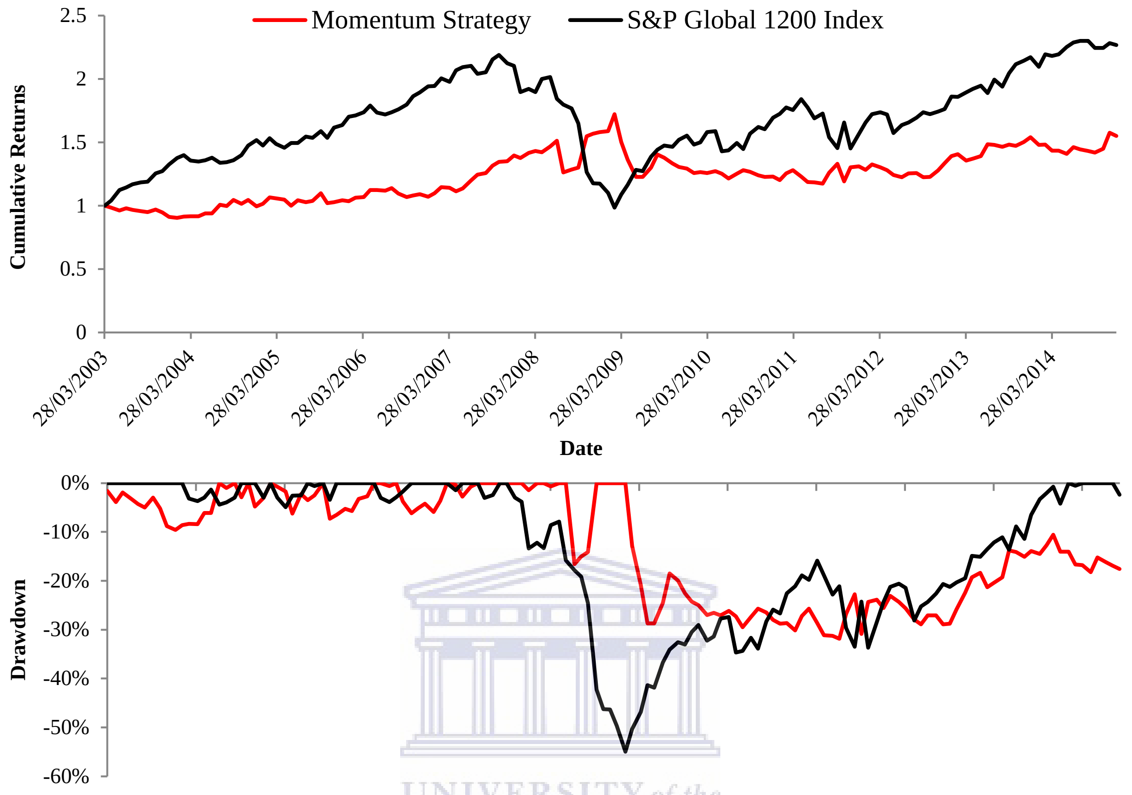
Table 7.2: Momentum Strategy Risk Statistics from 05/07/2002 to 26/12/2014

J **(Formation Period)**	***K*** **(Investment Period)**					
	1	**3**	**6**	**9**	**12**	**Market**
Panel A: Momentum Portfolio Annualised Standard Deviation						
3	19.29%	14.46%	11.28%	10.20%	9.09%	
6	35.20%	32.99%	31.40%*	32.09%*	32.37%	
9	33.61%	32.70%	32.10%	32.80%	33.25%	
12	35.25%	35.54%	35.25%	35.06%	35.07%	
Market						16.13%
Panel B: Momentum Portfolio Maximum Drawdown						
3	-46.70%	-31.87%	-34.68%	-29.15%	-22.83%	
6	-83.34%	-80.94%	-78.44%	-81.34%	-82.39%	
9	-82.04%	-81.11%	-81.96%	-83.53%	-83.62%	
12	-79.96%	-82.61%	-84.22%	-85.06%	-84.90%	
Market						-54.97%

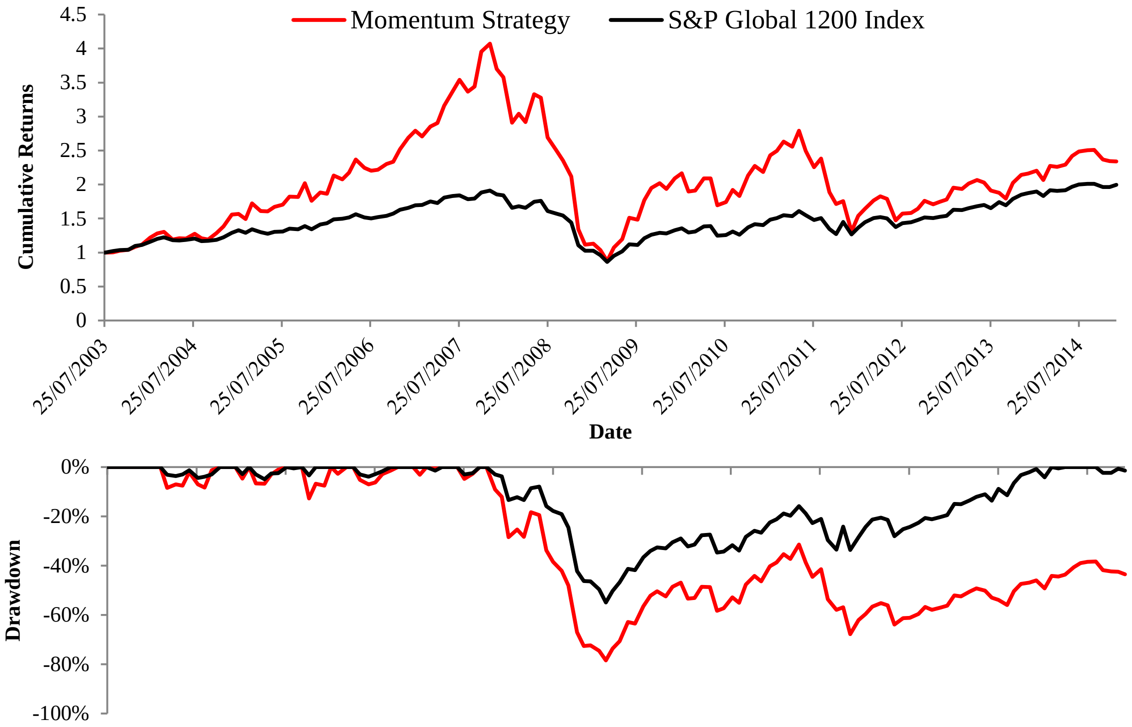
*Statistical Significance is denoted by ***, ** and * for 1%, 5% and 10% levels, respectively.*

Figure 7.2: Cumulative Return and Drawdown of Representative Momentum Strategies

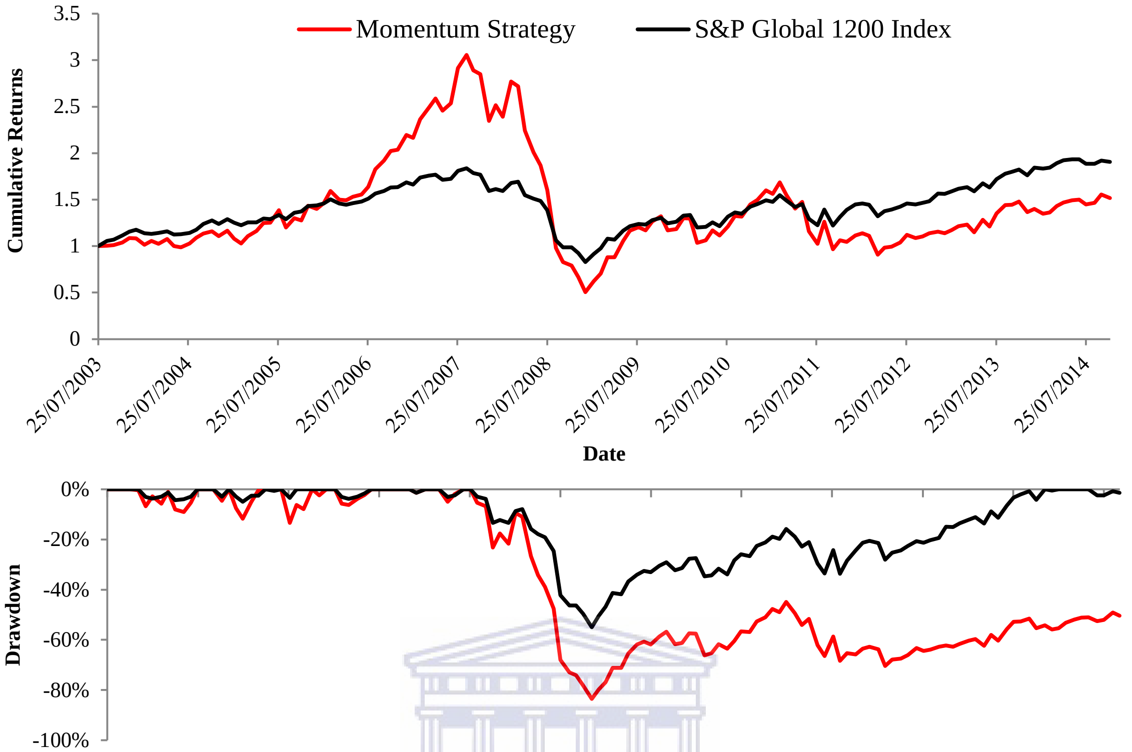
Panel A: 3,3 Momentum Strategy Cumulative Returns and Time-Series Drawdown



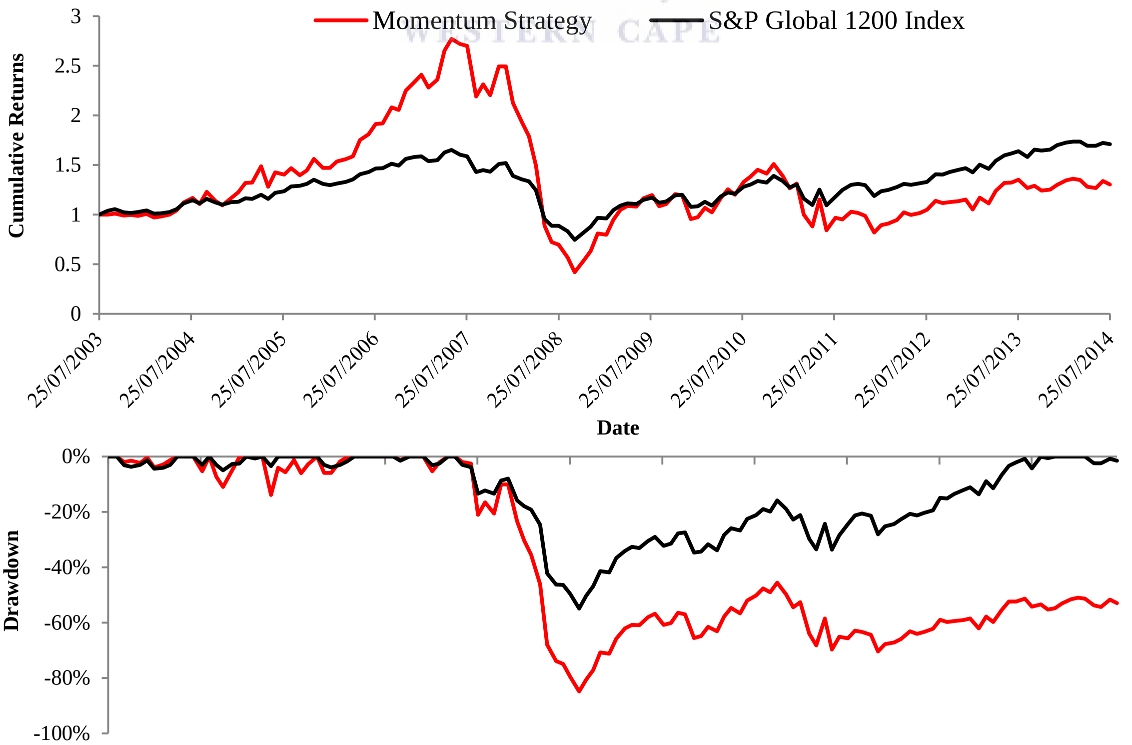
Panel B: 6,6 Momentum Strategy Cumulative Returns and Time-Series Drawdown



Panel C: 9,9 Momentum Strategy Cumulative Returns and Time-Series Drawdown



Panel D: 12,12 Momentum Strategy Cumulative Returns and Time-Series Drawdown



The cumulative returns of the 3 month formation period momentum portfolios generally remain flat and substantially underperform relative to the buy and hold strategy over the examination period, as illustrated in Panel A of Figure 7.2. Furthermore, apart from the 6,6 and 6,9 momentum portfolios, the remainder of the sector momentum strategies provide lower cumulative returns than the market proxy. Analysis of the cumulative return performance in Panel B, Panel C and Panel D of Figure 7.2 denotes that the momentum strategies significantly improve portfolio performance by investing in winner sectors and short selling loser sectors during bull markets, however the portfolios incur significant losses during bear markets. This is the case as the backward looking nature of momentum portfolios results in the strategy being unable to forecast and predict the onset of bear market phases. Consequently, the substantial losses during significant economic downturns such as the 2008 financial crisis and 2011 European debt crisis, nullifies the gains attained during bull market phases for the majority of the sector momentum portfolios.

The risk-adjusted performance statistics presented in Table 7.3 indicate that all sector momentum portfolios underperform relative to the buy and hold strategy. All sector based momentum portfolios provide lower excess returns per unit of total risk, as measured by the portfolios annualised Sharpe ratios, in comparison to the market proxy which has a Sharpe ratio of 42.75%. The highest Sharpe ratios are attributable to the 6,6 and 6,9 momentum portfolios, whereas the lowest Sharpe ratio is negative and attributable to the 3,6 portfolio. For the majority of the portfolios, the lower Sharpe ratios are attributable to the substantially higher standard deviations relative to the market proxy, rather than inferior portfolio returns.

Table 7.3: Momentum Strategy Sharpe Ratios from 05/07/2002 to 26/12/2014

J **(Formation Period)**	***K*** **(Investment Period)**					
	1	**3**	**6**	**9**	**12**	**Market**
3	26.87%	26.33%	-3.04%	20.13%	32.10%	
6	24.86%	31.37%	37.63%*	36.77%*	33.42%	
9	24.72%	27.74%	25.95%	25.87%	28.74%	
12	18.91%	22.47%	23.65%	22.00%	22.61%	
Market						42.75%

Although, the results in Table 7.1 illustrate that the sector momentum strategy can provide higher returns than a passive buy and hold strategy, the results do not guarantee economic significance as they are not adjusted for transaction costs. In order to infer economic relevance of the strategy, the study computes the maximum breakeven transaction costs using Equation 7.5, in order to determine after what level of costs the strategy would become less profitable than the passive buy and hold approach (Andreu, *et al.*, 2013).

$$Breakeven\ Cost_{J,K} = \frac{r_{mom,(J,K)} - r_{market}}{trades\ p.a._K} \tag{7.5}$$

where

$r_{mom,i}$ the annualised return on the *J,K* momentum strategy;
r_{market} the annualised return on the passive buy and hold strategy (market);and
$trades\ p.a._K$ the average number of trades per annum based on investment period *K*.

The number of trades per year is based on the investment period, for instance a strategy with a 6 month holding period requires trading eight times on average, as twice a year the investor has to sell the previous winner, buy back the previous loser, buy the new winner and sell short the new loser (Andreu, *et al.*, 2013). Similarly, the 1, 3, 9 and 12 month investment period portfolios would incur an average of 48, 16, 6 and 4 trades per year, respectively. The breakeven transaction costs of the sector momentum portfolios are depicted in Table 7.4. The results show that none of the portfolios are superior to the passive investment strategy, as all portfolios have a lower breakeven cost than the assumed 2% transaction costs incurred by individual investors (Hsieh, 2010). Furthermore, based on the lower 0.70% average real-life transaction costs on the S&P Global 1200 Sector ETF's (Refer to Chapter 5), only two momentum portfolios, highlighted in bold, are more profitable than the passive buy and hold strategy in the S&P Global 1200 index. Henceforth, the sector momentum returns are not economically significant as the strategy is not feasible after accounting for the transaction costs and the relatively higher risks, which result in inferior risk-adjusted performance.

Table 7.4: Momentum Strategy Breakeven Trading costs from 05/07/2002 to 26/12/2014

J **(Formation Period)**	***K*** **(Investment Period)**				
	1	**3**	**6**	**9**	**12**
3	-0.04%	-0.19%	-0.90%	-0.81%	-0.99%
6	0.04%	0.22%	0.62%	**0.82%**	**0.98%**
9	0.03%	0.14%	0.18%	0.27%	0.67%
12	0.00%	0.07%	0.18%	0.14%	0.26%

7.4. Results: Exponential Moving Average Trend Timing Model

In line with the study by Hsieh (2010), this research avoids data mining bias by presenting the annualised return, standard deviation, Sharpe ratio and percentage of weeks the sector strategy spends in cash, for all EMA trend timing model permutations tested in the in-sample, out-of-sample and overall study periods in the tables in Appendix A, Appendix B and Appendix C, respectively. The best performing EMA permutations from the in-sample period are selected based on the highest Sharpe ratio given that the strategy spends less than 50% of the examination period in cash, in order to maintain investment practicality. The selected optimal EMA trading rule permutations for each sector are denoted by the bold black border in each table of the appendix.

The performance statistics of the in-sample optimal permutations for all 10 global sectors are extracted and summarised in Table 7.5. For each sector, the table displays the EMA timing strategies performance relative to the passive buy and hold strategy. The optimal slow exponential moving averages (SEMA) range between 10% and 40% for the timing strategies, whereas the fast exponential moving averages (FEMA) range between 60% and 90%. The optimal permutations of the healthcare sector set the FEMA to be 2 times the SEMA (80% FEMA and 40% SEMA) which is the lowest ratio, whereas the utilities sector has the highest ratio as it sets the FEMA to be 9 times of the SEMA (90% FEMA and 10% SEMA). The lower FEMA to SEMA ratio indicates that the moving averages move closer to each other, whereas the higher ratio denotes greater disparities in the index tracking speed of the two exponential moving averages.

The annualised returns of the EMA timing strategies are higher than the buy and hold strategy for all 10 global sectors, with the materials sector achieving the highest return of 18.05%. Apart from the consumer staples sector, the returns of all the EMA timing strategies are statistically significantly different from the buy and hold strategy. The EMA strategy employing the telecommunication services and utilities sectors earn significantly positive returns at a 5% level and the remaining 7 sectors earn statistically significant returns at a 1% level. The total risk of the EMA timing strategies is also substantially lower than the buy and hold strategy for all 10 sectors. Furthermore, as long as any EMA timing strategy is implemented, all sectors provide lower standard deviations than the passive buy and hold strategy as depicted in Table 2 of Appendix A.

Consequently, the EMA timing strategies achieve significantly higher risk-adjusted returns as measured by the Sharpe ratio. The EMA timing strategy on the materials sector provides the highest Sharpe ratio of 117.31%, followed by the utilities sector which provides 114.19% over the in-sample period. The lowest Sharpe ratio is attributable to the healthcare sector and amounts to 31.80%. In addition, all ten EMA strategies incur lower maximum drawdowns in comparison to their respective buy and hold benchmarks and as per the selection criteria of the optimal EMA permutations, all ten EMA strategies spend less than 40% of the examination period in cash. The EMA trend timing model generates an average of 2 to 3 hedge signals per year for the majority of the sectors, with the strategies on the information technology and healthcare sector generating an average of 4 and 6 signals, respectively. The comparatively higher frequency of hedging in the healthcare sector is congruent with the lower FEMA to SEMA ratio of 2, which results in more crossover signals possibly driven by short-term price fluctuations, as the two price averages move more tightly in comparison to other EMA timing strategies.

In order to infer economic relevance of the strategy, the study computes the Sharpe ratio after accounting for 2% assumed transaction costs that are incurred by individual investors. Analysis of the results depicted in Table 7.5 shows that the optimal EMA timing strategies provide higher risk-adjusted performance than the passive buy and hold strategy over the in-sample period, even after taking into account the transaction costs. Furthermore, it is important to note that the 2% transaction costs are a pessimistic assumption, given that investors can trade the S&P Global 1200 sector ETF's at a much lower average cost of 0.70% (Refer to Chapter 5).

Table 7.5: In-Sample Period Performance of the Exponential Moving Average Timing Strategy on the S&P Global 1200 Sector Indices from 05/07/2002 to 26/12/2008.

S&P Global 1200 Sector	EMA %	Strategy	Annualised Return	*p*-value	Standard Deviation	Sharpe Ratio	Max. Drawdown	% of Weeks in Cash	Hedge Signals Per Year	Sharpe Ratio Net of Costs
Healthcare	**SEMA = 40%**	**Buy and Hold**	1.98%		17.16%	3.70%	-36.38%	0.00%	0	
	FEMA = 80%	**EMA Timing**	4.19%	0.0000***	8.94%	31.80%	-12.08%	32.84%	6	9.42%
Energy	**SEMA = 10%**	**Buy and Hold**	9.85%		25.18%	33.77%	-50.68%	0.00%	0	
	FEMA = 70%	**EMA Timing**	9.58%	0.0000***	15.80%	52.09%	-16.63%	23.37%	2	39.43%
Industrials	**SEMA = 20%**	**Buy and Hold**	2.00%		18.90%	3.47%	-54.97%	0.00%	0	
	FEMA = 80%	**EMA Timing**	10.92%	0.0000***	10.00%	95.66%	-12.93%	33.14%	3	75.67%
Tele. Serv.	**SEMA = 20%**	**Buy and Hold**	6.33%		18.56%	26.85%	-48.08%	0.00%	0	
	FEMA = 70%	**EMA Timing**	10.53%	0.0357**	10.50%	87.45%	-13.25%	37.28%	3	68.40%
Cons. Stap.	**SEMA = 10%**	**Buy and Hold**	3.62%		13.92%	16.31%	-30.87%	0.00%	0	
	FEMA = 70%	**EMA Timing**	5.92%	0.2169	7.35%	62.21%	-7.00%	29.88%	2	35.00%
Financials	**SEMA = 20%**	**Buy and Hold**	-3.47%		24.15%	-19.96%	-70.31%	0.00%	0	
	FEMA = 60%	**EMA Timing**	8.84%	0.0000***	10.39%	72.12%	-10.99%	36.69%	2	52.87%
Materials	**SEMA = 20%**	**Buy and Hold**	8.53%		26.35%	27.26%	-65.03%	0.00%	0	
	FEMA = 70%	**EMA Timing**	18.05%	0.0000***	14.24%	117.31%	-19.00%	29.59%	3	103.26%
Con. Disc.	**SEMA = 10%**	**Buy and Hold**	-0.51%		20.43%	-9.06%	-56.06%	0.00%	0	
	FEMA = 70%	**EMA Timing**	6.47%	0.0003***	10.00%	51.23%	-11.00%	39.05%	2	31.23%
Info. Tech.	**SEMA = 20%**	**Buy and Hold**	1.96%		24.47%	2.49%	-53.38%	0.00%	0	
	FEMA = 70%	**EMA Timing**	6.24%	0.0008***	15.06%	32.51%	-24.77%	33.14%	4	19.23%
Utilities	**SEMA = 10%**	**Buy and Hold**	8.59%		17.67%	41.00%	-44.12%	0.00%	0	
	FEMA = 90%	**EMA Timing**	12.90%	0.0181**	10.12%	114.19%	-10.79%	25.44%	2	94.43%

*Statistical Significance is denoted by ***, ** and * for 1%, 5% and 10% levels, respectively.*

The optimal EMA permutations from the in-sample period are tested for robustness in the out-of-sample period from January 2nd, 2009 to February 6th, 2015 and the results are displayed in Table 7.6. The annualised returns of the EMA timing strategies are lower than the buy and hold sector returns for the majority of the sectors. The energy and utilities sectors are the only sectors in which the EMA strategies provide higher returns than the passive buy and hold approach. In line with the performance in the in-sample period, the EMA timing strategy provides substantially lower standard deviations than the buy and hold strategy over the out-of-sample period. Furthermore, the maximum drawdowns are also significantly lower for all EMA timing strategies, with strategies in the healthcare, industrials, telecommunication services and consumer staples sectors experiencing almost half the maximum drawdown incurred by the buy and hold strategies.

In terms of risk-adjusted performance as measured by the Sharpe ratio, the EMA timing strategies provide superior performance in 8 of the sectors relative to the buy and hold strategy. The EMA timing strategy based on in-sample permutations provides lower risk-adjusted returns in the consumer staples and financials sectors. In addition, after accounting for transaction costs, 6 EMA strategies maintain higher risk-adjusted returns than the buy and hold strategy, with the timing strategies in the telecommunication services, consumer staples, financials and utilities sectors providing inferior risk-adjusted performance. The EMA timing strategies also maintain longer periods of market exposure during the out-of-sample period with all strategies spending less than 35% of the examination period in cash. The number of trading signals generated by the trading rules are also similar to the in-sample period, with the majority of the strategies generating between 3 and 4 trade signals per year, and the healthcare sector maintaining its relatively higher trading frequency of 5 signals per year.

The study also computes the performance statistics of all EMA permutations in the out-of-sample period and the results are depicted in Appendix B. The optimal EMA permutations from the out-of-sample period are denoted by the bold dashed border in each table of the Appendix. The study evaluates the performance of the out-of-sample optimal permutations in the in-sample period, and the results show that the out-of-sample optimal permutations are robust in the in-sample period for the majority of the sectors, except for the energy and industrials sectors which have lower risk-adjusted returns than the buy and hold approach.

Table 7.6: Out-of-Sample Period Performance of the Exponential Moving Average Timing Strategy on the S&P Global 1200 Sector Indices from 02/01/2009 to 06/02/2015.

S&P Global 1200 Sector	EMA %	Strategy	Annualised Return	*p*-value	Standard Deviation	Sharpe Ratio	Max. Drawdown	% of Weeks in Cash	Hedge Signals Per Year	Sharpe Ratio Net of Costs
Healthcare	**SEMA = 40%**	**Buy and Hold**	15.44%		13.71%	102.78%	-21.03%	0.00%	0	
	FEMA = 80%	**EMA Timing**	12.50%	0.0769*	8.69%	128.36%	-10.90%	19.75%	5	105.35%
Energy	**SEMA = 10%**	**Buy and Hold**	6.01%		22.41%	20.80%	-28.97%	0.00%	0	
	FEMA = 70%	**EMA Timing**	7.66%	0.0883*	14.92%	42.33%	-22.76%	31.07%	2	28.93%
Industrials	**SEMA = 20%**	**Buy and Hold**	13.60%		20.03%	61.18%	-32.20%	0.00%	0	
	FEMA = 80%	**EMA Timing**	11.33%	0.0000***	12.57%	79.43%	-11.87%	21.60%	4	63.52%
Tele. Serv.	**SEMA = 20%**	**Buy and Hold**	5.95%		14.16%	32.48%	-21.36%	0.00%	0	
	FEMA = 70%	**EMA Timing**	4.64%	0.0000***	8.05%	40.93%	-11.94%	34.91%	4	16.10%
Cons. Stap.	**SEMA = 10%**	**Buy and Hold**	11.94%		11.70%	90.56%	-20.28%	0.00%	0	
	FEMA = 70%	**EMA Timing**	6.91%	0.0000***	9.01%	61.68%	-10.29%	15.68%	2	39.49%
Financials	**SEMA = 20%**	**Buy and Hold**	11.93%		26.57%	39.82%	-44.32%	0.00%	0	
	FEMA = 60%	**EMA Timing**	7.07%	0.3502	16.21%	35.30%	-26.81%	26.04%	4	22.96%
Materials	**SEMA = 20%**	**Buy and Hold**	9.62%		24.07%	34.36%	-32.02%	0.00%	0	
	FEMA = 70%	**EMA Timing**	8.67%	0.0316**	14.73%	49.70%	-21.21%	35.21%	3	36.12%
Con. Disc.	**SEMA = 10%**	**Buy and Hold**	19.22%		18.17%	98.37%	-23.30%	0.00%	0	
	FEMA = 70%	**EMA Timing**	17.09%	0.7124	12.28%	128.25%	-17.25%	24.56%	2	111.96%
Info. Tech.	**SEMA = 20%**	**Buy and Hold**	18.19%		17.81%	94.57%	-20.38%	0.00%	0	
	FEMA = 70%	**EMA Timing**	15.40%	0.3842	11.07%	126.98%	-19.12%	26.33%	3	108.92%
Utilities	**SEMA = 10%**	**Buy and Hold**	1.87%		14.42%	3.61%	-25.22%	0.00%	0	
	FEMA = 90%	**EMA Timing**	2.27%	0.0000***	8.01%	11.55%	-17.48%	34.91%	4	-13.43%

*Statistical Significance is denoted by ***, ** and * for 1%, 5% and 10% levels, respectively.*

In addition to the out-of sample period, the study evaluates the performance of the in-sample period optimal EMA permutations over the entire examination period spanning from July 5^{th}, 2002 to February 6^{th}, 2015. The EMA timing strategies provide lower returns than the buy and hold strategies for 6 of the sectors with only 4 sectors providing higher returns, namely the industrials, financials, materials and utilities sectors. Furthermore, the returns of all EMA timing strategies are statistically significant at a 1% significance level. All EMA strategies provide considerably lower standard deviations and consequently, higher Sharpe ratios than the passive buy and hold strategies. The maximum drawdowns of the EMA timing strategies are also substantially lower than the buy and hold strategy over the entire examination period. The majority of the EMA timing strategies spend less than 30% of the study period hedged in cash with approximately 3 to 4 hedging signals per year, except for the healthcare sector which generates an average of 6 hedge signals per year.

After taking into account the transaction costs, the Sharpe ratios for half of the EMA timing strategies decrease substantially, and only 5 sectors provide higher returns over the overall study period namely, the healthcare, industrials, financials, materials and consumer discretionary sectors. The energy, telecommunication services, consumer staples, information technology and utilities sectors all provide lower risk-adjusted returns than the buy and hold strategy after accounting for 2% transaction costs.

The optimal EMA permutations from the overall examination period are also tested for robustness in the in-sample period. The performance statistics of all EMA permutations over the entire examination period are depicted in the heat maps in Appendix C. The optimal permutations are denoted by the bold dashed border in each table. The results show that the overall period optimal permutations are in similar regions as the in-sample optimal permutations for 4 of the sectors namely the energy, industrials, telecommunication services and materials sectors. However, for the remaining sectors the optimal EMA permutations that maximise the Sharpe ratio, differ substantially and provide higher returns over the entire examination period in comparison to the in-sample optimal permutations. Furthermore, in line with the findings of Hsieh (2010), the optimal EMA permutations from the overall study period are robust across all in-sample periods, which suggests that the overall period optimal permutations are more reliable.

Table 7.7: Overall Period Performance of the Exponential Moving Average Timing Strategy on the S&P Global 1200 Sector Indices from 05/07/2002 to 06/02/2015.

S&P Global 1200 Sector	EMA %	Strategy	Annualised Return	*p*-value	Standard Deviation	Sharpe Ratio	Max. Drawdown	% of Weeks in Cash	Hedge Signals Per Year	Sharpe Ratio Net of Costs
Healthcare	**SEMA = 40%**	**Buy and Hold**	8.63%		15.62%	46.60%	-41.51%	0.00%	0	
	FEMA = 80%	**EMA Timing**	7.66%	0.0002***	8.88%	71.08%	-12.08%	26.33%	6	48.55%
Energy	**SEMA = 10%**	**Buy and Hold**	8.82%		24.00%	31.13%	-54.51%	0.00%	0	
	FEMA = 70%	**EMA Timing**	7.31%	0.0000***	14.66%	40.65%	-22.98%	29.83%	2	27.01%
Industrials	**SEMA = 20%**	**Buy and Hold**	8.01%		19.52%	34.14%	-62.96%	0.00%	0	
	FEMA = 80%	**EMA Timing**	8.47%	0.0000***	11.82%	60.26%	-15.79%	27.40%	4	43.33%
Tele. Serv.	**SEMA = 20%**	**Buy and Hold**	6.49%		16.59%	30.98%	-50.25%	0.00%	0	
	FEMA = 70%	**EMA Timing**	5.30%	0.0000***	10.18%	38.87%	-20.68%	32.12%	4	19.22%
Cons. Stap.	**SEMA = 10%**	**Buy and Hold**	7.87%		12.92%	50.46%	-39.48%	0.00%	0	
	FEMA = 70%	**EMA Timing**	6.46%	0.0009***	8.11%	63.01%	-10.87%	23.90%	2	38.36%
Financials	**SEMA = 20%**	**Buy and Hold**	4.21%		25.39%	11.30%	-79.00%	0.00%	0	
	FEMA = 60%	**EMA Timing**	7.86%	0.0000***	13.47%	48.38%	-27.93%	32.72%	3	33.53%
Materials	**SEMA = 20%**	**Buy and Hold**	9.74%		25.33%	33.15%	-65.03%	0.00%	0	
	FEMA = 70%	**EMA Timing**	11.45%	0.0000***	14.79%	68.28%	-31.53%	33.18%	3	54.76%
Con. Disc.	**SEMA = 10%**	**Buy and Hold**	9.11%		19.45%	39.92%	-59.55%	0.00%	0	
	FEMA = 70%	**EMA Timing**	8.60%	0.0000***	11.80%	61.51%	-22.12%	29.98%	2	44.56%
Info. Tech.	**SEMA = 20%**	**Buy and Hold**	10.00%		21.54%	40.17%	-54.75%	0.00%	0	
	FEMA = 70%	**EMA Timing**	8.23%	0.0000***	13.60%	50.62%	-27.52%	29.53%	4	35.91%
Utilities	**SEMA = 10%**	**Buy and Hold**	5.68%		16.22%	26.74%	-50.38%	0.00%	0	
	FEMA = 90%	**EMA Timing**	5.78%	0.0000***	9.37%	47.27%	-26.08%	28.77%	3	25.93%

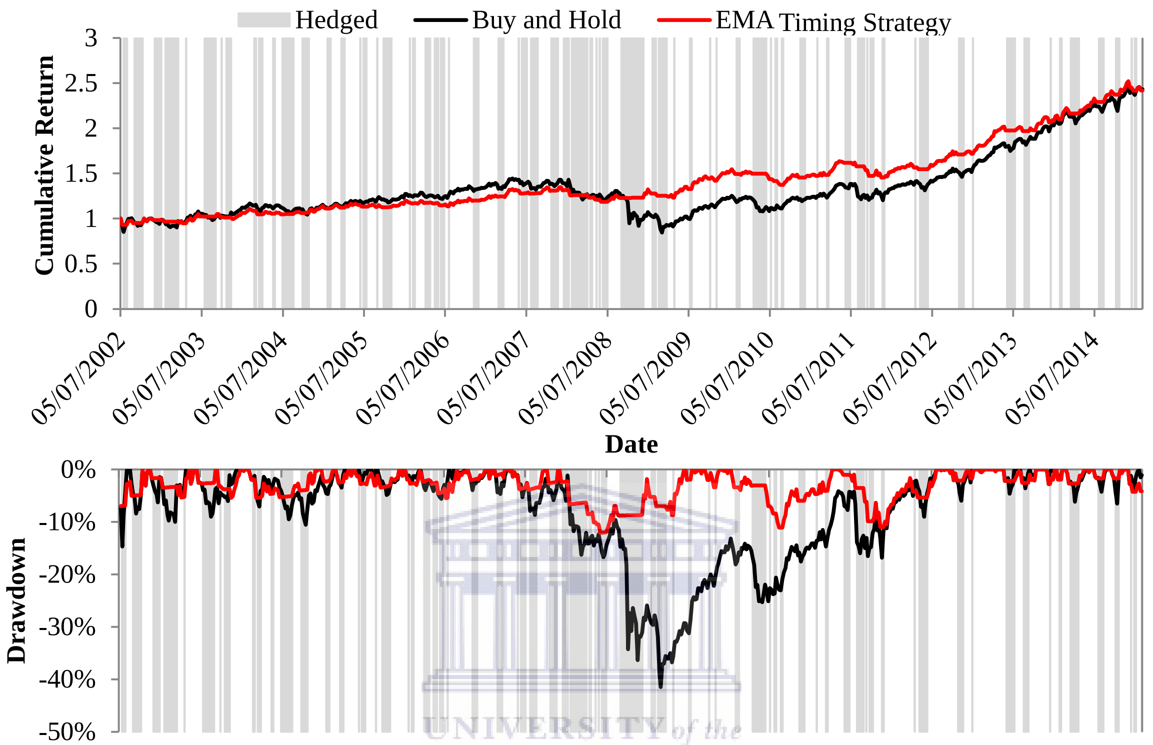
*Statistical Significance is denoted by ***, ** and * for 1%, 5% and 10% levels, respectively.*

Panel A to Panel J in Figure 7.3 illustrates the performance of the EMA timing strategies on the S&P Global 1200 sector indices relative to the performance of the sector indices or equivalent passive buy and hold strategies. The EMA timing strategies employ the optimal EMA permutations for each sector from the in-sample period and apply them over the entire study period. The grey shaded regions on the cumulative return and drawdown graphs in Figure 7.3 indicate the periods when the strategy is hedged in cash. Analysis of the cumulative return graphs highlights that 6 strategies provide higher cumulative returns than the buy and hold approach over the study period. The healthcare, telecommunication services and information technology sectors provide similar cumulative returns as the buy and hold strategy, whereas the EMA timing strategy on the consumer staples sector provides lower cumulative returns. More importantly, all 10 EMA timing strategies kick into cash during major economic downturns such as the 2008 financial crisis and the 2011 European debt crisis. As a result, the EMA timing strategies protect the value of the portfolio and avoid significant losses, which translates into substantially lower time-series drawdowns than the buy and hold approach as depicted in the second chart in each panel of Figure 7.3.

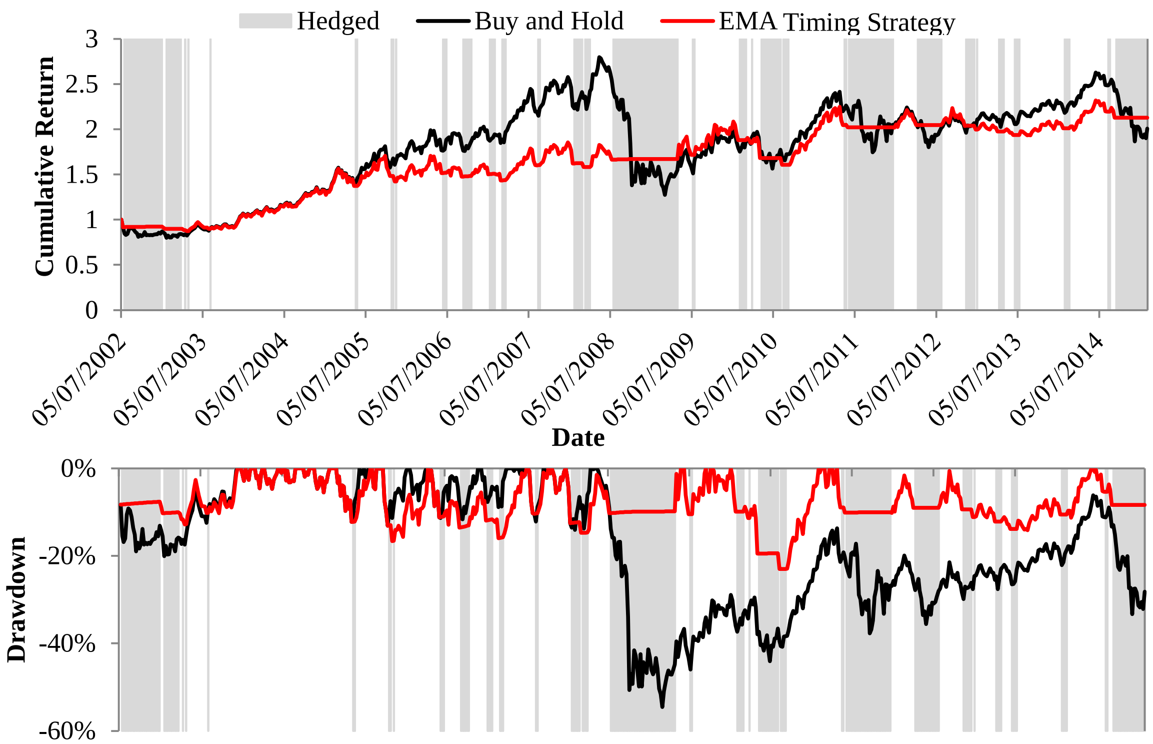
The results also show that the gains from timing and avoiding significant drawdowns during major economic downturns compensates for the smaller timing errors over the study period which is congruent with the findings of Hsieh (2010). This can be observed in the cumulative return graphs of all the EMA timing strategies which show significant disparities in performance from the buy and hold strategy during the 2008 financial crisis. The cumulative return performance of the EMA timing strategies in the industrials, financials, materials and utilities sectors denote the best performance, as they avoid losses during the 2008 financial crisis and maintain higher cumulative returns than the buy and hold strategy over the remainder of the examination period. However, for certain sectors this initial outperformance during the 2008 crisis is nullified by the timing errors mainly experienced during the relatively more stable market phase characterised by short-term drawdowns, corresponding with the out-of-sample period. EMA timing strategies that reflect this trend include strategies in the healthcare, telecommunication services, consumer staples and information technology sectors depicted in Panel A, Panel D, Panel E and Panel I of Figure 7.3.

Figure 7.3: Cumulative Returns and Time-Series Drawdown of the Exponential Moving Average Timing Strategy on the S&P Global 1200 Sector Indices from 05/07/2002 to 06/02/2015 (Overall Examination Period).

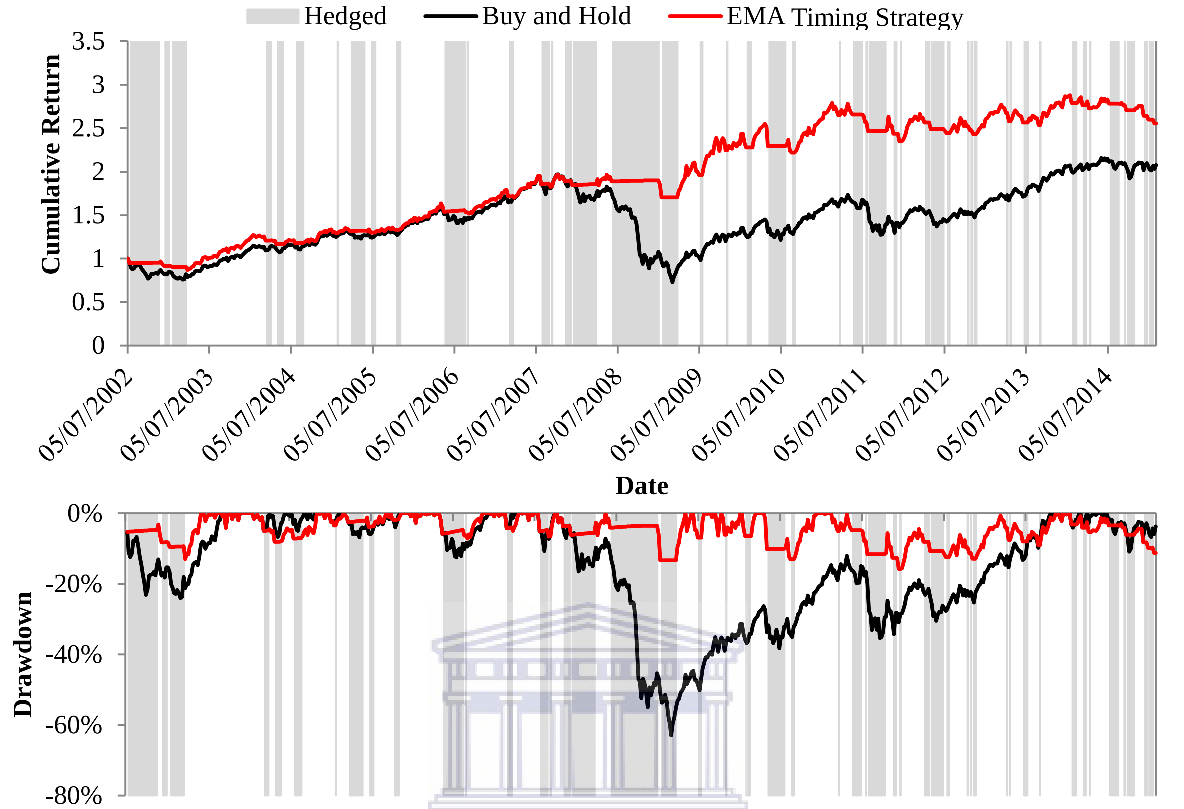
Panel A: S&P Global 1200 Healthcare Sector (SEMA = 40%, FEMA = 80%)



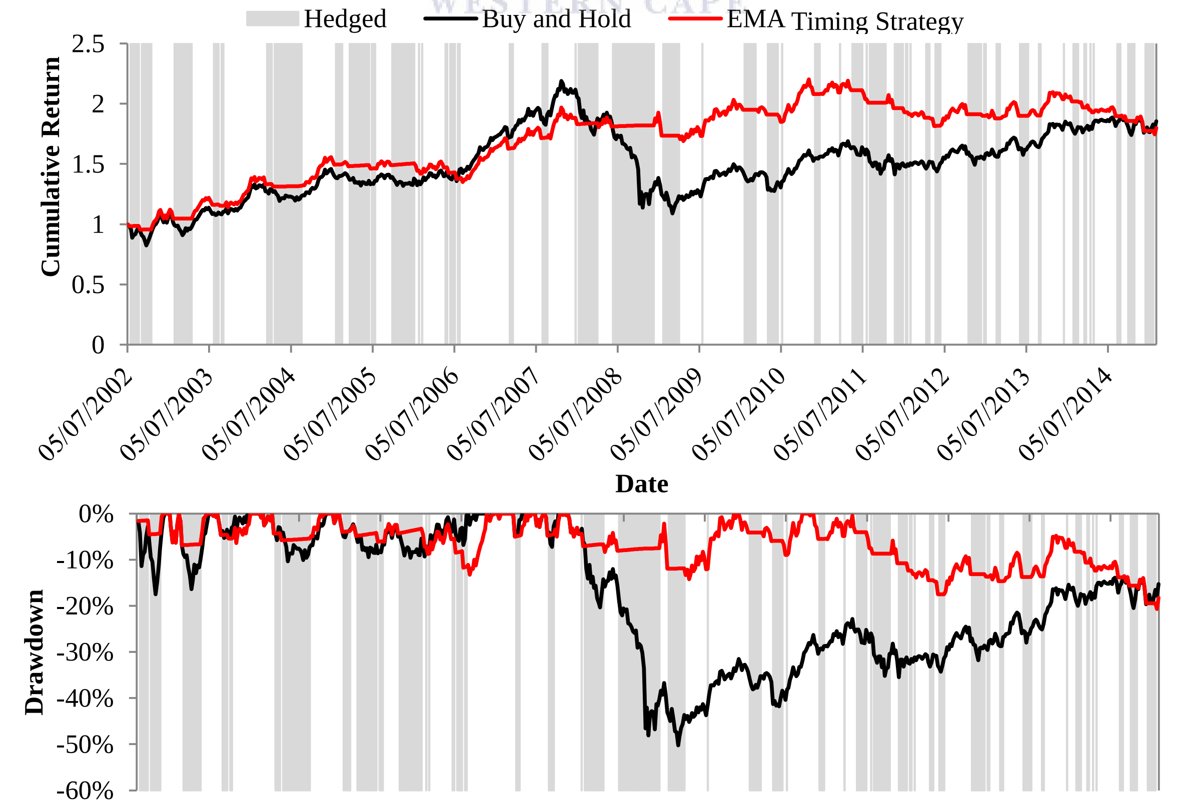
Panel B: S&P Global 1200 Energy Sector (SEMA = 10%, FEMA = 70%)



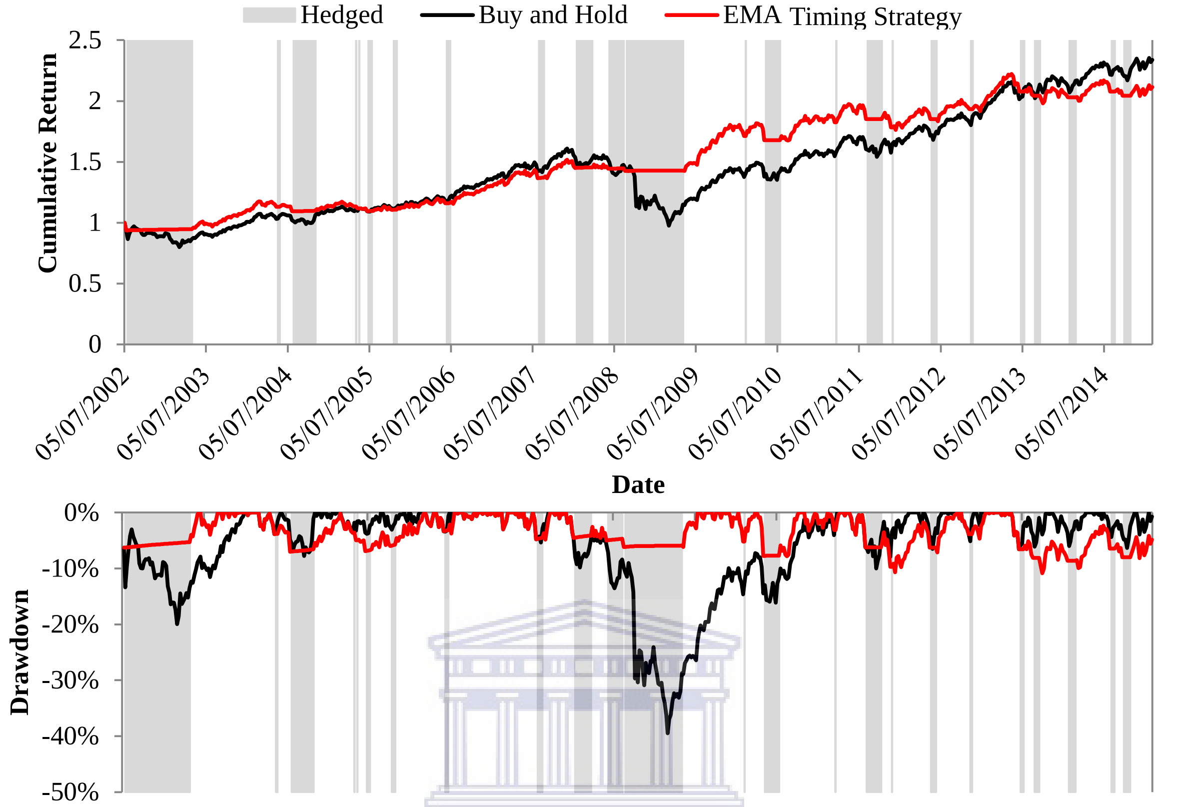
Panel C: S&P Global 1200 Industrials Sector (SEMA = 20%, FEMA = 80%)



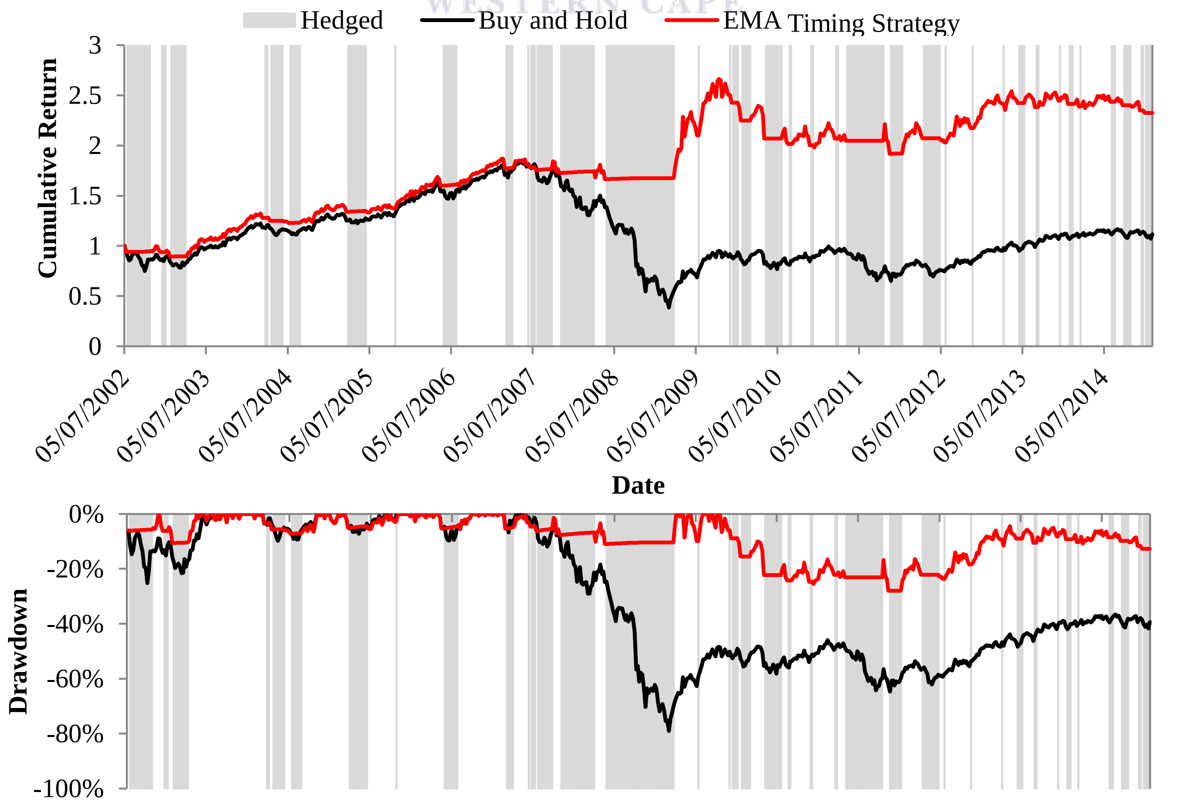
Panel D: S&P Global 1200 Telecom. Services Sector (SEMA = 20%, FEMA = 70%)



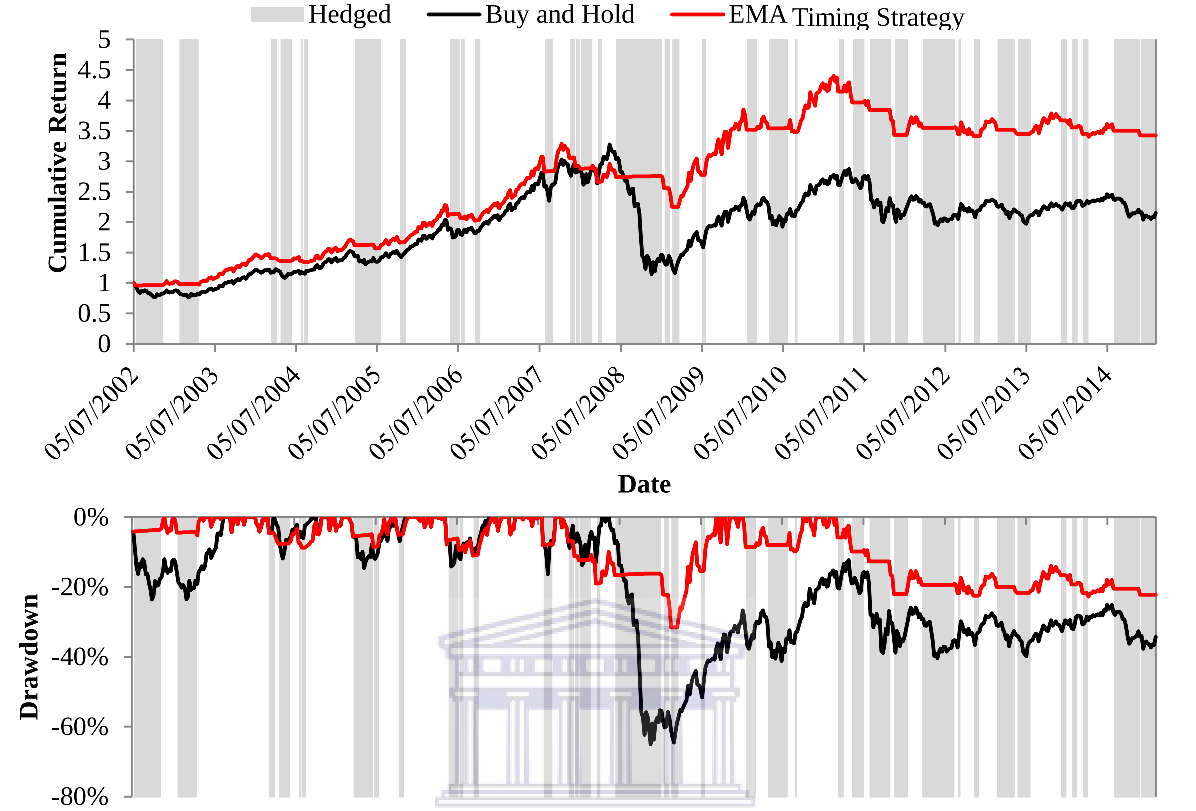
Panel E: S&P Global 1200 Consumer Staples Sector (SEMA = 10%, FEMA = 70%)



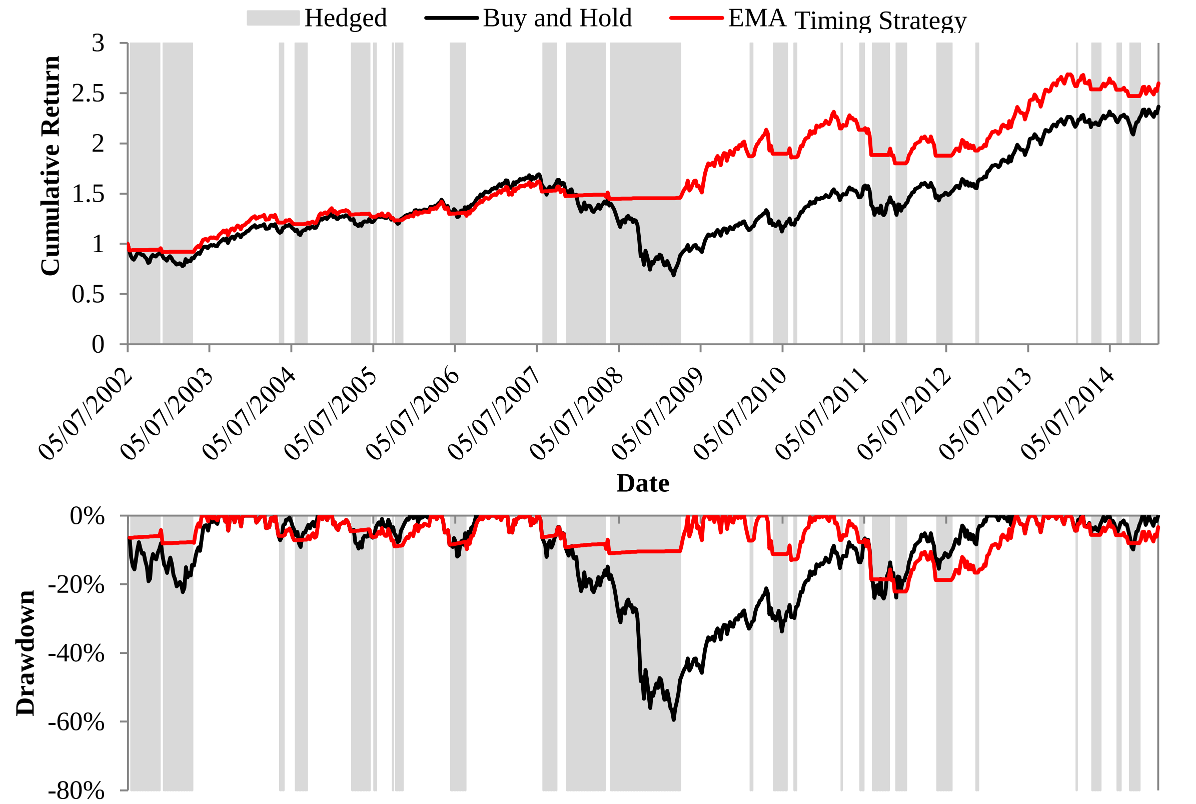
Panel F: S&P Global 1200 Financial Sector (SEMA = 20%, FEMA = 60%)



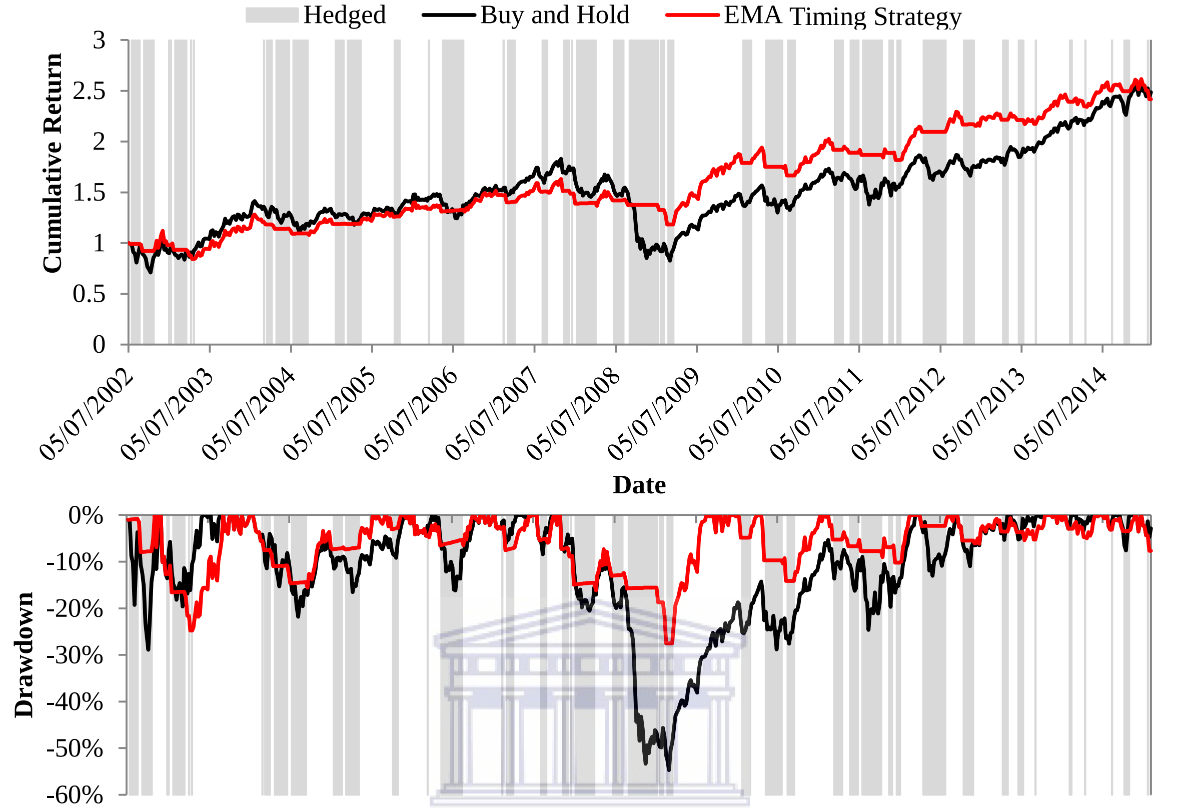
Panel G: S&P Global 1200 Materials Sector (SEMA = 20%, FEMA = 70%)



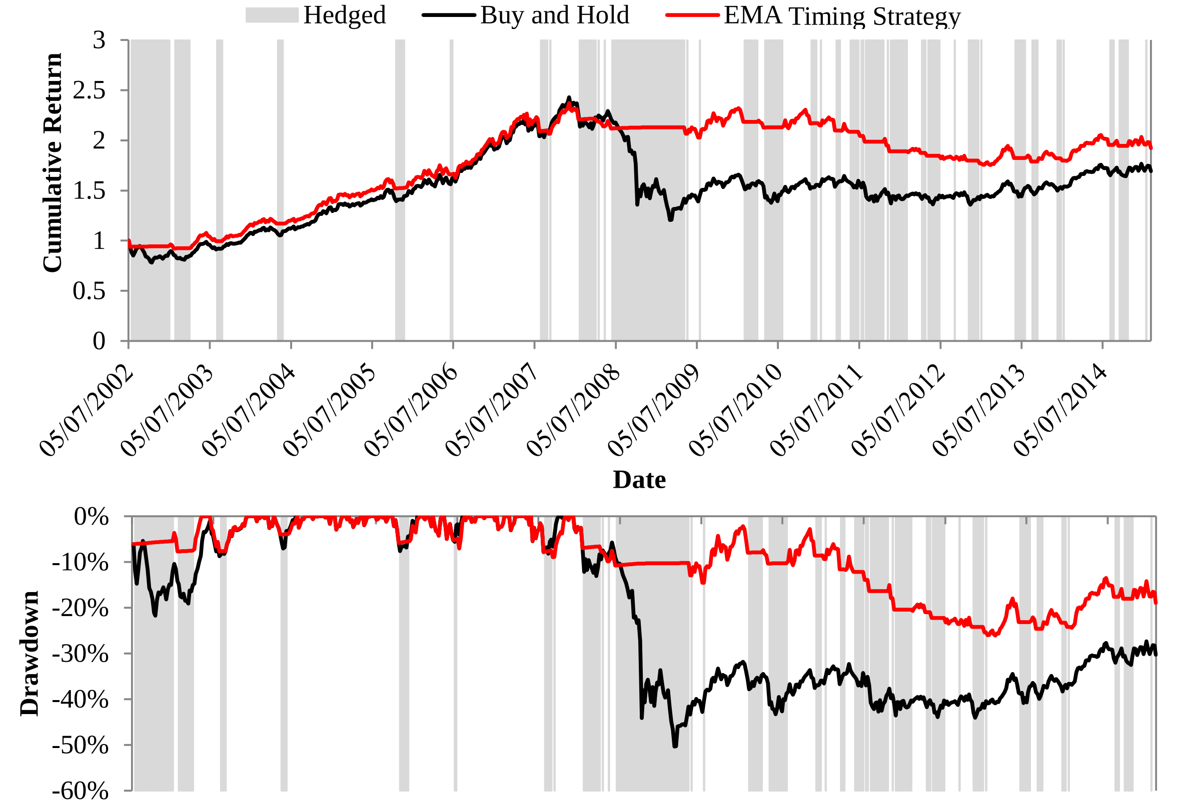
Panel H: S&P Global 1200 Cons. Discretionary Sector (SEMA = 10%, FEMA = 70%)



Panel I: S&P Global 1200 Information Technology Sector (SEMA = 10%, FEMA = 90%)



Panel J: S&P Global 1200 Utilities Sector (SEMA = 10%, FEMA = 90%)



7.5. Results: Technical Charting Heuristics Trend Timing Model

In order to avoid data mining bias, the performance statistics which include the annualised return, standard deviation, Sharpe ratio and percentage of weeks the charting strategy spends in cash, for all technical charting trading rule permutations from the in-sample, out-of-sample and overall study periods are displayed in the tables in Appendix D, Appendix E and Appendix F, respectively. In line with the EMA strategy, the best performing technical charting permutations from the in-sample period are selected based on the highest Sharpe ratio given that the strategy spends less than 50% of the period in cash. The selected optimal technical charting trading rule permutations for each global sector are denoted by the bold black border in each table of the appendix.

The performance statistics of the optimal bull and bear flag permutations for the charting strategies from the in-sample period are presented in Table 7.8. All optimal trading rules have higher bear flag fit thresholds relative to the bull flag thresholds except in the case of the consumer discretionary sector, which has equal fit thresholds of 4. In theory, the relatively lower bull flag threshold denotes that the charting strategies more readily enter the market, however selectively kick into cash in order to minimise bear market timing errors. The findings also support this premise, as the charting based trading rules experience lower hedge signals per year than the EMA strategies promulgated by Hsieh (2010), with most strategies only hedging 1 or 2 times annually. However, the percentage of weeks the strategies spend in cash during the in-sample period is higher for the charting strategies relative to EMA strategies, which suggests that the strategies remain hedged for longer periods.

The optimal charting based trading rule strategies from the in-sample period provide higher annualised returns than the passive buy and hold strategies for all 10 sectors, with the returns being significant at a 1% level for 6 sectors. The returns for the utilities sector are significant at a 10% level, whereas the returns for the charting strategies in the consumer staples, materials and consumer discretionary sectors are not statistically significantly different from the buy and hold strategy returns. The technical charting timing strategies also possess lower total risk as measured by the standard deviation, and incur considerably lower maximum drawdowns than the buy and hold approach. In addition, all charting strategies provide higher risk-adjusted returns as measured by the Sharpe ratio, both gross and net of transaction costs.

Table 7.8: In-Sample Period Performance of the Technical Charting Heuristics Timing Strategy on the S&P Global 1200 Sector Indices from 05/07/2002 to 26/12/2008.

S&P Global 1200 Sector	Fit Threshold (σ_{fit})	Strategy	Annualised Return	*p*-values	Standard Deviation	Sharpe Ratio	Max. Drawdown	% of Weeks in Cash	Hedge Signals Per Year	Sharpe Ratio Net of Costs
Healthcare	**Bear = 2**	**Buy and Hold**	2.42%		16.36%	6.55%	-36.38%	0.00%	0	
	Bull = 0	**Tech. Charting**	6.19%	0.0000***	8.94%	54.17%	-12.93%	46.77%	2	31.79%
Energy	**Bear = 2**	**Buy and Hold**	13.70%		25.37%	48.66%	-50.68%	0.00%	0	
	Bull = 0	**Tech. Charting**	19.30%	0.0000***	18.03%	99.60%	-14.20%	38.71%	2	88.50%
Industrials	**Bear = 3**	**Buy and Hold**	5.13%		18.72%	20.21%	-54.97%	0.00%	0	
	Bull = 0	**Tech. Charting**	11.59%	0.0002***	13.76%	74.43%	-21.97%	33.23%	2	59.90%
Tele. Serv.	**Bear = 2**	**Buy and Hold**	5.48%		17.99%	22.98%	-48.08%	0.00%	0	
	Bull = 0	**Tech. Charting**	11.28%	0.0000***	14.82%	66.99%	-32.85%	43.87%	1	53.50%
Cons. Stap.	**Bear = 4**	**Buy and Hold**	5.56%		13.53%	31.11%	-30.87%	0.00%	0	
	Bull = 0	**Tech. Charting**	8.42%	0.1267	7.53%	93.92%	-10.22%	30.97%	1	67.37%
Financials	**Bear = 3**	**Buy and Hold**	-2.09%		23.84%	-14.43%	-70.31%	0.00%	0	
	Bull = 2	**Tech. Charting**	10.84%	0.0000***	10.08%	94.16%	-17.53%	49.35%	1	74.32%
Materials	**Bear = 4**	**Buy and Hold**	11.67%		26.78%	38.54%	-65.03%	0.00%	0	
	Bull = 0	**Tech. Charting**	16.25%	0.7406	21.94%	67.92%	-40.90%	35.16%	1	58.80%
Con. Disc.	**Bear = 4**	**Buy and Hold**	1.78%		20.25%	2.14%	-56.06%	0.00%	0	
	Bull = 4	**Tech. Charting**	7.83%	0.1876	10.56%	61.34%	-20.71%	44.19%	1	42.41%
Info. Tech.	**Bear = 4**	**Buy and Hold**	1.55%		21.64%	0.94%	-53.38%	0.00%	0	
	Bull = 2	**Tech. Charting**	12.39%	0.0000***	13.62%	81.10%	-18.20%	39.35%	1	66.41%
Utilities	**Bear = 4**	**Buy and Hold**	11.45%		17.32%	58.33%	-44.12%	0.00%	0	
	Bull = 1	**Tech. Charting**	15.54%	0.0686*	9.24%	153.54%	-13.06%	31.29%	1	131.90%

*Statistical Significance is denoted by ***, ** and * for 1%, 5% and 10% levels, respectively.*

The performance statistics from applying the optimal in-sample charting based trading rules in the out-of-sample period are summarised in Table 7.9. The in-sample optimal permutations provide lower returns for 9 of the technical charting timing strategies relative to the buy and hold strategies, and the results are significant at a 1% level for all sectors except the materials sector. The charting strategy only provides higher returns in the energy sector and the returns are significantly different from the buy and hold strategy at a 1% significance level. Consistent with the in-sample optimal trading rule performance, the technical charting timing strategies continue to provide lower standard deviations across all sectors in comparison to the buy and hold strategy. Furthermore, the charting strategies achieve lower maximum drawdowns than the buy and hold approach in all sectors, except the utilities sector. However, the differences between the charting and buy and hold strategies maximum drawdowns are substantially smaller in comparison to the in-sample period.

The risk-adjusted performance of 8 charting strategies is inferior to the buy and hold strategy, and only 2 strategies, namely the energy and financials sectors provide higher Sharpe ratios. The Sharpe ratios of the charting strategies after accounting for 2% transaction costs provide the same results, as 80% of the trading rules underperform the buy and hold strategy. In terms of trading rule signals, the majority of the charting strategies generate 1 hedge signal per annum. However, the strategies spend long consecutive periods in cash, with 5 strategies hedging for more than 40% of the out-of-sample period. Consequently, portfolio managers may be pressurised by clients to override the trading rules especially during corresponding bull market trends. Furthermore, the performance of the majority of in-sample technical charting trading rules are not robust in the out-of-sample period, as they provide inaccurate hedge signals and lower risk-adjusted performance both gross and net of transaction costs.

In addition, the optimal bull and bear permutations from the out-of-sample period, denoted by the bold dashed border in the tables of Appendix E, are tested in the in-sample period. The findings indicate that the out-of-sample optimal permutations are robust in the in-sample period, as they provide higher returns, lower standard deviations and thus, higher risk-adjusted returns than the buy and hold strategy for all indices except the materials sector. However, for some optimal out-of-sample permutations, the percentage of time in the market during the in-sample period is less than 50%, which may not be desirable to investors.

Table 7.9: Out-of-Sample Period Performance of the Technical Charting Heuristics Timing Strategy on the S&P Global 1200 Sector Indices from 02/01/2009 to 06/02/2015.

S&P Global 1200 Sector	Fit Threshold (σ_{fit})	Strategy	Annualised Return	*p*-values	Standard Deviation	Sharpe Ratio	Max. Drawdown	% of Weeks in Cash	Hedge Signals Per Year	Sharpe Ratio Net of Costs
Healthcare	**Bear = 2**	**Buy and Hold**	19.49%		12.96%	139.99%	-13.96%	0.00%	0	
	Bull = 0	**Tech. Charting**	12.31%	0.0000***	10.05%	109.05%	-11.61%	40.32%	1	89.16%
Energy	**Bear = 2**	**Buy and Hold**	9.47%		22.03%	36.86%	-28.97%	0.00%	0	
	Bull = 0	**Tech. Charting**	10.96%	0.0000***	15.35%	62.66%	-21.95%	50.00%	2	49.63%
Industrials	**Bear = 3**	**Buy and Hold**	19.73%		19.18%	95.85%	-26.44%	0.00%	0	
	Bull = 0	**Tech. Charting**	14.54%	0.0000***	16.90%	78.06%	-25.35%	32.90%	1	66.23%
Tele. Serv.	**Bear = 2**	**Buy and Hold**	9.32%		13.59%	58.67%	-16.35%	0.00%	0	
	Bull = 0	**Tech. Charting**	6.57%	0.0000***	11.35%	46.08%	-13.07%	38.71%	2	28.45%
Cons. Stap.	**Bear = 4**	**Buy and Hold**	15.53%		11.40%	124.45%	-9.98%	0.00%	0	
	Bull = 0	**Tech. Charting**	10.78%	0.0000***	9.69%	97.31%	-9.10%	20.97%	1	76.68%
Financials	**Bear = 3**	**Buy and Hold**	19.73%		24.84%	74.02%	-34.79%	0.00%	0	
	Bull = 2	**Tech. Charting**	19.10%	0.0000***	20.17%	88.04%	-24.06%	57.10%	1	78.12%
Materials	**Bear = 4**	**Buy and Hold**	13.13%		23.35%	50.48%	-32.02%	0.00%	0	
	Bull = 0	**Tech. Charting**	8.59%	0.4351	19.73%	36.68%	-30.78%	32.26%	1	26.55%
Con. Disc.	**Bear = 4**	**Buy and Hold**	23.67%		17.62%	126.70%	-18.81%	0.00%	0	
	Bull = 4	**Tech. Charting**	10.50%	0.0000***	11.97%	76.43%	-14.96%	64.52%	1	59.72%
Info. Tech.	**Bear = 4**	**Buy and Hold**	21.11%		17.21%	114.82%	-20.38%	0.00%	0	
	Bull = 2	**Tech. Charting**	13.86%	0.0000***	13.67%	91.52%	-17.19%	47.74%	1	76.90%
Utilities	**Bear = 4**	**Buy and Hold**	5.61%		13.94%	30.60%	-17.97%	0.00%	0	
	Bull = 1	**Tech. Charting**	3.94%	0.0000***	11.91%	21.73%	-21.46%	23.55%	1	4.95%

*Statistical Significance is denoted by ***, ** and * for 1%, 5% and 10% levels, respectively.*

The optimal trading rule thresholds from the in-sample period are also tested over the entire study period, and the summarised performance statistics are presented in Table 7.10. Analysis of the performance of the technical charting timing strategies indicates that all 10 timing strategies earn higher risk-adjusted returns than the buy and hold strategy, as denoted by the Sharpe ratios. The improvement in Sharpe ratios is mainly attributable to the drastic risk reduction benefits for the charting strategies, with all 10 strategies providing lower standard deviations than the buy and hold strategy. Furthermore, 6 of the strategies achieve higher annualised returns than the passive buy and hold approach and the returns are statistically significant at a 1% level. The remaining 4 charting strategies provide lower returns than the passive strategy, with only the materials sector providing insignificant returns. The charting strategies also provide lower maximum drawdowns, with the majority of the timing strategies experiencing less than half the drawdowns of the comparative buy and hold strategies.

With regard to trading frequency, the technical charting based strategies generate between 1 and 2 hedge signals per year, which is comparatively lower than the EMA based strategy over the same examination period. However, the proportion of the overall study period that the strategy stays in cash is much higher for the technical charting based strategy. This is evident in Table 7.10, as 6 strategies kick into cash for 40% to 60% of the weeks and the remaining 4 strategies are hedged for 25% to 35% of the examination period. As noted earlier, this may result in conflict of interest between the portfolio manager and clients. Furthermore, the Sharpe ratios after transaction costs suggest that the technical charting timing strategies based on in-sample permutations are not robust and lack economic significance, as only 3 strategies provide higher risk-adjusted returns than the passive buy and hold approach.

The study also tests the robustness of the overall period optimal bull and bear flag permutations in the in-sample period. The complete results of the permutations tested are presented in Appendix F and the optimal overall period trading rule thresholds are denoted by the bold dashed borders in each table. Examining the performance of the overall period optimal permutations in the in-sample period indicates that the overall period optimal permutations are robust in the in-sample period. Therefore, the overall period optimal thresholds are more reliable than the in-sample permutations, as they provide higher risk-adjusted returns than the passive buy and hold strategy over all sub-periods examined.

Table 7.10: Overall Period Performance of the Technical Charting Heuristics Timing Strategy on the S&P Global 1200 Sector Indices from 05/07/2002 to 06/02/2015.

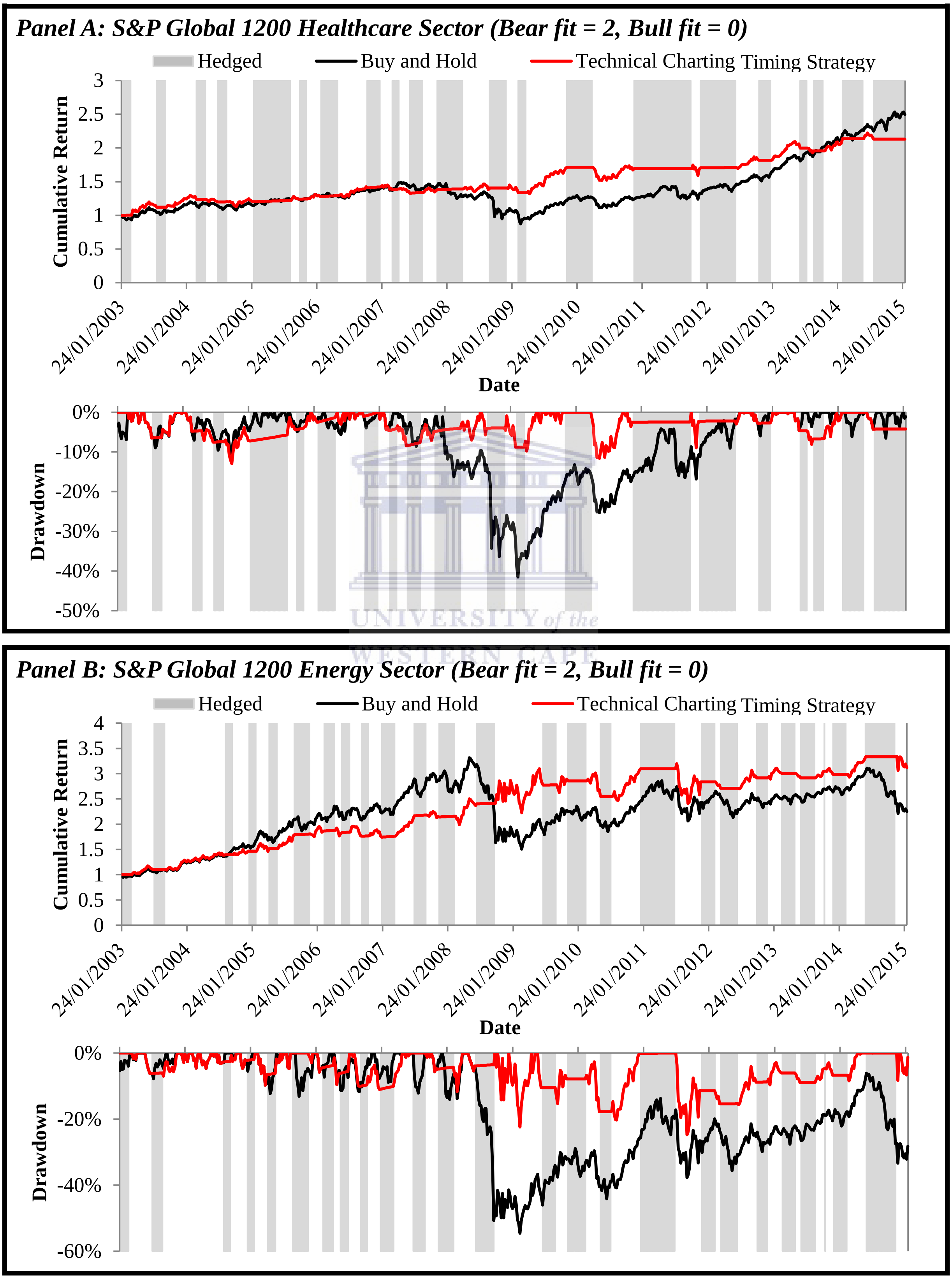
S&P Global 1200 Sector	Fit Threshold (σ_{fit})	Strategy	Annualised Return	*p*-values	Standard Deviation	Sharpe Ratio	Max. Drawdown	% of Weeks in Cash	Hedge Signals Per Year	Sharpe Ratio Net of Costs
Healthcare	**Bear = 2**	**Buy and Hold**	9.16%		15.12%	51.69%	-41.51%	0.00%	0	
	Bull = 0	**Tech. Charting**	6.89%	0.0000***	9.08%	61.06%	-12.93%	49.92%	2	39.02%
Energy	**Bear = 2**	**Buy and Hold**	10.64%		24.05%	38.62%	-54.51%	0.00%	0	
	Bull = 0	**Tech. Charting**	12.16%	0.0000***	18.07%	59.87%	-24.76%	43.88%	2	48.80%
Industrials	**Bear = 3**	**Buy and Hold**	9.91%		19.46%	44.01%	-62.96%	0.00%	0	
	Bull = 0	**Tech. Charting**	10.18%	0.0000***	16.00%	55.17%	-35.82%	34.82%	2	42.28%
Tele. Serv.	**Bear = 2**	**Buy and Hold**	6.07%		16.18%	29.20%	-50.25%	0.00%	0	
	Bull = 0	**Tech. Charting**	6.95%	0.0000***	13.13%	42.65%	-32.85%	44.04%	2	26.95%
Cons. Stap.	**Bear = 4**	**Buy and Hold**	9.05%		12.66%	60.85%	-39.48%	0.00%	0	
	Bull = 0	**Tech. Charting**	6.86%	0.0001***	8.68%	63.51%	-22.94%	29.89%	1	40.46%
Financials	**Bear = 3**	**Buy and Hold**	5.30%		25.29%	15.64%	-79.00%	0.00%	0	
	Bull = 2	**Tech. Charting**	8.41%	0.0000***	17.23%	40.98%	-40.06%	56.28%	1	29.37%
Materials	**Bear = 4**	**Buy and Hold**	11.35%		25.51%	39.23%	-65.03%	0.00%	0	
	Bull = 0	**Tech. Charting**	11.31%	0.5284	21.40%	46.55%	-40.90%	33.23%	1	37.20%
Con. Disc.	**Bear = 4**	**Buy and Hold**	10.79%		19.30%	48.93%	-59.55%	0.00%	0	
	Bull = 4	**Tech. Charting**	7.41%	0.0000***	11.77%	51.51%	-38.16%	53.74%	1	34.51%
Info. Tech.	**Bear = 4**	**Buy and Hold**	10.16%		19.85%	44.38%	-54.75%	0.00%	0	
	Bull = 2	**Tech. Charting**	11.98%	0.0000***	13.56%	78.44%	-21.53%	46.42%	1	63.68%
Utilities	**Bear = 4**	**Buy and Hold**	6.92%		15.97%	34.88%	-50.38%	0.00%	0	
	Bull = 1	**Tech. Charting**	7.37%	0.0000***	11.67%	51.60%	-29.84%	25.44%	1	33.94%

*Statistical Significance is denoted by ***, ** and * for 1%, 5% and 10% levels, respectively.*

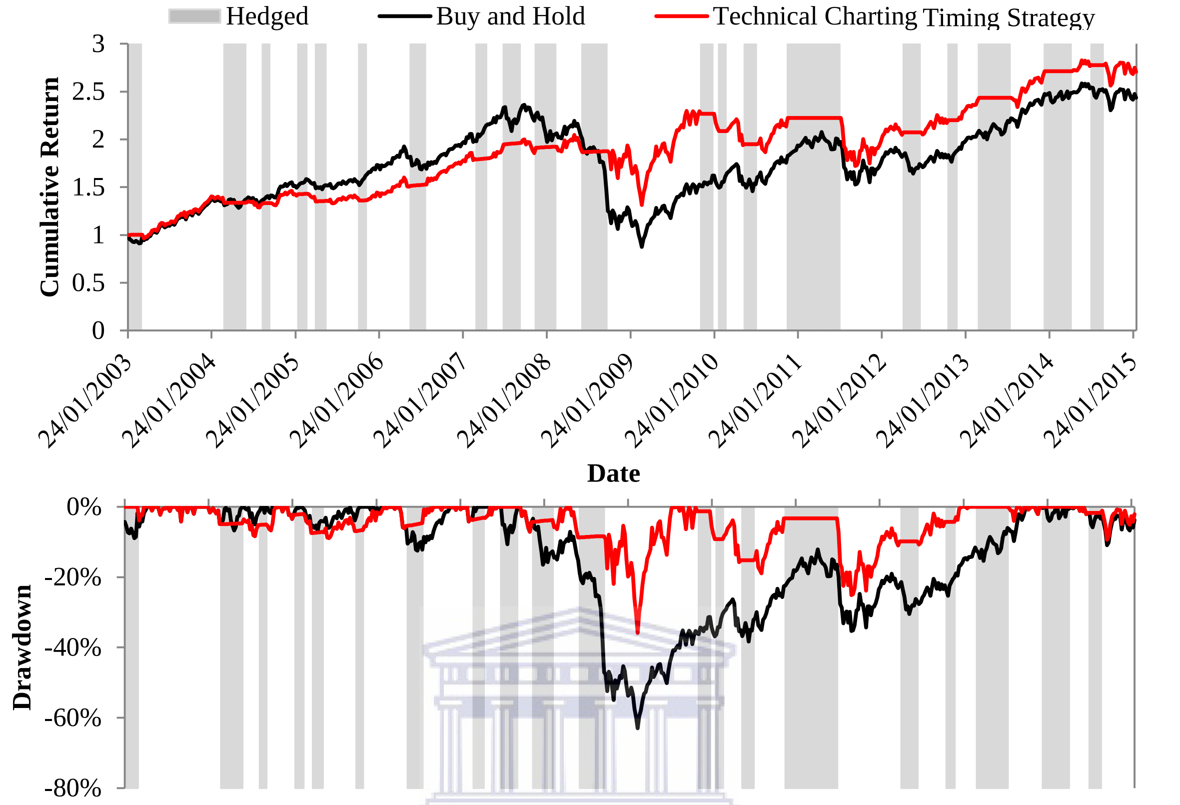
The time-series cumulative returns and drawdowns of the technical charting timing strategies relative to the buy and hold approach over the entire examination period, are graphically depicted in Panel A to Panel J of Figure 7.4. The charting strategies employ each sectors optimal bull and bear flag thresholds from the in-sample period. The grey shaded hedged regions in the graphs indicate that the technical charting strategies are less sensitive and kick into cash fewer times than the EMA timing strategy. However, the continuous hedging periods are much longer especially for the financials, consumer discretionary and information technology sectors in Panel F, Panel H, and Panel I of Figure 7.4. As a result, these strategies are bound to experience substantial performance drags especially given that many hedging periods incorrectly correspond with bull market phases. Similar to the EMA timing strategies, the technical charting rules at large avoid the 2008 financial crisis, however certain sectors such as the telecommunication services, materials and consumer discretionary sectors incorrectly generate re-entry signals during periods of economic turmoil. Furthermore, the charting based timing strategies in the energy, industrials, financials, materials, information technology and utilities sectors either fail to recognise the economic downturn following the 2011 European debt crisis, or incorrectly re-enter the market before it reaches the trough or local minima. Henceforth, although the technical charting timing strategies incur lower maximum drawdowns than the buy and hold strategy, the drawdowns experienced during the economic crises are higher than the EMA timing strategies.

In terms of cumulative returns, technical charting strategies provide higher cumulative returns than the buy and hold strategy in 7 sectors. Similar to the finding of the EMA timing strategy, the charting based rules largely benefit from the avoiding losses during major economic downturns, which compensates for the smaller timing error over the study period. Furthermore, the gains from avoiding the 2008 financial crisis are gradually wiped away during the out-of-sample period for the majority of the sectors, as smaller timing errors and cash drags due to long hedging period's cause the cumulative returns of the technical charting and passive buy and hold strategies to converge.

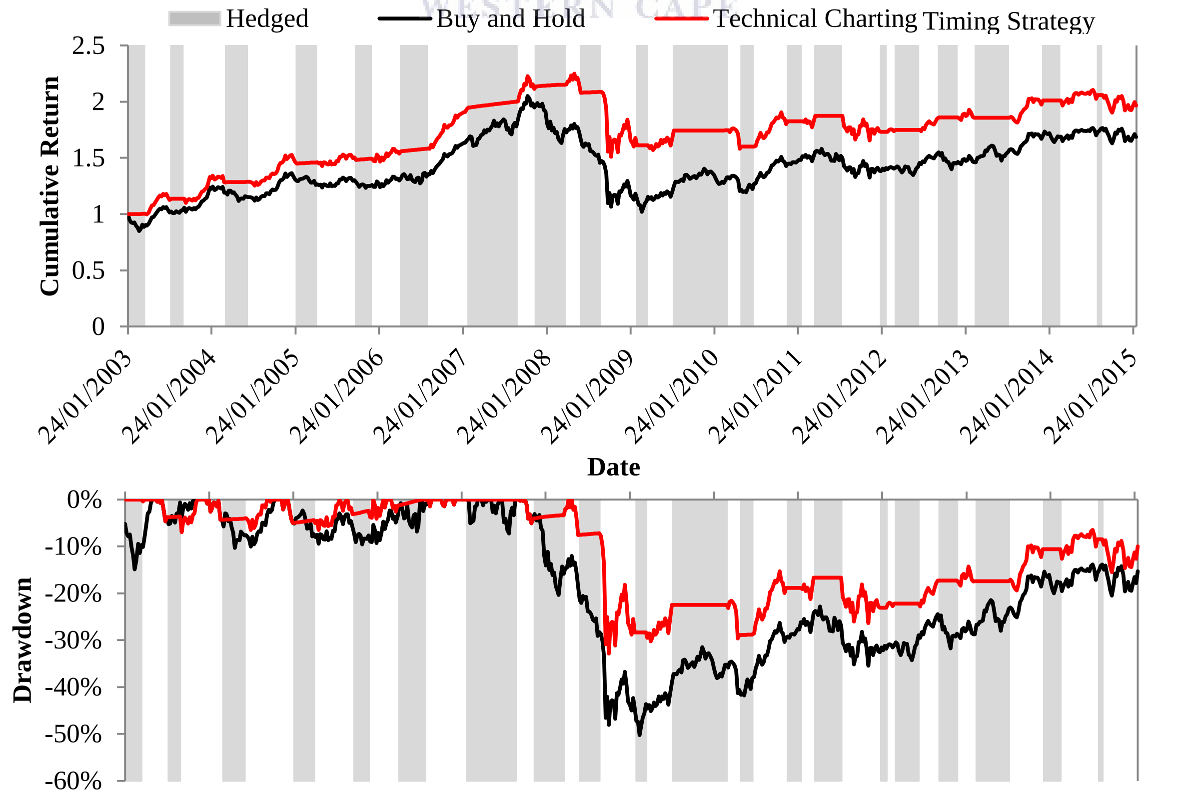
Figure 7.4: Cumulative Returns and Time-Series Drawdown of the Technical Charting Heuristics Timing Strategy on the S&P Global 1200 Sector Indices from 05/07/2002 to 06/02/2015 (Overall Examination Period).



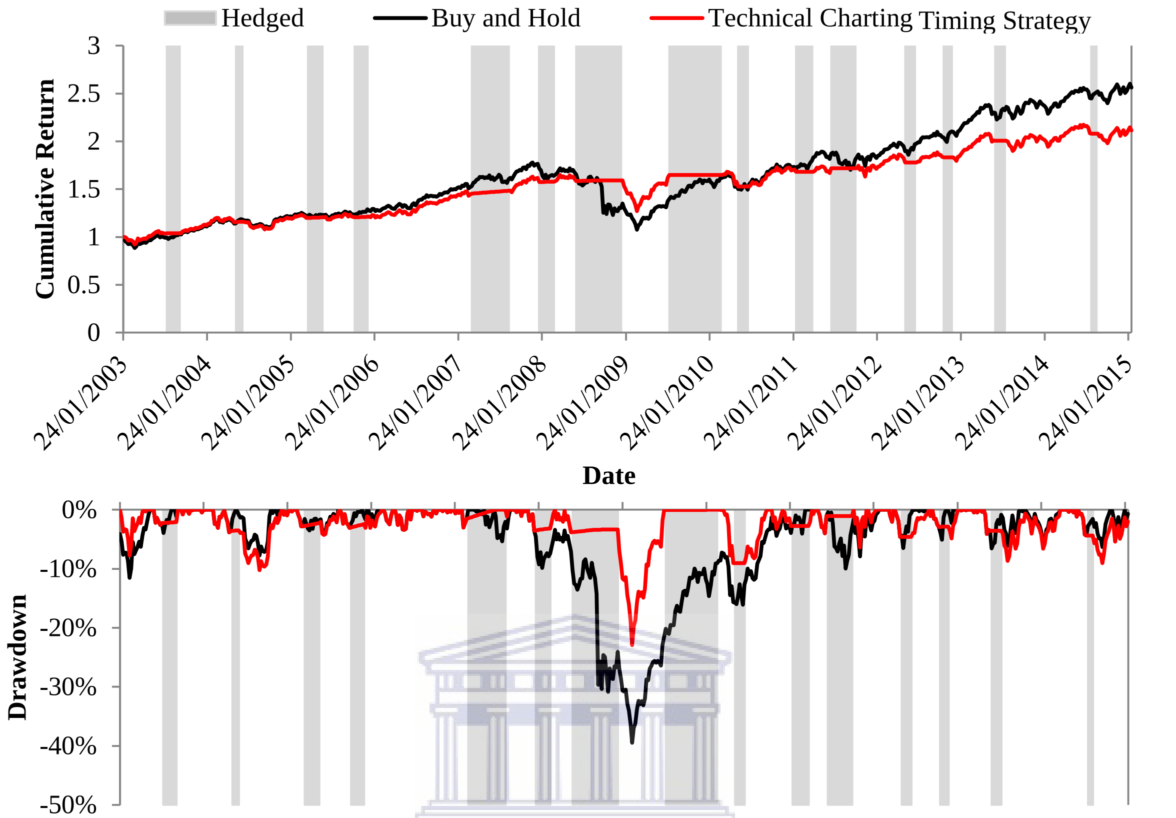
Panel C: S&P Global 1200 Industrials Sector (Bear fit = 3, Bull fit = 0)



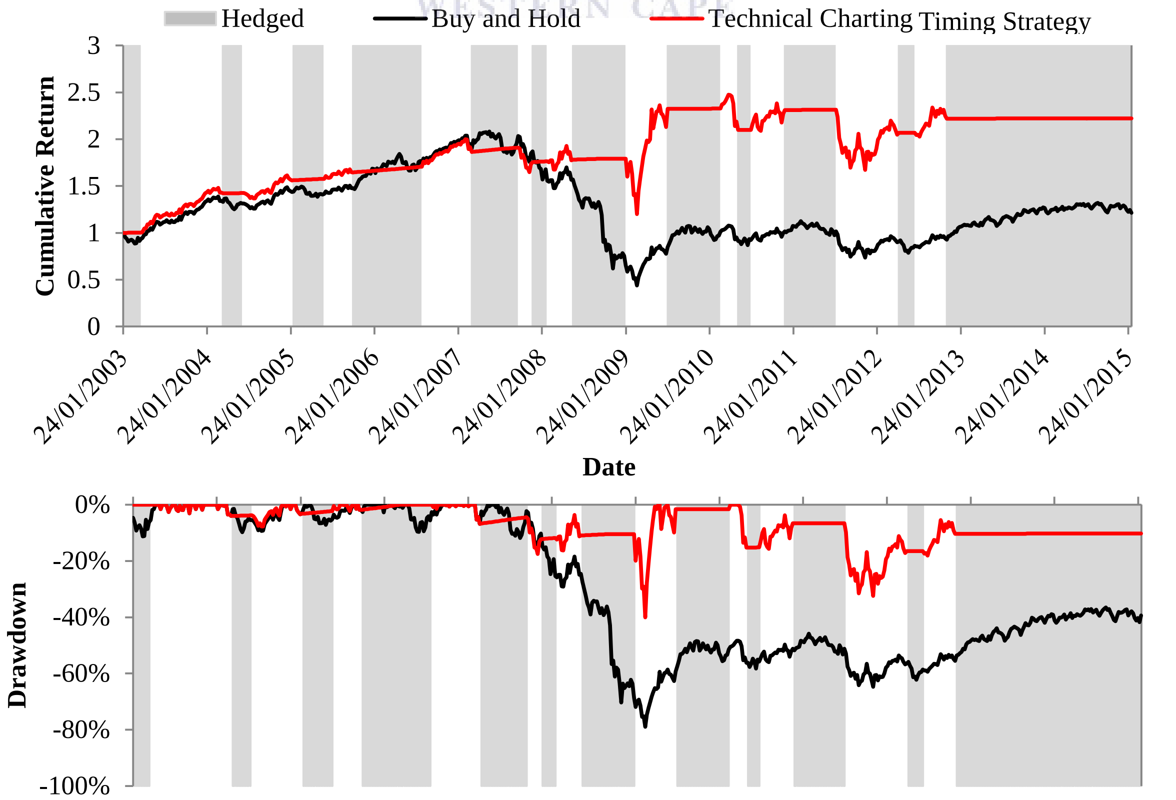
Panel D: S&P Global 1200 Telecommunication Serv. Sector (Bear fit = 2, Bull fit = 0)



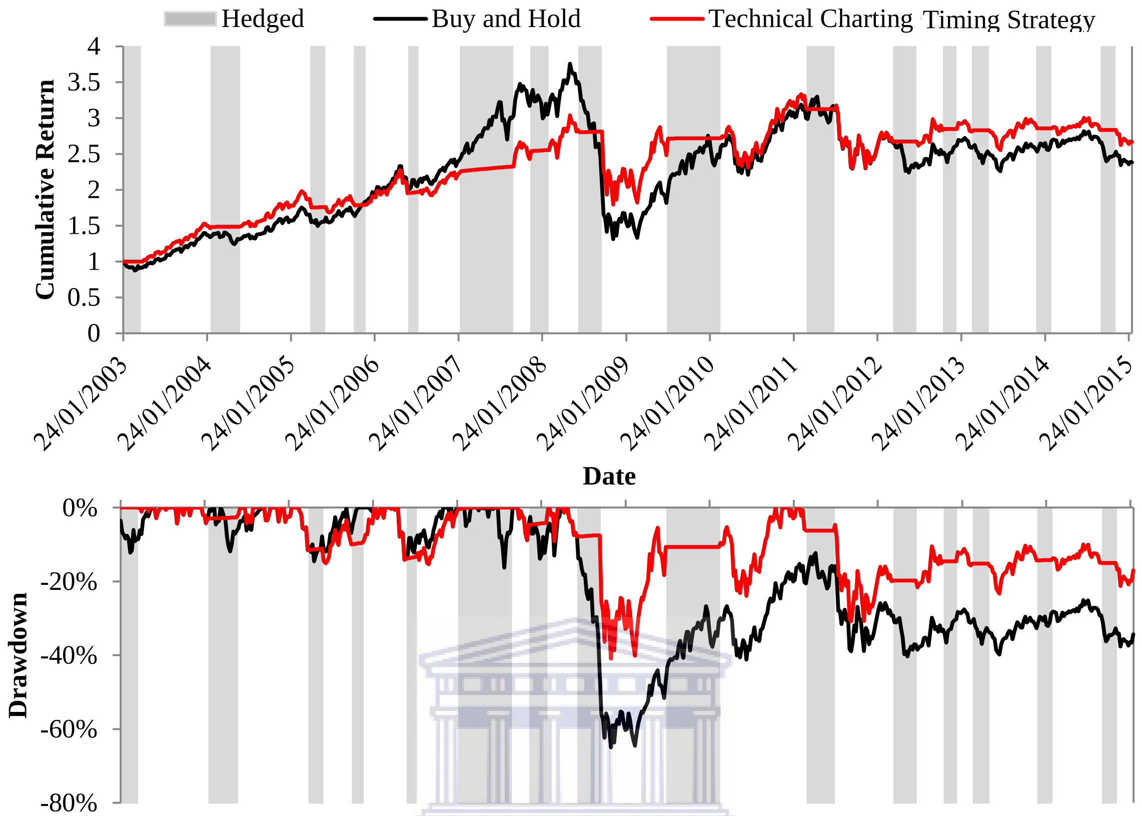
Panel E: S&P Global 1200 Consumer Staples Sector (Bear fit = 4, Bull fit = 0)



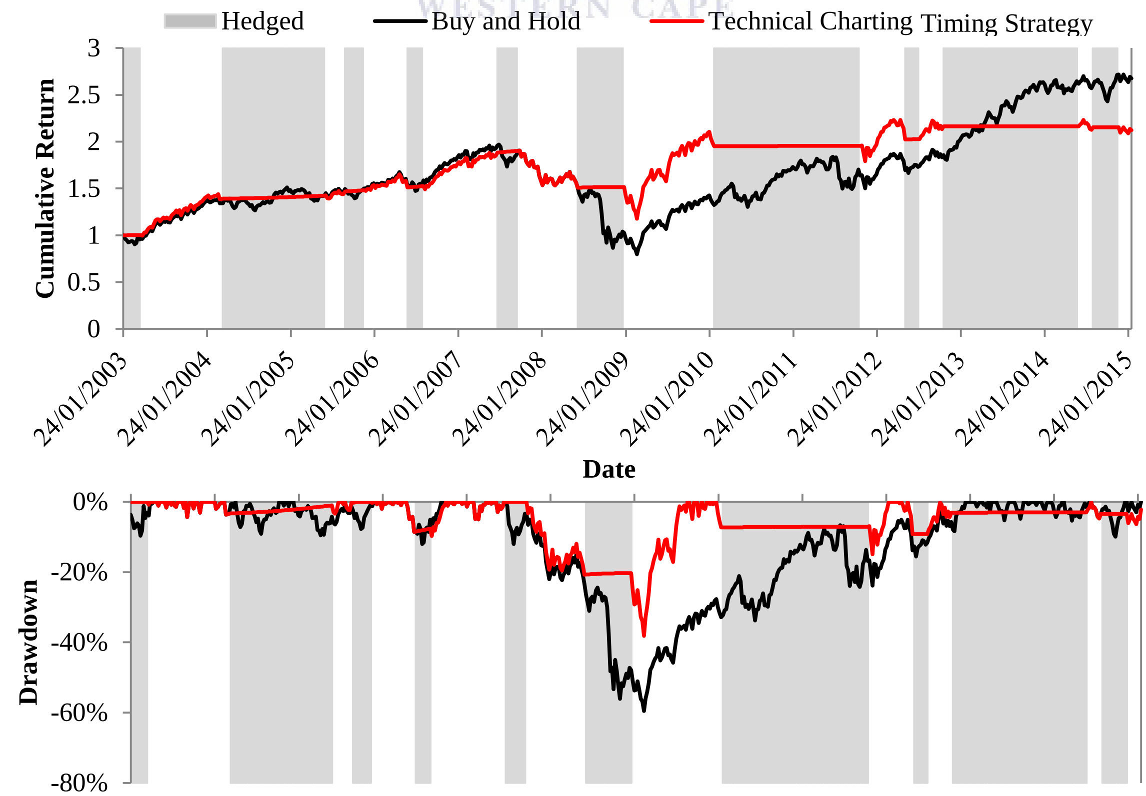
Panel F: S&P Global 1200 Financial Sector (Bear fit = 3, Bull fit = 2)



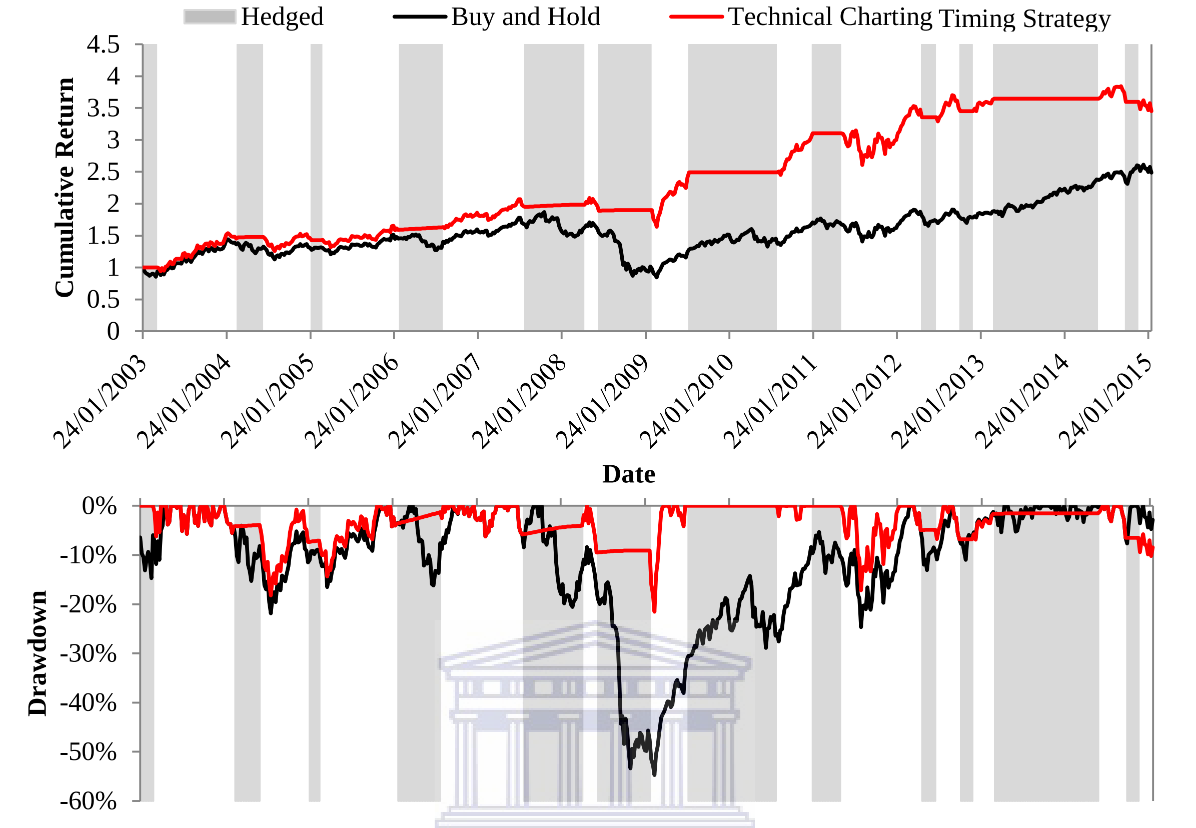
Panel G: S&P Global 1200 Materials Sector (Bear fit = 4, Bull fit = 0)



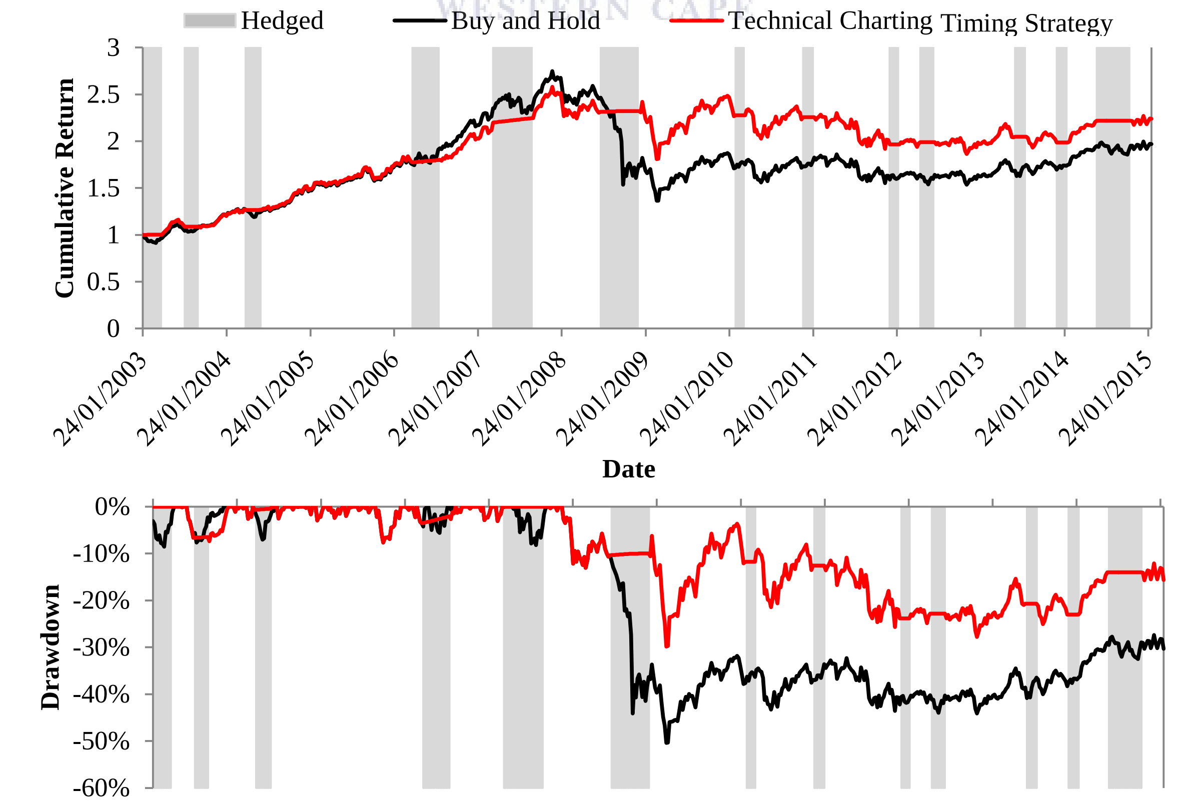
Panel H: S&P Global 1200 Consumer Discretionary Sector (Bear fit = 4, Bull fit = 4)



Panel I: S&P Global 1200 Information Technology Sector (Bear fit = 4, Bull fit = 2)



Panel J: S&P Global 1200 Utilities Sector (Bear fit = 4, Bull fit = 1)



7.6. Results: Global Tactical Sector Allocation Model

The research develops a global tactical sector allocation (GTSA) model which employs the EMA and technical charting trend timing models in the context of an investor's portfolio. The GTSA model is based on the methodology suggested by Faber (2013). The model allocates equal weighting or capital to each of the 10 global sectors, which are either invested in the sector or in cash based on the signals generated by the trend timing tool employed. Constant equal weighting of each sector is adopted in order to avoid excessive trading costs associated with reallocating portfolio weightings and exposure every time a buy or sell signal is generated for a sector. The test adopts the best performing trading rule permutations from the in-sample period tested in Section 7.4 and 7.5, and the performance statistics from applying the GTSA models over the entire examination period are presented in Table 7.11. The results of the portfolio based technical strategies are analysed relative to the buy and hold strategy in the S&P Global 1200 index and the equally weighted global sector portfolio.

Evaluation of the results reveals that both GTSA models provide higher annualised returns and cumulative returns in comparison to the buy and hold strategies. Furthermore, the returns of both strategies are statistically significant at a 1% significance level. The GTSA model employing the technical charting timing tool earns the highest returns of 8.79% per annum, whereas the EMA based strategy provides 8.01% annualised returns. Similarly, the charting strategy provides marginally higher cumulative returns than the EMA based GTSA model. The GTSA models also provide superior risk statistics than the buy and hold strategies, as both models provide lower standard deviations and maximum drawdowns. The EMA based GTSA model provides the lowest total risk with only half the standard deviation of the buy and hold strategies. Furthermore, the EMA based GTSA model experiences only a fifth of the maximum drawdown incurred by the buy and hold strategies. The charting based portfolio strategy also provides impressive risk statistics with standard deviation of 10.46%, and almost 50% lower maximum drawdown than the comparative passive strategies in the S&P Global 1200 index and equally weighted sector benchmark.

As a result, both GTSA models earn higher risk-adjusted returns than the comparative buy and hold strategies. The drastic improvement in Sharpe ratios of the GTSA portfolio approach is mainly attributable to the substantial risk reduction benefits from the technical trend timing tools, rather than higher returns. The EMA based GTSA model provides the highest Sharpe ratio of 77.17% whereas the technical charting based model has a Sharpe ratio of 71.12%. Henceforth, the portfolio based technical strategies provide Sharpe ratios that are almost double that of the passive buy and hold strategies. In addition, the returns of the GTSA models are economically significant, as both models outperform the passive buy and hold strategies on a risk-adjusted basis after accounting for the 2% transaction cost.

Table 7.11: Performance Statistics of Global Tactical Sector Allocation (GTSA) Model relative to the Buy and Hold Benchmarks from 05/07/2002 to 06/02/2015.

	S&P Global 1200 Buy and Hold	Equally Weighted Buy and Hold	Exponential Moving Average GTSA Model	Technical Charting Heuristics GTSA Model
Cumulative return	1.905	2.126	2.525	2.589
Annualised returns	6.98%	7.76%	8.01%	8.79%
***p*-value**			0.0000***	0.0000***
Standard Deviation	18.03%	17.24%	8.63%	10.46%
Maximum Drawdown	-58.51%	-54.84%	-11.77%	-24.70%
Sharpe Ratio	31.26%	37.22%	77.15%	71.12%
Sharpe Ratio Net of Costs			53.98%	52.00%

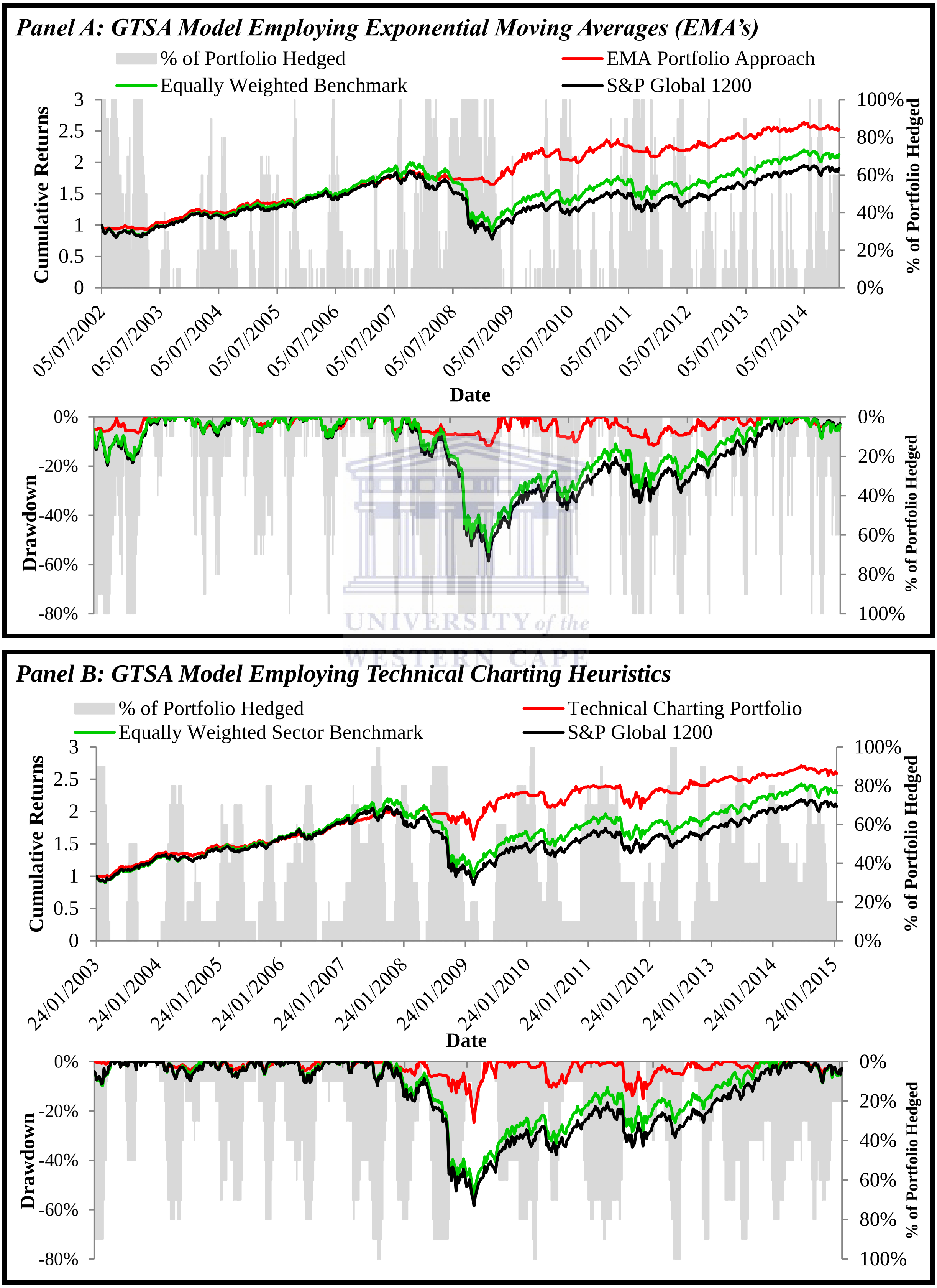
*Statistical Significance is denoted by ***, ** and * for 1%, 5% and 10% levels, respectively.*

Figure 7.5 demonstrates the performance of the EMA and technical charting based GTSA models in Panel A and Panel B, respectively. The first chart in each panel depicts the cumulative returns of the GTSA models relative to the S&P Global 1200 index and equally weighted sector portfolio. The grey shaded bars represent the percentage of the portfolio that is invested in cash in each period. The cumulative returns of the EMA based GTSA model show that the strategy successfully avoids the post 2002, 2008 and 2011 economic downturns, and this is confirmed by the strategies low exposure to the sector indices during these periods. The EMA portfolio strategy shows impressive risk management capabilities during periods corresponding with bear market trends as the entire portfolio exposure is shifted into cash. Similarly, the technical charting strategy protects substantial portfolio value during the 2008 financial crisis, however it kicks out of cash before the market trough which results in losses. Analysis of the cumulative return disparities between the technical charting strategy and buy and hold strategies in Panel B of Figure 7.5, show that the timing errors of the technical charting trading rules in the second sub-period of the study cause the superior cumulative returns of the GTSA model to decrease gradually after the 2008 financial crisis.

The second chart in each panel of Figure 7.6 graphically depicts the time-series drawdowns of the GTSA model relative to the buy and hold strategies. The EMA based GTSA model experiences exceptionally lower drawdowns than the passive investment strategies throughout the examination period. The charting based GTSA model also provides significantly lower drawdowns than the buy and hold approach. However, the charting based GTSA model experiences slightly higher drawdowns than the EMA based GTSA model during periods corresponding with the 2008 financial crisis and 2011 European debt crisis.

The overall analysis of the GTSA model results suggest that the strategy is more robust and reliable than applying trend timing mechanisms to individual sectors. This can be seen from the results presented in Section 7.4 and Section 7.5, which show that certain EMA and technical charting strategies on individual sectors are not economically significant and provide inferior performance in comparison to the buy and hold approach. However, when the same trading rule permutations are applied in the context of a portfolio developed based on the GTSA model, the strategies outperform their respective benchmarks even after taking into account transaction costs. The superior performance of the GTSA models can be attributed to the benefits of portfolio diversification, as small trend timing errors in certain sectors are compensated for by the gains experienced in correctly timed sectors. The GTSA model also experiences lower total risks and drawdowns than the majority of the EMA and charting based trend timing strategies tested in individual sectors.

Figure 7.5: Cumulative Returns and Time-Series Drawdown of the Global Tactical Sector Allocation (GTSA) Models from 05/07/2002 to 06/02/2015.



7.7. Conclusion

There are three technical analysis strategies tested in this chapter, namely the sector momentum strategy, exponential moving averages (EMA) trend timing strategy and the technical charting heuristics trend timing strategy. All three strategies employ the S&P Global 1200 sector indices and use past data in order to predict future trends.

The results of the momentum strategy suggest that although the majority of the momentum portfolios can provide higher returns than the buy and hold strategy, they have significantly higher total risks and maximum drawdowns during economic downturns. As a result the sector momentum strategy provides inferior risk-adjusted performance as measured by the Sharpe ratio in comparison to the buy and hold approach. Furthermore, the returns are not economically significant for the majority of the portfolios developed, as they provide lower returns than the passive investment strategy after accounting for transaction costs.

The performance statistics of the EMA timing strategy proposed by Hsieh (2010) are more impressive than the momentum strategy, as 5 out of the 10 EMA timing strategies provide higher Sharpe ratios than the passive buy and hold strategy after accounting for transaction costs. In reality, the proportion of economically significant EMA timing strategies could be higher, considering that actual transaction costs associated with trading the S&P Global sector ETF's are lower than the pessimistic 2% costs assumed in this chapter. The EMA timing strategy also provides higher Sharpe ratios than the passive buy and hold strategy for all sectors over the entire study period. The EMA strategy delivers remarkable risk management statistics, as strategies in all sectors provide substantially lower standard deviations and maximum drawdowns. The main gains from the EMA strategy are a result of reduced risk statistics during periods of economic turmoil, rather than improved returns which is consistent with the findings of Faber (2007) and Hsieh (2010). Furthermore, the results also show that the optimal out-of-sample and overall period EMA permutations are more robust and reliable than the in-sample permutations.

The technical charting timing strategy provides mixed results, with only 2 strategies providing higher risk-adjusted returns after trading costs in comparison to the buy and hold approach during the out-of-sample period. Similarly, only 3 technical charting timing strategies outperform the buy and hold approach after adjusting for transaction costs, over the entire examination period. The inferior performance of the technical charting timing strategies is attributable to the long consecutive hedging periods, which result in significant cash drags during bull market phases. Furthermore, in certain sectors the charting based approach kicks out of cash before the end of the bear market phase or fails to identify market downturns for instance during the 2011 European debt crisis, which suggests that the strategy is subject to larger timing errors. However, the out-of-sample and overall period optimal trading rule permutations are robust in the in-sample period, as they provide higher risk-adjusted returns than the passive benchmarks. This is the case, as the presence of any sort of timing strategy during the in-sample period which entirely or partially avoids the 2008 financial crisis, is due to provide favourable in-sample performance.

The global tactical sector allocation (GTSA) models also provide remarkable performance. The GTSA models provide higher returns and lower risk statistics than the S&P Global 1200 index and the equally weighted sector portfolio. Consequently, both the EMA and technical charting based portfolio strategies outperform the respective buy and hold benchmarks on a risk-adjusted basis, even after accounting for transaction costs. The superior performance of both strategies highlights the benefits of a portfolio strategy, as the timing errors and losses in a particular sector are nullified or compensated for by gains in other sectors.

Overall, the findings suggest that the EMA trend timing model promulgated by Hsieh (2010) provides a more robust trend timing tool than the technical charting technique developed in this research. The EMA strategy also provides superior performance relative to the buy and hold strategies. The technical trend timing models mainly benefit from identifying and avoiding major economic downturns, which compensates for smaller timing errors. Furthermore, the technical trading tools tested in this chapter work better over longer periods of drawdown due to slight lags in generating hedge and market re-entry signals, as observed during the 2008 and 2011 bear market phases. The results reiterate that the performance of the EMA and technical charting model is best assessed over the entire business cycle which is in line with the findings of Faber (2007) and Hsieh (2010).

8

Conclusion

The modern portfolio theory (MPT) pioneered by Markowitz (1952) provides investors with an asset allocation approach guided by the tenets of achieving maximum mean-variance efficiency by investing in the feasible set of risky assets. According to the MPT all investors must hold the optimal market portfolio which contains all risky assets in proportion to their relative market values. Tobin (1958) subsequently suggests the separation theorem which allows investors to tailor investments to their individual risk appetites by splitting the investment between the market portfolio and risk-free asset. The capital asset pricing model (CAPM) extends upon the application of the market portfolio by providing an asset pricing model as well as a tool for computing risk-adjusted returns based on the systematic or market risk of an asset, as unsystematic risk can be diversified away. Henceforth, the MPT and CAPM provide mechanisms to guide asset allocation decisions within efficient capital markets as defined by the efficient market hypothesis (EMH). According to the EMH which was formalised by Fama (1970, 1991), markets fully and fairly reflect all available information in a timely manner, thereby preventing investors from consistently outperforming the mean-variance efficient market portfolio.

The EMH implicitly promulgates a passive investment strategy without actively attempting to identify mispriced assets or timing market trends. Passive investment strategies include the long-term buy and hold strategy and the indexing approach. The indexing approach refers to a strategy that attempts to replicate the performance of a specified index. Traditionally investors would implement indexing strategies by holding multiple securities in order to replicate the returns of an index, however the advent of index tracking instruments such as mutual funds and exchange traded funds (ETF's) has simplified the indexing process. ETF's have gained significant traction in the investment industry, as they provide investors with a cost-effective means of buying into an index in the same manner a stock is purchased on a securities exchange. The increasing demand of ETF products and the potentially higher inefficiencies of global ETF's motivate this research to test the performance of sector ETF's in the global equity market. There are a total of 10 Standard and Poor's (S&P) Global 1200 sector indices and respective ETF's examined in this research over the period from July 5th, 2002 to February 6^{th}, 2015. All 10 sector ETF's possess positive tracking errors and tracking differences from their respective underlying indices, which can be attributed to the time zone differences in global securities trading, management replication errors, exclusion of dividends in computing index returns and trading illiquidity. However, the tracking ability measures are statistically insignificant for all ETF's sampled, which suggests that the ETF's neither significantly underperform nor outperform their respective underlying sector indices. Comparison of the sector ETF and respective underlying index performances also reveals that the ETF investors would successfully replicate the index performance over the study period.

In addition, the research investigates the pricing efficiency of the global sector ETF's by assessing the deviations in ETF prices and their net asset values (NAV's). It is found that all 10 sector ETF's trade at a statistically significant premium to the NAV which is in line with an earlier study on international country ETF's by Engle and Sarkar (2006). The price deviations are also higher than the deviations on domestic ETF's documented in prior literature, and the differences can be attributed to non-synchronous trading hours, illiquidity of international securities, international securities trading risks and aggressive short-term trading. The persistence of the premiums for more than 2 trading days suggests that the global sector ETF's sampled are not entirely price efficient over the examination period. The lack of pricing efficiency provides investors with an opportunity to earn arbitrage profits using technical trading rules extrapolated from the relationship between past price deviations and ETF returns. The application of the trading strategy produces outstanding performances with all 10 sector strategies earning higher cumulative returns and lower total risks than the buy and hold approach. Furthermore, 7 out of the 10 trading rule strategies tested are economically significant as they provide higher returns than the buy and hold strategy even after accounting for transaction costs, which suggests that actively trading ETF's provides better performances than a simple passive indexing strategy.

Similarly, proponents of behavioural finance oppose the notion of market efficiency and covertly reject the superiority of passive investment strategies. According to behaviourists, investors are irrational as purported by the prospect theory of Kahneman and Tversky (1979). Under the prospect theory, the irrationality of investors translates into cognitive errors such as mental accounting, the certainty effect and loss aversion which prompts investors to take higher risks in the negative domain. Investors can also be influenced by psychological biases such as heuristic simplification, emotional loss of control, self-deception, herding, over-optimism and overconfidence amongst others. These behavioural biases violate the assumption of rationality that underpins the EMH, and suggest that in the real world investors could be prone to making decisions that are inconsistent with maximising the mean-variance criterion of an investment. Furthermore, behavioural biases and investor overreaction could lead asset prices to overshoot their intrinsic values, which introduces a potential drag in the performance of cap-weighted indices as overvalued assets are over-weighted and undervalued assets are under-weighted. Henceforth, the cap-weighted market portfolio promulgated by the MPT does not necessarily reflect the most mean-variance efficient asset allocation option.

In order to assess the sector allocation of the cap-weighted benchmark portfolio, the study decomposes and evaluates the sector composition of the S&P Global 1200 index relative to the optimal historical sector composition that maximises the Sharpe ratio over the examination period. The cap-weighted sector exposures of the S&P Global 1200 index remain fairly stable throughout the examination period with notable changes between 2002 and 2004 as well as during major economic downturns. The financial sector retains the highest weighting in the majority of the years with slight decline in exposures during the 2008 financial crisis and following the 2011 European debt crisis, during which the exposure to the relatively more resilient consumer staples sector increases. In contrast, the optimal sector composition experiences substantial changes in sector exposures from one period to the next, thereby supporting the premise that different sectors are in favour at different points of the economic cycle. The sector exposures of the optimal sector composition highlights that the cap-weighted S&P Global 1200 index on average overweights cyclical sectors such as the financial, industrials and materials sectors over the study period. To its disadvantage, cap-weighting underweights resilient or defensive sectors such as the healthcare sector during the 2008 and 2011 economic downturns.

The potential inefficiencies and sub-optimal sector allocations of the S&P Global 1200 index motivates the development and evaluation of an alternative asset allocation mechanism, namely portfolio optimisation under different objectives and real world portfolio constraints. The optimisation process employs the benchmark S&P Global 1200 index and the 10 global sector indices. All 4 optimisation strategies provide superior risk-adjusted performance in comparison to the cap-weighted benchmark portfolio. In line with the findings of Hsieh (2010), the long-only mean-variance efficient and mean-tracking error optimal portfolios provide similar risk-return attributes, which suggests that the two optimisation objectives are equivalent. Relaxing the long-only constraint allows the long-short and market neutral strategies to achieve higher Sharpe ratios than the long-only counterparts, as the strategies can manage risks on the long positions by short selling less efficient indices. All 4 optimised portfolios hold long positions in the S&P Global 1200 sector indices with both the long-short and market neutral optimised portfolios holding short positions in the less efficient S&P Global 1200 index. However, the two short-sale enabled strategies achieve the optimal portfolios at different leverage levels, which can be attributed to the 50% cap on the short positions of the long-short strategy as per the Reg-T requirement that applies to individual investors in the United States. The long-short optimised portfolio achieves the highest Sharpe ratio of all the optimised strategies tested over the examination period, when 108% leverage is used. Furthermore, both the long-short and market neutral strategies achieve near zero systematic risk as measured by the beta coefficient against the S&P Global 1200 index. As a result, the strategies provide significantly higher Treynor measures than the long-only counterparts, which in turn outperform the cap-weighted benchmark or market portfolio. The similarities in trends of the risk-adjusted performance statistics between the global sector based optimal portfolios tested in this research and the global style based portfolios developed by Hsieh (2010), further suggest that the use of the two optimisation constituent classifications are analogous. Furthermore, although the portfolios constructed are optimised *ex post* and there is no indication that favourable results could be obtained in the out-of-sample, it nevertheless provide solid evidence that the cap-weighting methodology employed by the S&P Global 1200 index is not mean-variance efficient.

In addition to examining the performance of alternative optimised asset allocation strategies, this research further investigates the benefits of market timing strategies using three distinct technical tools in the global equity market. Technical analysts believe that prices do not necessarily follow a random walk and can be characterised by gradually shifting, long term repetitive trend patterns with serial dependencies. The presence of information asymmetry, long market memory and investors behavioural biases support the potential occurrence of repetitive episodes of momentum from overreactions and subsequent reversals as documented in prior literature. Consequently, investors could identify more mean-variance efficient strategies than a passive cap-weighted buy and hold approach, by using past price and volume data to identify future market trends and optimal trading points.

The momentum portfolios developed in this research support the presence of the sector momentum effect as all portfolios provide positive returns. However, the returns of the 3 month formation period portfolios are less than the benchmark S&P Global 1200 index. Furthermore, only 2 out of the 20 momentum portfolios constructed in this research provide statistically significant returns, with the 6 month formation period portfolios providing the highest returns. The majority of the momentum portfolios that provide higher returns than the market proxy experience significant positive returns prior to major economic downturns such as the 2008 financial crisis and 2011 European debt crisis. However, the backward looking nature of momentum portfolios results in substantial losses and drawdown during major economic downturns, which wipes away a significant proportion of the profits and translates into higher portfolio volatility. As a result, all the momentum portfolios constructed in this research fail to provide higher risk-adjusted returns than the passive buy and hold strategy in the S&P Global 1200 index. Analysis of the momentum portfolio performance also reveals that the portfolio returns are not economically significant, as transaction costs nullify any profits in excess of the passive buy and hold strategy in the cap-weighted market proxy.

The performances of the exponential moving average (EMA) trend timing model promulgated by Hsieh (2010) are more impressive over the examination period. The EMA timing strategies provide similar return statistics coupled with substantially lower total risks than the buy and hold strategy in the corresponding sectors. As a result, all 10 EMA timing strategies earn higher risk-adjusted returns than the buy and hold strategies. The EMA timing strategy also provides substantially lower time-series drawdown for all sectors and sub-periods tested in the research. Furthermore, half of the EMA timing strategies based on the in-sample trading rule permutations are robust, and provide economically significant performance after accounting for transaction costs over the entire study period. The outperformance of the EMA timing strategies can be attributed to the successful avoidance of significant losses during periods of major economic crises such as the 2008 financial crisis and 2011 European debt crisis, which compensates for the losses and costs incurred during smaller timing errors. In line with the findings of Faber (2007) and Hsieh (2010), the performance of the in-sample permutations over the out-of-sample and entire study period, suggests that the EMA timing strategy is most effective over long periods of drawdown due to lagged signals. Furthermore, the trading rule reliability and robustness is best assessed over the entire economic cycle.

In contrast to the EMA model proposed by Hsieh (2010), the technical charting heuristics trend timing model developed in this research provides less convincing performances over the examination period. Although some of the technical charting strategies employing the in-sample optimal permutations provide higher Sharpe ratios over the out-of-sample and overall study periods, after accounting for transaction costs only 2 and 3 strategies respectively, outperform the buy and hold strategy. The charting based strategy also incurs greater timing errors than the EMA timing strategy, with the strategy kicking out of cash prior to the end of bear market periods and in certain sectors the strategy fails to identify and avoid the drawdowns during the 2011 European debt crisis. The technical charting strategy also generates fewer hedge signals than the EMA timing strategy, however the charting based strategies experience longer periods invested in cash. The long hedging periods introduce performance drags for most charting strategies, as the incorrect hedge signals could correspond with bull market phases. Furthermore, the incorrect and excessively long periods in cash would result in conflict of interest between portfolio managers and clients.

The global tactical sector allocation (GTSA) model developed in this research performs exceptionally well over the examination period. The EMA and technical charting based GTSA models outperform the passive buy and hold strategy in the equally weighted sector benchmark and the cap-weighted S&P Global 1200 index. Both GTSA models provide higher returns and substantially lower risks, thereby earning double the Sharpe ratios of the passive strategies. The performances of the GTSA models are also statistically and economically significant, as the strategies earn superior risk-adjusted returns gross and net of transaction costs. Furthermore, the strategies successfully avoid the post 2002, 2008 and 2011 economic downturns, and experience significantly lower drawdowns than the passive investment strategies throughout the study period. Interestingly, when each sectors in-sample trading rules for both the EMA and technical charting strategies are employed in the context of an equally weighted sector portfolio, the timing errors and inefficiencies experienced on individual sector indices are nullified. This is the case as the portfolio approach of the GTSA model provides diversification benefits, with the timing errors in one sector being compensated for by gains in another sector.

Overall, the findings of this research support the superior mean-variance efficiency of active management strategies through both optimised asset allocation strategies and optimally conditioned technical analysis strategies such as the EMA and GTSA models. The tracking performance of the iShares S&P Global 1200 sector ETF's suggests that the ETF's provide a cost-effective and convenient means of implementing active global se ctor based strategies, in order to earn higher risk-adjusted returns than passive cap-weighted strategies. Although the study takes into consideration and adjusts for transaction costs, the tax implications are not explicitly accounted for. In addition, this research develops portfolios that are consistent with the Regulation-T (Reg-T) requirements in the United States, however the regulations governing short selling and leverage differ between countries. Furthermore, the costs associated with leverage and implementing short positions through the use of inverse ETF's demands additional investigation. Areas of further research include an investigation into the exact sources of pricing inefficiencies of the global sector ETF's, as well as the performances of global inverse and leveraged ETF's. Further studies could also explore the development of tactical sector allocation models, to profit during both bull and bear market phases through the use of leveraged ETF's and inverse ETF's, respectively. The other areas that necessitate subsequent research are the sources of serial dependencies in prices supporting technical trading rules. Exhaustive tests of charting patterns and template window sizes employed by the technical charting heuristics trend timing strategy also remain to be explored.

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APPENDIX A

Exponential Moving Average (EMA) Trend Timing Strategy (2002 to 2008)

The exponential moving average (EMA) trend timing strategy promulgated by Hsieh (2010) is employed to identify changes in market trends, in order to determine optimal market entry and exit points. The EMA timing strategy is tested on the 10 S&P Global 1200 sector indices over the 339 week in-sample period from July 5th, 2002 to December 26th, 2008. The objective of employing the EMA timing strategy is to identify bear market trends and avoid significant drawdown during economic downturns. The EMA based strategy is designed to hedge or kick into cash when the fast exponential moving average (FEMA) cuts through the slow exponential moving average (SEMA) from above. On the other hand, when the FEMA cuts through the SEMA from below, hedging is removed and the strategy earns the sector returns. The study adopts the 100% hedging mechanism, thus the full exposure to the sector is shifted into cash when a hedge signal is generated (Faber, 2007; Hsieh, 2010).

Following the study by Hsieh (2010), the performance statistics of all the EMA permutations tested for each sector during the in-sample period are presented in the heat maps in Appendix A.1 to Appendix A.10. The study tests a series of EMA strategies with FEMA and SEMA ranging from 0% to 100% at 10% intervals, for each sector index (Hsieh, 2010). The cells in the top-right region of each table of the appendix are blank as the FEMA always tracks the index at a higher rate than the SEMA. Furthermore, when the FEMA is equal to the SEMA, the strategy earns the sector performance.

The annualised return, standard deviation, Sharpe ratio, and percentage of study period in cash, for each sectors EMA timing strategy are depicted in Tables 1 to 4 of the respective appendices. The bold black border in each table denotes the optimal EMA permutations that maximise the Sharpe ratio during the in-sample period given that the strategy is hedged for less than 50% of the period.

APPENDIX B

Exponential Moving Average (EMA) Trend Timing Strategy (2009 to 2015)

The exponential moving average (EMA) trend timing strategy promulgated by Hsieh (2010) is employed to identify changes in market trends, in order to determine optimal market entry and exit points. The EMA timing strategy is tested on the 10 S&P Global 1200 sector indices over the 319 week out-of-sample period from January 2^{nd}, 2009 to February 6^{th}, 2015. The objective of employing the EMA timing strategy is to identify bear market trends and avoid significant drawdown during economic downturns. The EMA based strategy is designed to hedge or kick into cash when the fast exponential moving average (FEMA) cuts through the slow exponential moving average (SEMA) from above. On the other hand, when the FEMA cuts through the SEMA from below, hedging is removed and the strategy earns the sector returns. The study adopts the 100% hedging mechanism, thus the full exposure to the sector is shifted into cash when a hedge signal is generated (Faber, 2007; Hsieh, 2010).

Following the study by Hsieh (2010), the performance statistics of all the EMA permutations tested for each sector during the out-of-sample period are presented in the heat maps in Appendix B.1 to Appendix B.10. The study tests a series of EMA strategies with FEMA and SEMA ranging from 0% to 100% at 10% intervals, for each sector index (Hsieh, 2010). The cells in the top-right region of each table of the appendix are blank as the FEMA always tracks the index at a higher rate than the SEMA. Furthermore, when the FEMA is equal to the SEMA, the strategy earns the sector performance.

The annualised return, standard deviation, Sharpe ratio, and percentage of study period in cash, for each sectors EMA timing strategy are depicted in Tables 1 to 4 of the respective appendices. The bold black border in each table denotes the optimal EMA permutations that maximise the Sharpe ratio during the in-sample period, given that the strategy is hedged for less than 50% of the period. The out-of-sample optimal EMA permutations are highlighted by the bold dashed border in each table in Appendix B.

APPENDIX C

Exponential Moving Average (EMA) Trend Timing Strategy (2002 to 2015)

The exponential moving average (EMA) trend timing strategy promulgated by Hsieh (2010) is employed to identify changes in market trends, in order to determine optimal market entry and exit points. The EMA timing strategy is tested on the 10 S&P Global 1200 sector indices over the entire examination period from July 5th, 2002 to February 6th, 2015. The objective of employing the EMA timing strategy is to identify bear market trends and avoid significant drawdown during economic downturns. The EMA based strategy is designed to hedge or kick into cash when the fast exponential moving average (FEMA) cuts through the slow exponential moving average (SEMA) from above. On the other hand, when the FEMA cuts through the SEMA from below, hedging is removed and the strategy earns the sector returns. The study adopts the 100% hedging mechanism, thus the full exposure to the sector is shifted into cash when a hedge signal is generated (Faber, 2007; Hsieh, 2010).

Following the study by Hsieh (2010), the performance statistics of all the EMA permutations tested for each sector during the overall study period are presented in the heat maps in Appendix C.1 to Appendix C.10. The study tests a series of EMA strategies with FEMA and SEMA ranging from 0% to 100% at 10% intervals, for each sector index (Hsieh, 2010). The cells in the top-right region of each table of the appendix are blank as the FEMA always tracks the index at a higher rate than the SEMA. Furthermore, when the FEMA is equal to the SEMA, the strategy earns the sector performance.

The annualised return, standard deviation, Sharpe ratio, and percentage of study period in cash, for each sectors EMA timing strategy are depicted in Tables 1 to 4 of the respective appendices. The bold black border in each table denotes the optimal EMA permutations that maximise the Sharpe ratio during the in-sample period, given that the strategy is hedged for less than 50% of the period. In instances where the overall period optimal EMA permutations differ from the in-sample permutation, the overall period optimal permutations are highlighted by the bold dashed border in each table in Appendix C.

APPENDIX D

Technical Charting Heuristics Trend Timing Strategy (2002 to 2008)

The technical charting heuristics trend timing model is employed to predict changes in market trends based on current price patterns, in order to determine optimal market entry and exit points. The technical charting timing strategy is tested on the 10 S&P Global 1200 sector indices over the 339 week in-sample period from July 5th, 2002 to December 26th, 2008. The objective of employing the technical charting timing strategy is to predict bear market trends and avoid significant drawdown during economic downturns while profiting from timing bull market phases. The technical charting timing strategy is designed to hedge or kick into cash when the sloping bear flag pattern is identified. On the other hand, when the sloping bull flag pattern is identified, hedging is removed and the strategy earns the sector returns. In order to identify the occurrence of the bull or bear flag pattern a pattern fit value is computed, and a market entry or hedge signal is generated when the pattern fit value exceeds the trading rule fit thresholds. The study adopts the 100% hedging mechanism, thus the full exposure to the sector is shifted into cash when a hedge signal is generated (Faber, 2007; Hsieh, 2010).

The performance statistics of all the bull and bear flag fit thresholds tested for each sector during the in-sample period, are presented in the heat maps in Appendix D.1 to Appendix D.10. The study tests a series of charting strategies with bull and bear flag fit thresholds ranging from 0 to 4 in one unit increments, for each sector index.

The annualised return, standard deviation, Sharpe ratio, and percentage of study period in cash, for each sectors technical charting timing strategy are depicted in Tables 1 to 4 of the respective appendices. The bold black border in each table denotes the optimal bull and bear flag fit thresholds that maximise the Sharpe ratio during the in-sample period, given that the strategy is hedged for less than 50% of the period.

APPENDIX E

Technical Charting Heuristics Trend Timing Strategy (2009 to 2015)

The technical charting heuristics trend timing model is employed to predict changes in market trends based on current price patterns, in order to determine optimal market entry and exit points. The technical charting timing strategy is tested on the 10 S&P Global 1200 sector indices over the 319 week out-of-sample period from January 2nd, 2009 to February 6th, 2015. The objective of employing the technical charting timing strategy is to predict bear market trends and avoid significant drawdown during economic downturns while profiting from timing bull market phases. The technical charting timing strategy is designed to hedge or kick into cash when the sloping bear flag pattern is identified. On the other hand, when the sloping bull flag pattern is identified, hedging is removed and the strategy earns the sector returns. In order to identify the occurrence of the bull or bear flag pattern a pattern fit value is computed, and a market entry or hedge signal is generated when the pattern fit value exceeds the trading rule fit thresholds. The study adopts the 100% hedging mechanism, thus the full exposure to the sector is shifted into cash when a hedge signal is generated (Faber, 2007; Hsieh, 2010).

The performance statistics of all the bull and bear flag fit thresholds tested for each sector during the out-of-sample period, are presented in the heat maps in Appendix E.1 to Appendix E.10. The study tests a series of charting strategies with bull and bear flag fit thresholds ranging from 0 to 4 in one unit increments, for each sector index.

The annualised return, standard deviation, Sharpe ratio, and percentage of study period in cash, for each sectors technical charting timing strategy are depicted in Tables 1 to 4 of the respective appendices. The bold black border in each table denotes the optimal bull and bear flag fit thresholds that maximise the Sharpe ratio during the in-sample period, given that the strategy is hedged for less than 50% of the period. In instances where the out-of-sample and in-sample optimal permutations are not equal, the out-of-sample optimal bull and bear flag fit thresholds are highlighted by the bold dashed border in each table of Appendix E.

APPENDIX F

Technical Charting Heuristics Trend Timing Strategy (2002 to 2015)

The technical charting heuristics trend timing model is employed to predict changes in market trends based on current price patterns, in order to determine optimal market entry and exit points. The technical charting timing strategy is tested on the 10 S&P Global 1200 sector indices over the entire examination period from July 5th, 2002 to February 6th, 2015. The objective of employing the technical charting timing strategy is to predict bear market trends and avoid significant drawdown during economic downturns while profiting from timing bull market phases. The technical charting timing strategy is designed to hedge or kick into cash when the sloping bear flag pattern is identified. On the other hand, when the sloping bull flag pattern is identified, hedging is removed and the strategy earns the sector returns. In order to identify the occurrence of the bull or bear flag pattern a pattern fit value is computed, and a market entry or hedge signal is generated when the pattern fit value exceeds the trading rule fit thresholds. The study adopts the 100% hedging mechanism, thus the full exposure to the sector is shifted into cash when a hedge signal is generated (Faber, 2007; Hsieh, 2010).

The performance statistics of all the bull and bear flag fit thresholds tested for each sector during the overall study period, are presented in the heat maps in Appendix F.1 to Appendix F.10. The study tests a series of charting strategies with bull and bear flag fit thresholds ranging from 0 to 4 in one unit increments, for each sector index.

The annualised return, standard deviation, Sharpe ratio, and percentage of study period in cash, for each sectors technical charting timing strategy are depicted in Tables 1 to 4 of the respective appendices. The bold black border in each table denotes the optimal bull and bear flag fit thresholds that maximise the Sharpe ratio during the in-sample period, given that the strategy is hedged for less than 50% of the period. In instances where the overall period and in-sample optimal permutations are not the same, the overall period optimal bull and bear flag fit thresholds are highlighted by the bold dashed border in each table in Appendix F.

Appendix A: Exponential Moving Average Trend Timing Strategy (2002 to 2008)

A:1 Healthcare Sector

Table A.1.1. Annualised Return

Fast Moving Average (columns) / Slow Moving Average (rows)

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	1.98%										
90%	0.12%										
80%	0.12%	1.31%									
70%	1.40%	2.72%	2.74%								
60%	3.22%	3.39%	2.36%	2.80%							
50%	3.88%	3.29%	3.74%	4.05%	3.27%						
40%	2.87%	3.77%	4.19%	3.03%	0.85%	-1.49%					
30%	3.35%	2.90%	1.67%	-0.65%	-2.19%	-2.58%	-2.57%				
20%	0.21%	-0.92%	-1.16%	-3.08%	-2.62%	-2.31%	-3.00%	-2.38%			
10%	-1.61%	-1.39%	-2.64%	-2.59%	-3.06%	-2.61%	-3.06%	-0.39%	-0.03%		
0%	-5.25%	-4.05%	-4.05%	-2.10%	-1.85%	-2.14%	-2.04%	-0.17%	-0.02%	-0.47%	1.98%

Table A.1.2. Annualised Standard Deviation

Fast Moving Average (columns) / Slow Moving Average (rows)

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	17.16%										
90%	9.33%										
80%	9.20%	9.12%									
70%	9.12%	8.92%	8.69%								
60%	8.69%	8.78%	8.58%	8.66%							
50%	8.84%	8.65%	8.74%	8.86%	9.12%						
40%	8.76%	8.89%	8.94%	9.21%	8.97%	9.01%					
30%	8.82%	8.91%	8.88%	9.14%	8.81%	8.67%	8.66%				
20%	9.09%	8.85%	8.85%	8.80%	8.72%	8.78%	8.80%	8.91%			
10%	8.74%	8.81%	8.88%	8.97%	8.99%	9.11%	9.41%	9.45%	9.73%		
0%	14.20%	14.40%	14.40%	14.95%	14.94%	14.92%	14.92%	15.18%	15.21%	15.18%	17.16%

Table A.1.3. Annualised Sharpe Ratio

Fast Moving Average (columns) / Slow Moving Average (rows)

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	3.70%										
90%	-13.10%										
80%	-13.32%	-0.35%									
70%	0.60%	15.37%	15.99%								
60%	21.59%	23.29%	11.87%	16.76%							
50%	28.61%	22.53%	27.43%	30.53%	21.10%						
40%	17.37%	27.29%	31.80%	18.32%	-5.48%	-31.46%					
30%	22.75%	17.48%	3.60%	-21.89%	-40.15%	-45.32%	-45.22%				
20%	-12.56%	-25.60%	-28.30%	-50.37%	-45.45%	-41.68%	-49.44%	-41.78%			
10%	-33.79%	-31.08%	-44.85%	-43.92%	-48.97%	-43.46%	-46.85%	-18.32%	-14.14%		
0%	-46.48%	-37.47%	-37.47%	-23.03%	-21.38%	-23.40%	-22.68%	-9.98%	-8.98%	-11.94%	3.70%

Table A.1.4. Percentage of Time in Cash

Fast Moving Average (columns) / Slow Moving Average (rows)

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	23.67%										
80%	25.15%	27.51%									
70%	28.11%	30.77%	32.25%								
60%	31.66%	31.95%	32.84%	34.32%							
50%	32.25%	33.43%	34.32%	33.43%	31.95%						
40%	33.14%	33.73%	32.84%	31.95%	33.14%	33.43%					
30%	31.95%	32.25%	32.84%	32.54%	34.02%	34.91%	34.91%				
20%	30.77%	32.54%	33.14%	33.14%	34.32%	34.62%	32.84%	32.84%			
10%	29.29%	29.29%	29.59%	28.70%	28.70%	29.88%	29.29%	30.77%	31.07%		
0%	11.24%	12.13%	12.13%	13.02%	13.61%	13.91%	13.61%	13.31%	13.61%	14.20%	0.00%

A:2 Energy Sector

Table A.2.1. Annualised Return

Fast Moving Average (columns) / Slow Moving Average (rows)

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	9.85%										
90%	5.09%										
80%	3.64%	2.44%									
70%	1.20%	1.00%	2.29%								
60%	1.48%	2.03%	3.94%	3.37%							
50%	1.35%	4.13%	3.07%	4.71%	3.94%						
40%	2.33%	3.50%	4.96%	3.43%	4.99%	7.40%					
30%	3.28%	4.73%	4.49%	7.25%	7.63%	5.66%	6.35%				
20%	6.13%	5.79%	7.00%	7.59%	5.78%	7.71%	9.04%	8.08%			
10%	7.21%	8.33%	9.26%	9.58%	7.14%	8.17%	8.31%	8.77%	8.71%		
0%	7.75%	7.75%	7.75%	7.75%	7.75%	7.75%	7.65%	7.25%	7.46%	7.32%	9.85%

Table A.2.2. Annualised Standard Deviation

Fast Moving Average (columns) / Slow Moving Average (rows)

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	25.18%										
90%	15.27%										
80%	15.66%	15.46%									
70%	15.62%	15.34%	15.38%								
60%	15.18%	15.45%	15.44%	15.26%							
50%	15.37%	15.47%	15.24%	14.94%	15.15%						
40%	15.55%	15.14%	14.97%	15.06%	14.94%	14.21%					
30%	15.07%	15.04%	15.07%	14.03%	14.41%	14.53%	15.04%				
20%	14.43%	14.43%	14.32%	14.47%	14.89%	15.26%	15.32%	15.52%			
10%	15.40%	15.55%	15.63%	15.80%	15.91%	15.93%	16.05%	16.15%	16.09%		
0%	23.92%	23.92%	23.92%	23.92%	23.92%	23.92%	23.92%	23.90%	23.89%	23.84%	25.18%

Table A.2.3. Annualised Sharpe Ratio

Fast Moving Average (columns) / Slow Moving Average (rows)

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	33.77%										
90%	24.52%										
80%	14.64%	7.09%									
70%	-0.93%	-2.23%	6.15%								
60%	0.85%	4.44%	16.78%	13.27%							
50%	0.02%	18.01%	11.29%	22.51%	17.08%						
40%	6.35%	14.21%	24.16%	13.81%	24.41%	42.63%					
30%	12.85%	22.52%	20.85%	42.06%	43.60%	29.69%	33.25%				
20%	33.18%	30.76%	39.46%	43.15%	29.77%	41.70%	50.22%	43.39%			
10%	38.06%	44.93%	50.61%	52.09%	36.39%	42.88%	43.38%	48.35%	48.16%		
0%	26.76%	26.76%	26.76%	26.76%	26.76%	26.76%	26.37%	24.71%	25.60%	25.07%	33.77%

Table A.2.4. Percentage of Time in Cash

Fast Moving Average (columns) / Slow Moving Average (rows)

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	19.23%										
80%	18.64%	21.01%									
70%	19.82%	21.01%	23.08%								
60%	21.60%	22.49%	23.96%	26.04%							
50%	22.78%	23.67%	26.33%	26.92%	27.22%						
40%	23.67%	25.74%	27.51%	27.22%	27.22%	28.70%					
30%	25.15%	26.04%	26.04%	28.11%	28.40%	29.59%	29.59%				
20%	26.04%	26.33%	27.51%	28.70%	27.81%	27.51%	28.70%	27.81%			
10%	23.08%	23.67%	23.67%	23.37%	23.37%	23.96%	24.56%	24.85%	24.56%		
0%	21.89%	21.89%	21.89%	21.89%	21.89%	21.89%	22.19%	22.49%	22.78%	24.26%	0.00%

Appendix A: Exponential Moving Average Trend Timing Strategy (2002 to 2008)

A:3 Industrial Sector

Table A.3.1. Annualised Return

Fast Moving Average (columns) / Slow Moving Average (rows)

Slow \ Fast	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	2.00%										
90%	1.22%										
80%	0.25%	-1.09%									
70%	-1.72%	-2.78%	-1.73%								
60%	-1.48%	0.32%	0.91%	3.47%							
50%	1.60%	1.09%	3.11%	4.46%	6.95%						
40%	2.39%	3.47%	5.97%	7.60%	7.39%	9.48%					
30%	6.65%	6.59%	8.20%	8.61%	9.50%	10.43%	10.14%				
20%	8.45%	10.20%	10.92%	9.58%	8.45%	7.80%	8.78%	6.72%			
10%	7.95%	8.41%	8.35%	8.16%	7.89%	8.70%	8.76%	9.95%	10.01%		
0%	-2.61%	-2.61%	-2.61%	-2.73%	-2.73%	-0.77%	-1.31%	-1.40%	0.56%	0.01%	2.00%

Table A.3.2. Annualised Standard Deviation

Fast Moving Average (columns) / Slow Moving Average (rows)

Slow \ Fast	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	18.90%										
90%	11.05%										
80%	11.17%	10.69%									
70%	10.56%	10.60%	10.27%								
60%	10.47%	9.99%	10.31%	10.20%							
50%	10.17%	10.32%	10.21%	10.40%	10.70%						
40%	10.34%	10.24%	10.52%	10.54%	10.51%	10.35%					
30%	10.34%	10.14%	10.09%	10.23%	10.35%	10.18%	10.20%				
20%	9.92%	9.96%	10.00%	10.08%	10.07%	10.18%	10.11%	10.41%			
10%	10.48%	10.48%	10.44%	10.40%	10.40%	10.31%	10.36%	10.57%	10.76%		
0%	15.26%	15.26%	15.26%	15.26%	15.26%	15.92%	16.13%	16.13%	17.04%	16.98%	18.90%

Table A.3.3. Annualised Sharpe Ratio

Fast Moving Average (columns) / Slow Moving Average (rows)

Slow \ Fast	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	3.47%										
90%	-1.19%										
80%	-9.79%	-22.76%									
70%	-29.07%	-38.96%	-29.91%								
60%	-26.99%	-10.25%	-4.28%	20.83%							
50%	2.53%	-2.50%	17.27%	29.92%	52.37%						
40%	10.06%	20.73%	43.96%	59.33%	57.49%	78.58%					
30%	51.32%	51.73%	67.90%	70.95%	78.76%	89.24%	86.26%				
20%	71.63%	88.88%	95.66%	81.69%	70.52%	63.37%	73.45%	51.67%			
10%	63.01%	67.42%	67.12%	65.53%	62.91%	71.39%	71.53%	81.40%	80.45%		
0%	-25.94%	-25.94%	-25.94%	-26.71%	-26.71%	-13.32%	-16.50%	-17.01%	-4.63%	-7.87%	3.47%

Table A.3.4. Percentage of Time in Cash

Fast Moving Average (columns) / Slow Moving Average (rows)

Slow \ Fast	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	18.93%										
80%	18.93%	20.12%									
70%	20.41%	20.41%	22.19%								
60%	20.41%	22.78%	23.08%	25.74%							
50%	23.08%	22.78%	25.44%	25.74%	26.92%						
40%	24.56%	25.44%	26.92%	27.22%	28.11%	31.07%					
30%	26.33%	27.81%	30.18%	30.77%	31.07%	32.54%	31.95%				
20%	30.47%	32.54%	33.14%	32.25%	32.25%	32.84%	34.02%	34.32%			
10%	29.29%	29.88%	31.07%	31.36%	32.54%	33.43%	33.43%	33.14%	31.07%		
0%	19.23%	19.23%	19.23%	19.53%	19.53%	19.82%	20.12%	20.41%	19.82%	21.60%	0.00%

A:4 Telecommunication Services Sector

Table A.4.1. Annualised Return

Fast Moving Average (columns) / Slow Moving Average (rows)

Slow \ Fast	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	6.33%										
90%	4.06%										
80%	4.61%	5.83%									
70%	5.24%	6.87%	6.13%								
60%	6.47%	4.95%	7.58%	7.73%							
50%	4.89%	7.62%	8.70%	8.18%	7.97%						
40%	8.59%	8.33%	9.40%	9.13%	8.66%	8.43%					
30%	8.50%	8.65%	7.89%	7.77%	8.93%	9.02%	8.92%				
20%	7.79%	8.60%	9.77%	10.53%	10.14%	9.53%	9.36%	9.27%			
10%	10.05%	9.74%	9.71%	9.26%	9.30%	8.00%	7.13%	7.13%	6.23%		
0%	5.65%	5.23%	5.23%	4.67%	4.67%	4.67%	4.04%	3.52%	2.75%	2.34%	6.33%

Table A.4.2. Annualised Standard Deviation

Fast Moving Average (columns) / Slow Moving Average (rows)

Slow \ Fast	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	18.56%										
90%	11.51%										
80%	11.90%	11.95%									
70%	11.87%	10.89%	11.04%								
60%	10.96%	11.14%	10.66%	10.75%							
50%	10.84%	10.74%	10.63%	10.82%	10.86%						
40%	10.37%	10.45%	10.43%	10.56%	10.50%	10.51%					
30%	10.50%	10.50%	10.47%	10.52%	10.55%	10.51%	10.47%				
20%	10.41%	10.34%	10.44%	10.50%	10.49%	10.34%	10.29%	10.36%			
10%	10.64%	10.68%	10.48%	10.43%	10.43%	10.69%	10.58%	10.41%	10.89%		
0%	17.32%	17.29%	17.29%	17.26%	17.26%	17.26%	17.18%	17.22%	17.22%	16.94%	18.56%

Table A.4.3. Annualised Sharpe Ratio

Fast Moving Average (columns) / Slow Moving Average (rows)

Slow \ Fast	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	26.85%										
90%	23.59%										
80%	27.41%	37.54%									
70%	32.80%	50.67%	43.28%								
60%	46.71%	32.34%	58.46%	59.37%							
50%	32.64%	58.42%	69.18%	63.17%	60.99%						
40%	69.84%	66.81%	77.22%	73.65%	69.65%	67.42%					
30%	68.11%	69.57%	62.49%	61.03%	71.91%	73.03%	72.45%				
20%	61.85%	70.18%	80.60%	87.45%	83.90%	79.75%	77.60%	76.51%			
10%	81.75%	78.61%	79.83%	75.92%	76.22%	62.22%	54.63%	55.57%	44.83%		
0%	24.85%	22.47%	22.47%	19.27%	19.27%	19.27%	15.67%	12.62%	8.13%	5.87%	26.85%

Table A.4.4. Percentage of Time in Cash

Fast Moving Average (columns) / Slow Moving Average (rows)

Slow \ Fast	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	18.05%										
80%	19.53%	22.49%									
70%	21.60%	26.63%	26.63%								
60%	24.85%	26.63%	31.36%	30.77%							
50%	27.81%	29.88%	31.36%	31.36%	32.25%						
40%	30.77%	31.95%	32.54%	32.25%	33.43%	34.91%					
30%	31.66%	31.66%	31.95%	33.73%	35.21%	36.69%	38.46%				
20%	33.73%	35.21%	37.28%	37.28%	37.57%	38.46%	38.76%	36.98%			
10%	32.84%	32.54%	34.02%	34.62%	34.91%	34.62%	35.21%	36.39%	34.91%		
0%	7.99%	8.28%	8.28%	8.28%	8.28%	8.28%	8.28%	8.28%	8.58%	10.65%	0.00%

Appendix A: Exponential Moving Average Trend Timing Strategy (2002 to 2008)

A:5 Consumer Staples Sector

Table A.5.1. Annualised Return

Rows: Slow Moving Average; columns: Fast Moving Average

Slow \ Fast	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	3.62%										
90%	2.41%										
80%	2.67%	3.26%									
70%	2.94%	4.06%	2.60%								
60%	3.10%	2.63%	2.03%	3.43%							
50%	3.00%	2.45%	2.97%	3.50%	3.63%						
40%	3.08%	3.50%	3.99%	3.33%	4.16%	3.54%					
30%	3.26%	3.59%	3.77%	4.03%	3.47%	4.04%	5.08%				
20%	3.46%	3.93%	4.29%	4.49%	5.36%	4.53%	4.30%	4.91%			
10%	5.36%	5.27%	5.76%	5.92%	5.64%	5.54%	5.52%	5.23%	5.51%		
0%	2.28%	2.03%	2.03%	1.99%	2.23%	2.23%	2.61%	2.39%	2.39%	1.56%	3.62%

Table A.5.2. Annualised Standard Deviation

Rows: Slow Moving Average; columns: Fast Moving Average

Slow \ Fast	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	13.92%										
90%	7.82%										
80%	7.90%	7.50%									
70%	7.43%	7.49%	7.20%								
60%	7.43%	7.20%	7.57%	7.66%							
50%	7.27%	7.48%	7.65%	7.74%	7.40%						
40%	7.59%	7.75%	7.59%	7.41%	7.49%	7.43%					
30%	7.34%	7.38%	7.45%	7.44%	7.45%	7.49%	7.49%				
20%	7.42%	7.49%	7.53%	7.56%	7.53%	7.38%	7.53%	7.46%			
10%	7.39%	7.38%	7.33%	7.35%	7.49%	7.53%	7.54%	7.61%	7.79%		
0%	12.48%	12.46%	12.46%	12.46%	12.48%	12.48%	12.49%	12.48%	12.48%	12.42%	13.92%

Table A.5.3. Annualised Sharpe Ratio

Rows: Slow Moving Average; columns: Fast Moving Average

Slow \ Fast	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	16.31%										
90%	13.61%										
80%	16.74%	25.47%									
70%	21.48%	36.28%	17.40%								
60%	23.59%	17.78%	8.98%	27.13%							
50%	22.69%	14.70%	21.23%	27.84%	30.79%						
40%	22.79%	27.82%	34.85%	26.72%	37.64%	29.54%					
30%	26.10%	30.38%	32.50%	36.08%	28.47%	35.98%	49.85%				
20%	28.54%	34.44%	39.10%	41.57%	53.32%	43.16%	39.29%	47.72%			
10%	54.33%	53.12%	60.22%	62.21%	57.39%	55.60%	55.31%	50.09%	53.43%		
0%	7.48%	5.47%	5.47%	5.20%	7.04%	7.04%	10.07%	8.34%	8.39%	1.72%	16.31%

Table A.5.4. Percentage of Time in Cash

Rows: Slow Moving Average; columns: Fast Moving Average

Slow \ Fast	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	18.34%										
80%	19.53%	20.71%									
70%	20.71%	22.78%	23.96%								
60%	21.60%	23.67%	25.15%	25.44%							
50%	22.78%	25.15%	24.56%	25.74%	27.22%						
40%	23.96%	24.56%	25.15%	26.92%	27.51%	27.51%					
30%	26.92%	27.22%	27.22%	27.51%	27.51%	29.88%	29.29%				
20%	27.51%	27.51%	27.51%	28.11%	29.59%	29.88%	30.18%	31.36%			
10%	27.81%	28.99%	30.18%	29.88%	29.88%	29.59%	29.29%	28.99%	27.81%		
0%	22.78%	23.08%	23.08%	22.78%	23.08%	23.08%	23.08%	23.37%	23.67%	24.85%	0.00%

A:6 Financials Sector

Table A.6.1. Annualised Return

Rows: Slow Moving Average; columns: Fast Moving Average

Slow \ Fast	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	-3.47%										
90%	0.07%										
80%	0.18%	-0.04%									
70%	-0.90%	1.42%	1.06%								
60%	1.80%	2.50%	1.32%	2.58%							
50%	1.90%	3.10%	3.41%	4.61%	4.49%						
40%	1.45%	2.20%	3.67%	3.92%	5.13%	6.69%					
30%	3.39%	3.99%	6.12%	7.32%	6.15%	8.39%	8.85%				
20%	6.28%	5.89%	7.23%	7.83%	8.84%	8.89%	8.87%	7.05%			
10%	7.27%	8.42%	7.03%	4.34%	4.78%	4.31%	4.15%	6.19%	7.98%		
0%	-2.96%	-2.96%	-2.68%	-2.62%	-3.16%	-3.16%	-3.16%	-2.72%	-4.17%	-5.75%	-3.47%

Table A.6.2. Annualised Standard Deviation

Rows: Slow Moving Average; columns: Fast Moving Average

Slow \ Fast	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	24.15%										
90%	11.94%										
80%	12.14%	12.12%									
70%	12.01%	11.64%	11.49%								
60%	11.58%	11.30%	11.57%	11.30%							
50%	11.34%	11.61%	11.14%	11.27%	11.27%						
40%	11.39%	11.26%	11.43%	11.44%	11.16%	11.11%					
30%	11.16%	11.27%	10.92%	11.05%	10.77%	10.48%	10.39%				
20%	10.73%	10.76%	10.48%	10.45%	10.39%	10.41%	10.46%	10.18%			
10%	10.52%	10.39%	10.24%	10.45%	10.41%	10.35%	10.36%	10.20%	9.73%		
0%	17.28%	17.28%	17.26%	17.26%	17.20%	17.20%	17.20%	17.24%	17.91%	18.71%	24.15%

Table A.6.3. Annualised Sharpe Ratio

Rows: Slow Moving Average; columns: Fast Moving Average

Slow \ Fast	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	-19.96%										
90%	-10.72%										
80%	-9.62%	-11.44%									
70%	-18.69%	0.61%	-2.46%								
60%	3.88%	10.24%	-0.21%	10.92%							
50%	4.84%	15.13%	18.48%	28.93%	27.91%						
40%	0.87%	7.60%	20.30%	22.48%	33.88%	48.13%					
30%	18.28%	23.48%	43.68%	54.06%	44.56%	67.18%	71.15%				
20%	45.96%	42.23%	56.14%	61.98%	72.12%	71.42%	71.86%	55.99%			
10%	56.26%	68.08%	55.50%	28.65%	32.97%	28.66%	27.04%	47.49%	68.19%		
0%	-24.94%	-24.94%	-23.32%	-22.99%	-26.18%	-26.18%	-26.18%	-23.61%	-30.81%	-37.95%	-19.96%

Table A.6.4. Percentage of Time in Cash

Rows: Slow Moving Average; columns: Fast Moving Average

Slow \ Fast	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	22.78%										
80%	23.08%	23.08%									
70%	22.49%	25.44%	26.63%								
60%	25.44%	26.92%	27.51%	28.99%							
50%	27.81%	28.70%	29.29%	30.18%	30.77%						
40%	28.40%	28.99%	29.59%	30.47%	31.07%	32.84%					
30%	30.18%	30.77%	32.54%	33.14%	33.73%	35.50%	36.39%				
20%	32.54%	32.25%	33.73%	34.91%	36.69%	36.69%	36.39%	37.57%			
10%	34.32%	36.09%	36.39%	36.39%	36.39%	36.69%	36.69%	40.24%	42.01%		
0%	19.82%	19.82%	20.41%	20.71%	21.01%	21.01%	21.01%	20.71%	20.71%	21.01%	0.00%

A:7 Materials Sector

Table A.7.1. Annualised Return

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	8.53%										
90%	6.45%										
80%	6.93%	7.03%									
70%	9.46%	8.32%	6.85%								
60%	7.58%	7.70%	7.45%	11.61%							
50%	10.01%	9.90%	11.36%	14.06%	14.63%						
40%	13.71%	14.48%	14.00%	15.63%	14.55%	15.89%					
30%	15.20%	16.13%	16.19%	16.11%	15.13%	16.53%	16.81%				
20%	16.49%	16.54%	17.62%	**18.05%**	18.07%	16.59%	12.08%	12.00%			
10%	11.94%	11.53%	11.01%	11.80%	9.54%	9.01%	10.12%	12.33%	13.47%		
0%	7.14%	7.10%	7.10%	7.10%	7.39%	7.39%	7.39%	7.21%	6.96%	6.29%	8.53%

Table A.7.2. Annualised Standard Deviation

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	26.35%										
90%	16.08%										
80%	15.85%	16.27%									
70%	15.73%	15.88%	15.68%								
60%	15.28%	15.90%	15.87%	15.64%							
50%	15.64%	15.68%	15.66%	14.97%	14.09%						
40%	15.04%	14.93%	14.96%	14.22%	14.45%	14.29%					
30%	14.46%	14.53%	14.59%	14.37%	14.25%	14.21%	14.14%				
20%	14.43%	14.54%	14.33%	**14.24%**	14.26%	14.20%	14.97%	15.21%			
10%	15.56%	15.32%	15.20%	15.30%	15.73%	15.80%	15.67%	16.17%	16.49%		
0%	25.11%	25.11%	25.11%	25.11%	25.13%	25.13%	25.13%	25.13%	25.02%	24.97%	26.35%

Table A.7.3. Annualised Sharpe Ratio

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	27.26%										
90%	31.74%										
80%	35.23%	34.93%									
70%	51.59%	43.94%	35.11%								
60%	40.79%	39.98%	38.47%	65.61%							
50%	55.36%	54.54%	63.93%	84.97%	94.25%						
40%	82.20%	87.96%	84.53%	100.42%	91.36%	101.82%					
30%	95.78%	101.73%	101.68%	102.67%	96.71%	106.85%	109.55%				
20%	104.99%	104.54%	113.60%	**117.31%**	117.22%	107.34%	71.66%	70.03%			
10%	68.07%	66.47%	63.54%	68.32%	52.10%	48.50%	55.98%	67.94%	73.53%		
0%	23.05%	22.91%	22.91%	22.91%	24.05%	24.05%	24.05%	23.34%	22.45%	19.79%	27.26%

Table A.7.4. Percentage of Time in Cash

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	17.75%										
80%	20.41%	20.12%									
70%	21.01%	21.89%	23.67%								
60%	23.67%	23.37%	25.15%	26.63%							
50%	23.67%	24.85%	26.33%	26.92%	27.81%						
40%	24.85%	25.74%	26.04%	27.51%	26.04%	27.51%					
30%	24.85%	24.85%	24.85%	26.63%	28.11%	30.18%	30.47%				
20%	26.92%	26.92%	28.70%	**29.59%**	28.70%	30.47%	28.40%	28.40%			
10%	23.08%	24.26%	25.74%	26.04%	25.44%	25.44%	25.74%	24.85%	24.56%		
0%	16.86%	17.16%	17.16%	17.16%	17.46%	17.46%	17.75%	18.05%	18.93%	20.12%	0.00%

A:8 Consumer Discretionary Sector

Table A.8.1. Annualised Return

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	-0.51%										
90%	-0.56%										
80%	-2.44%	-1.11%									
70%	-1.82%	-2.34%	0.59%								
60%	-1.68%	0.59%	1.27%	2.07%							
50%	1.21%	1.43%	2.07%	2.42%	4.19%						
40%	1.99%	3.53%	2.99%	2.75%	4.29%	6.10%					
30%	2.64%	3.72%	5.56%	5.37%	5.72%	6.37%	6.43%				
20%	5.34%	6.20%	5.34%	6.54%	6.30%	6.32%	6.27%	5.62%			
10%	5.89%	6.45%	5.99%	**6.47%**	5.57%	5.67%	4.34%	4.34%	5.23%		
0%	-1.68%	-1.68%	-1.91%	-1.91%	-1.91%	-1.59%	-1.59%	-3.52%	-1.95%	-3.42%	-0.51%

Table A.8.2. Annualised Standard Deviation

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	20.43%										
90%	11.21%										
80%	10.94%	11.13%									
70%	10.86%	10.95%	9.95%								
60%	10.50%	9.95%	10.28%	10.60%							
50%	9.77%	10.09%	10.49%	10.66%	10.75%						
40%	10.18%	10.64%	10.64%	10.78%	10.68%	10.39%					
30%	10.49%	10.59%	10.49%	10.30%	10.35%	10.50%	10.42%				
20%	10.03%	10.04%	10.10%	10.23%	10.22%	10.12%	10.01%	10.17%			
10%	10.06%	10.12%	10.12%	**10.00%**	10.03%	10.04%	10.01%	9.90%	9.43%		
0%	15.34%	15.34%	15.33%	15.33%	15.33%	15.35%	15.35%	16.02%	17.63%	18.44%	20.43%

Table A.8.3. Annualised Sharpe Ratio

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	-9.06%										
90%	-16.98%										
80%	-34.63%	-22.09%									
70%	-29.19%	-33.70%	-7.57%								
60%	-28.78%	-7.57%	-0.76%	6.78%							
50%	-1.44%	0.79%	6.91%	10.07%	26.47%						
40%	6.34%	20.51%	15.42%	12.98%	27.54%	45.76%					
30%	12.35%	22.39%	40.22%	39.10%	42.20%	47.84%	48.72%				
20%	39.84%	48.35%	39.58%	50.72%	48.46%	49.12%	49.17%	42.03%			
10%	45.17%	50.48%	45.94%	**51.23%**	42.12%	43.03%	29.91%	30.23%	41.20%		
0%	-24.94%	-24.94%	-23.32%	-22.99%	-26.18%	-26.18%	-26.18%	-23.61%	-30.81%	-37.95%	-19.96%

Table A.8.4. Percentage of Time in Cash

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	10.50%										
80%	11.11%	11.57%									
70%	11.57%	12.18%	13.70%								
60%	12.18%	13.70%	14.16%	14.46%							
50%	13.70%	14.31%	14.76%	15.22%	14.61%						
40%	13.70%	14.31%	14.46%	14.46%	15.53%	16.89%					
30%	14.31%	14.76%	15.98%	16.59%	17.05%	17.20%	17.81%				
20%	17.05%	16.89%	17.35%	17.66%	17.96%	18.57%	19.18%	19.48%			
10%	18.87%	19.79%	19.63%	**20.09%**	20.24%	20.24%	20.24%	21.00%	22.07%		
0%	10.05%	10.05%	10.20%	10.20%	10.20%	10.05%	10.05%	10.05%	9.89%	10.20%	0.00%

Appendix A: Exponential Moving Average Trend Timing Strategy (2002 to 2008) A

A:9 Information Technology Sector

Table A.9.1. Annualised Return

Slow Moving Average \ Fast Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	1.96%										
90%	-3.40%										
80%	-3.81%	-4.18%									
70%	-4.10%	-4.08%	-2.25%								
60%	-3.76%	-2.02%	-0.26%	3.01%							
50%	1.60%	2.01%	4.75%	5.55%	4.34%						
40%	2.41%	2.94%	4.57%	4.85%	4.49%	4.24%					
30%	2.41%	3.58%	5.40%	4.70%	3.96%	4.36%	5.95%				
20%	3.22%	3.99%	4.42%	**6.24%**	4.95%	4.73%	6.05%	6.11%			
10%	3.94%	4.45%	4.72%	3.05%	3.37%	4.02%	5.76%	5.91%	5.10%		
0%	-2.21%	-2.21%	-2.05%	-2.05%	-3.25%	-1.76%	-0.37%	-1.30%	-0.51%	-1.04%	1.96%

Table A.9.2. Annualised Standard Deviation

Slow Moving Average \ Fast Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	24.47%										
90%	15.55%										
80%	14.94%	15.03%									
70%	15.03%	15.07%	15.57%								
60%	15.15%	15.58%	15.30%	15.14%							
50%	15.90%	15.84%	15.15%	15.22%	14.81%						
40%	15.06%	15.10%	14.73%	14.87%	14.67%	14.93%					
30%	14.75%	14.76%	14.65%	14.75%	14.85%	14.82%	14.97%				
20%	14.98%	14.76%	14.89%	**15.06%**	14.92%	14.98%	14.69%	14.33%			
10%	15.25%	15.28%	15.11%	14.74%	14.73%	14.93%	14.94%	14.44%	14.40%		
0%	18.37%	18.37%	18.27%	18.27%	18.54%	18.96%	18.54%	18.69%	19.04%	18.98%	24.47%

Table A.9.3. Annualised Sharpe Ratio

Slow Moving Average \ Fast Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	2.49%										
90%	-30.51%										
80%	-34.53%	-36.77%									
70%	-36.24%	-36.04%	-23.10%								
60%	-33.70%	-21.63%	-10.52%	10.96%							
50%	1.58%	4.20%	22.45%	27.61%	20.23%						
40%	7.04%	10.58%	21.87%	23.57%	21.45%	19.38%					
30%	7.23%	15.16%	27.64%	22.76%	17.61%	20.31%	30.74%				
20%	12.53%	17.90%	20.67%	**32.51%**	24.14%	22.60%	31.97%	33.22%			
10%	16.99%	20.29%	22.30%	11.53%	13.71%	17.88%	29.54%	31.59%	26.07%		
0%	23.05%	22.91%	22.91%	22.91%	24.05%	24.05%	24.05%	23.34%	22.45%	19.79%	27.26%

Table A.9.4. Percentage of Time in Cash

Slow Moving Average \ Fast Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	11.87%										
80%	12.94%	12.94%									
70%	12.48%	13.39%	13.24%								
60%	12.94%	13.24%	13.85%	15.98%							
50%	13.39%	14.16%	16.59%	16.59%	16.89%						
40%	15.22%	16.13%	16.74%	16.74%	17.20%	17.50%					
30%	16.13%	16.74%	17.35%	17.20%	17.20%	17.96%	18.42%				
20%	15.53%	16.13%	16.59%	**17.05%**	17.96%	17.66%	19.03%	20.24%			
10%	16.13%	16.29%	16.29%	16.74%	17.05%	17.81%	17.66%	17.81%	18.11%		
0%	7.15%	7.15%	7.61%	7.61%	7.46%	7.46%	7.91%	7.76%	7.76%	7.91%	0.00%

A:10 Utilities Sector

Table A.10.1. Annualised Return

Slow Moving Average \ Fast Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	8.59%										
90%	4.76%										
80%	4.94%	4.43%									
70%	4.88%	8.21%	7.81%								
60%	8.79%	7.80%	7.68%	7.81%							
50%	7.39%	7.33%	9.34%	9.43%	9.82%						
40%	8.83%	9.67%	9.16%	9.97%	11.04%	10.96%					
30%	9.78%	10.90%	11.08%	11.61%	11.56%	11.78%	12.00%				
20%	12.32%	11.76%	11.29%	11.12%	12.40%	11.18%	12.32%	11.87%			
10%	12.11%	**12.90%**	12.13%	12.36%	11.05%	11.08%	10.81%	10.37%	12.26%		
0%	7.37%	7.37%	7.37%	7.37%	7.37%	7.13%	7.13%	7.13%	6.79%	6.34%	8.59%

Table A.10.2. Annualised Standard Deviation

Slow Moving Average \ Fast Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	17.67%										
90%	10.34%										
80%	10.38%	10.50%									
70%	10.56%	10.29%	10.55%								
60%	10.34%	10.55%	10.42%	10.47%							
50%	10.43%	10.51%	10.12%	10.23%	10.33%						
40%	10.23%	10.26%	10.28%	9.77%	9.74%	9.74%					
30%	10.30%	9.70%	9.74%	9.76%	9.81%	9.96%	10.00%				
20%	9.89%	9.86%	9.94%	9.96%	10.02%	10.14%	10.11%	10.23%			
10%	10.06%	**10.12%**	10.14%	10.12%	10.40%	10.41%	10.57%	10.52%	10.55%		
0%	16.27%	16.27%	16.27%	16.27%	16.27%	16.27%	16.27%	16.27%	16.25%	16.23%	17.67%

Table A.10.3. Annualised Sharpe Ratio

Slow Moving Average \ Fast Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	41.00%										
90%	33.04%										
80%	34.64%	29.41%									
70%	33.51%	66.77%	61.20%								
60%	72.04%	61.23%	60.81%	61.71%							
50%	57.91%	56.89%	78.92%	79.02%	81.98%						
40%	73.14%	81.11%	75.99%	88.29%	99.61%	98.67%					
30%	81.82%	98.43%	99.87%	105.16%	104.13%	104.73%	106.51%				
20%	111.03%	105.68%	100.00%	98.12%	110.33%	96.95%	108.54%	102.82%			
10%	106.99%	**114.19%**	106.26%	108.78%	93.28%	93.57%	89.59%	85.83%	103.40%		
0%	37.00%	37.00%	37.00%	37.00%	37.00%	35.59%	35.59%	35.59%	33.49%	30.77%	41.00%

Table A.10.4. Percentage of Time in Cash

Slow Moving Average \ Fast Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	16.86%										
80%	16.86%	17.16%									
70%	17.16%	19.23%	21.89%								
60%	20.71%	22.19%	23.08%	23.96%							
50%	22.49%	22.49%	24.56%	25.44%	25.15%						
40%	22.78%	23.96%	24.26%	26.33%	26.33%	26.33%					
30%	23.37%	26.04%	26.04%	26.33%	25.44%	26.04%	26.63%				
20%	23.96%	25.44%	24.85%	25.15%	26.04%	25.74%	27.51%	27.22%			
10%	24.85%	**25.44%**	25.15%	25.74%	25.44%	25.74%	24.85%	24.56%	24.56%		
0%	21.30%	21.30%	21.30%	21.30%	21.30%	21.60%	21.60%	21.60%	21.89%	22.78%	0.00%

Appendix B: Exponential Moving Average Trend Timing Strategy (2009 to 2015)

B:1 Healthcare Sector

Table B.1.1. Annualised Return

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	15.67%										
90%	10.52%										
80%	11.43%	12.61%									
70%	13.13%	14.54%	13.81%								
60%	14.66%	14.10%	13.93%	13.74%							
50%	14.68%	13.98%	13.83%	13.09%	11.58%						
40%	13.81%	13.53%	12.50%	11.48%	11.78%	12.54%					
30%	12.25%	11.88%	12.94%	12.34%	11.43%	11.47%	9.74%				
20%	12.46%	12.10%	13.26%	12.66%	11.66%	8.76%	9.45%	11.21%			
10%	13.69%	13.71%	14.17%	14.17%	13.92%	13.78%	14.97%	13.95%	13.77%		
0%	14.94%	14.94%	14.75%	14.75%	14.75%	14.75%	14.87%	14.34%	14.35%	14.14%	15.67%

Table B.1.2. Annualised Standard Deviation

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	13.71%										
90%	8.55%										
80%	8.26%	8.50%									
70%	8.53%	8.55%	8.72%								
60%	8.55%	8.76%	8.83%	8.84%							
50%	8.67%	8.83%	8.84%	8.82%	8.69%						
40%	8.71%	8.79%	8.69%	8.68%	8.57%	8.64%					
30%	8.85%	8.65%	8.55%	8.56%	8.77%	8.66%	9.08%				
20%	8.96%	8.88%	8.88%	8.88%	8.99%	9.80%	9.92%	10.16%			
10%	10.03%	10.03%	10.13%	10.13%	10.08%	10.12%	10.33%	10.19%	10.37%		
0%	11.79%	11.79%	11.79%	11.79%	11.79%	11.79%	11.78%	11.74%	11.74%	11.70%	13.71%

Table B.1.3. Annualised Sharpe Ratio

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	104.44%										
90%	107.19%										
80%	122.06%	132.55%									
70%	138.08%	154.19%	142.99%								
60%	155.61%	145.63%	142.51%	140.27%							
50%	153.82%	143.05%	141.19%	133.21%	117.68%						
40%	143.10%	138.67%	128.36%	116.77%	121.77%	129.59%					
30%	123.21%	121.71%	135.59%	128.34%	115.01%	116.83%	92.44%				
20%	123.97%	121.11%	134.13%	127.43%	114.75%	75.69%	81.68%	97.10%			
10%	123.16%	123.30%	126.58%	126.58%	124.78%	122.85%	131.86%	123.73%	119.79%		
0%	115.33%	115.33%	113.74%	113.74%	113.74%	113.74%	114.83%	110.67%	110.77%	109.38%	104.44%

Table B.1.4. Percentage of Time in Cash

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	17.55%										
80%	19.12%	18.81%									
70%	18.50%	19.44%	18.81%								
60%	19.44%	18.50%	18.18%	18.18%							
50%	18.50%	18.18%	18.50%	19.44%	19.75%						
40%	19.12%	19.12%	19.75%	19.44%	20.06%	20.38%					
30%	17.87%	18.81%	19.75%	20.06%	18.81%	20.69%	19.75%				
20%	15.99%	17.55%	18.50%	20.06%	18.81%	17.87%	17.24%	16.30%			
10%	14.73%	15.05%	15.05%	15.05%	15.67%	16.61%	16.61%	17.55%	17.87%		
0%	11.24%	12.13%	12.13%	13.02%	13.61%	13.91%	13.61%	13.31%	13.61%	14.20%	0.00%

B:2 Energy Sector

Table B.2.1. Annualised Return

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	6.01%										
90%	6.86%										
80%	6.49%	7.33%									
70%	7.40%	6.53%	5.80%								
60%	7.30%	5.76%	6.59%	5.63%							
50%	5.60%	6.68%	4.72%	3.47%	3.36%						
40%	6.21%	4.05%	4.25%	5.68%	3.65%	4.23%					
30%	6.47%	6.59%	3.89%	5.62%	7.28%	10.68%	10.26%				
20%	10.51%	9.72%	8.09%	8.19%	9.67%	9.80%	6.06%	4.04%			
10%	9.20%	7.67%	6.52%	7.66%	6.81%	5.74%	3.40%	0.63%	4.73%		
0%	6.12%	4.47%	5.03%	4.68%	5.70%	5.70%	5.70%	5.76%	6.54%	7.98%	6.01%

Table B.2.2. Annualised Standard Deviation

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	22.41%										
90%	14.43%										
80%	14.60%	14.51%									
70%	14.51%	14.36%	14.47%								
60%	14.50%	14.49%	14.48%	14.58%							
50%	14.49%	14.58%	14.15%	14.03%	14.14%						
40%	14.43%	13.96%	14.20%	13.46%	15.65%	15.62%					
30%	13.42%	13.44%	15.94%	15.25%	14.96%	14.48%	14.53%				
20%	12.97%	13.03%	15.24%	15.27%	14.48%	14.52%	15.33%	15.25%			
10%	13.26%	15.46%	15.55%	14.92%	15.18%	15.16%	15.90%	16.18%	14.93%		
0%	11.47%	11.45%	11.53%	11.56%	11.30%	11.30%	11.30%	11.74%	11.54%	11.10%	22.41%

Table B.2.3. Annualised Sharpe Ratio

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	20.80%										
90%	38.18%										
80%	35.25%	41.22%									
70%	41.73%	36.11%	30.77%								
60%	41.03%	30.46%	36.23%	29.40%							
50%	29.32%	36.60%	23.87%	15.16%	14.23%						
40%	33.71%	19.35%	20.46%	32.19%	14.72%	18.46%					
30%	38.15%	39.03%	15.97%	28.01%	39.63%	64.46%	61.39%				
20%	70.65%	64.26%	44.29%	44.83%	57.49%	58.21%	30.76%	17.64%			
10%	59.26%	40.87%	33.26%	42.33%	35.98%	29.01%	12.90%	-4.42%	22.70%		
0%	41.62%	27.31%	31.96%	28.82%	38.53%	38.53%	38.53%	37.56%	45.02%	59.72%	20.80%

Table B.2.4. Percentage of Time in Cash

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	24.26%										
80%	23.96%	27.51%									
70%	27.51%	27.51%	27.22%								
60%	26.92%	26.92%	27.81%	28.11%							
50%	26.63%	27.22%	28.70%	28.99%	29.88%						
40%	28.70%	29.29%	28.70%	30.77%	30.18%	30.18%					
30%	29.88%	31.07%	28.99%	29.88%	31.66%	32.25%	32.25%				
20%	32.84%	32.25%	30.18%	30.18%	30.77%	32.25%	31.95%	37.28%			
10%	32.84%	29.59%	29.29%	31.07%	30.47%	30.77%	30.77%	29.88%	30.77%		
0%	4.79%	4.79%	4.79%	4.50%	5.09%	5.09%	5.09%	5.09%	5.98%	8.05%	0.00%

Appendix B: Exponential Moving Average Trend Timing Strategy (2009 to 2015)

B:3 Industrial Sector

Table B.3.1. Annualised Return

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	13.60%										
90%	14.47%										
80%	11.87%	12.37%									
70%	11.78%	11.68%	13.58%								
60%	11.68%	12.96%	12.68%	11.67%							
50%	13.07%	12.57%	11.76%	12.18%	10.08%						
40%	12.80%	12.40%	10.56%	13.24%	10.71%	9.54%					
30%	12.42%	11.23%	10.94%	10.91%	13.25%	10.46%	9.70%				
20%	10.93%	10.51%	11.33%	11.62%	12.11%	9.86%	8.83%	11.11%			
10%	12.37%	12.85%	12.46%	12.17%	11.12%	12.89%	12.74%	12.42%	9.62%		
0%	6.35%	6.35%	6.35%	6.26%	5.75%	6.57%	6.57%	6.06%	6.06%	5.66%	13.60%

Table B.3.2. Annualised Standard Deviation

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	20.03%										
90%	13.05%										
80%	12.77%	12.73%									
70%	12.67%	12.77%	12.95%								
60%	12.77%	13.02%	13.18%	12.78%							
50%	13.11%	12.98%	12.93%	12.87%	13.06%						
40%	12.86%	12.87%	12.89%	12.58%	12.23%	12.07%					
30%	12.53%	12.29%	12.26%	12.25%	12.30%	12.34%	12.64%				
20%	12.45%	12.49%	12.57%	12.59%	12.60%	12.99%	12.86%	13.31%			
10%	12.61%	12.65%	12.71%	12.70%	12.68%	12.90%	12.95%	13.01%	12.77%		
0%	6.75%	6.75%	6.75%	6.75%	6.65%	6.36%	6.36%	6.25%	6.25%	6.21%	20.03%

Table B.3.3. Annualised Sharpe Ratio

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	61.18%										
90%	100.61%										
80%	82.40%	86.60%									
70%	82.33%	80.88%	94.48%								
60%	80.88%	89.23%	85.99%	80.75%							
50%	89.43%	86.49%	80.56%	84.21%	66.84%						
40%	89.02%	85.86%	71.47%	94.53%	76.58%	67.89%					
30%	88.34%	80.44%	78.26%	78.06%	96.75%	73.81%	66.05%				
20%	76.99%	73.32%	79.43%	81.54%	85.36%	65.55%	58.19%	73.37%			
10%	87.40%	90.89%	87.47%	85.19%	77.10%	89.50%	87.99%	85.15%	64.82%		
0%	74.11%	74.11%	74.11%	72.76%	66.24%	82.16%	82.16%	75.38%	75.38%	69.37%	61.18%

Table B.3.4. Percentage of Time in Cash

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	19.53%										
80%	20.41%	21.30%									
70%	21.60%	21.01%	21.89%								
60%	21.01%	21.01%	21.01%	22.78%							
50%	21.30%	21.60%	22.49%	22.19%	21.30%						
40%	21.89%	21.89%	21.60%	22.19%	22.78%	23.67%					
30%	21.89%	21.89%	22.78%	22.19%	23.96%	23.96%	23.08%				
20%	21.89%	21.60%	21.60%	21.89%	22.49%	22.19%	22.19%	22.19%			
10%	20.71%	20.71%	20.41%	21.30%	21.60%	21.60%	22.78%	23.67%	23.37%		
0%	10.77%	10.77%	10.77%	11.07%	11.36%	11.95%	11.95%	12.25%	12.25%	13.14%	0.00%

B:4 Telecommunication Services Sector

Table B.4.1. Annualised Return

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	5.95%										
90%	3.62%										
80%	5.16%	5.54%									
70%	5.68%	6.26%	5.13%								
60%	5.71%	4.94%	2.99%	3.22%							
50%	4.41%	2.81%	3.78%	6.72%	7.73%						
40%	3.58%	6.23%	6.77%	7.73%	6.87%	5.54%					
30%	5.98%	7.76%	7.48%	5.64%	4.91%	4.82%	5.14%				
20%	4.52%	4.05%	4.97%	4.64%	4.87%	3.45%	5.31%	4.54%			
10%	3.41%	3.76%	4.70%	4.02%	4.94%	4.18%	3.44%	3.96%	3.35%		
0%	0.82%	0.82%	0.47%	0.16%	-0.09%	-0.09%	0.14%	-0.25%	0.84%	0.47%	5.95%

Table B.4.2. Annualised Standard Deviation

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	14.16%										
90%	8.95%										
80%	9.04%	9.09%									
70%	9.10%	9.15%	9.32%								
60%	9.20%	9.33%	9.38%	9.40%							
50%	9.37%	9.36%	9.10%	8.53%	8.39%						
40%	9.00%	8.73%	8.53%	8.39%	8.52%	8.38%					
30%	8.52%	8.48%	8.43%	8.48%	8.62%	8.64%	8.20%				
20%	8.52%	8.62%	8.07%	8.05%	8.04%	7.64%	9.08%	9.03%			
10%	8.51%	8.72%	8.72%	8.74%	8.77%	8.75%	8.89%	8.65%	9.31%		
0%	9.16%	9.16%	9.12%	9.13%	9.11%	9.11%	9.11%	9.07%	9.12%	9.00%	14.16%

Table B.4.3. Annualised Sharpe Ratio

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	32.48%										
90%	25.44%										
80%	42.21%	46.12%									
70%	47.60%	53.69%	40.56%								
60%	47.42%	38.47%	17.48%	19.93%							
50%	32.65%	15.69%	26.75%	62.97%	76.05%						
40%	24.80%	55.99%	63.57%	76.08%	64.84%	50.03%					
30%	54.34%	75.55%	72.80%	50.64%	41.36%	40.16%	46.26%				
20%	37.23%	31.35%	44.85%	40.93%	43.89%	27.52%	43.59%	35.36%			
10%	24.26%	27.63%	38.43%	30.60%	41.00%	32.34%	23.56%	30.15%	21.57%		
0%	-5.70%	-5.70%	-9.61%	-12.97%	-15.72%	-15.72%	-13.27%	-17.60%	-5.56%	-9.73%	32.48%

Table B.4.4. Percentage of Time in Cash

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	20.71%										
80%	21.01%	22.78%									
70%	22.78%	23.37%	22.78%								
60%	23.08%	22.49%	22.78%	24.26%							
50%	21.60%	23.37%	26.33%	30.18%	30.47%						
40%	26.63%	28.40%	29.88%	29.88%	29.59%	30.77%					
30%	28.70%	28.99%	29.59%	29.88%	29.88%	30.47%	36.09%				
20%	28.40%	28.99%	34.32%	34.91%	36.39%	42.60%	31.95%	33.14%			
10%	29.88%	29.29%	30.77%	30.77%	32.54%	32.84%	31.95%	33.43%	33.43%		
0%	15.33%	15.33%	15.62%	15.62%	15.92%	15.92%	16.21%	15.92%	15.92%	18.58%	0.00%

Appendix B: Exponential Moving Average Trend Timing Strategy (2009 to 2015)

B:5 Consumer Staples Sector

Table B.5.1. Annualised Return

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	11.94%										
90%	10.76%										
80%	11.51%	11.94%									
70%	11.61%	11.59%	11.75%								
60%	12.06%	11.22%	10.35%	9.66%							
50%	11.12%	10.86%	9.76%	10.72%	8.46%						
40%	10.54%	10.05%	8.18%	7.78%	6.73%	7.57%					
30%	8.32%	7.79%	7.99%	8.14%	9.20%	8.65%	7.65%				
20%	9.16%	9.46%	9.47%	8.07%	7.84%	6.60%	7.12%	6.79%			
10%	6.67%	6.80%	7.00%	6.91%	6.11%	6.00%	5.61%	6.37%	7.21%		
0%	10.93%	10.93%	10.93%	10.93%	10.62%	10.62%	10.62%	10.32%	10.47%	10.20%	11.94%

Table B.5.2. Annualised Standard Deviation

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	11.70%										
90%	7.89%										
80%	7.89%	7.86%									
70%	7.83%	7.75%	7.78%								
60%	7.79%	7.67%	7.63%	7.72%							
50%	7.74%	7.87%	7.80%	7.55%	7.55%						
40%	8.00%	7.95%	7.60%	7.65%	7.71%	7.84%					
30%	7.71%	7.64%	7.94%	7.88%	8.04%	8.10%	8.43%				
20%	8.01%	8.08%	8.00%	8.20%	8.41%	8.70%	8.78%	8.88%			
10%	8.76%	8.82%	9.04%	9.01%	9.04%	9.04%	9.08%	9.31%	9.61%		
0%	10.50%	10.50%	10.50%	10.50%	10.48%	10.48%	10.48%	10.46%	10.46%	10.43%	11.70%

Table B.5.3. Annualised Sharpe Ratio

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	90.56%										
90%	119.22%										
80%	128.80%	134.81%									
70%	131.05%	132.30%	133.72%								
60%	137.43%	128.72%	117.99%	107.70%							
50%	126.22%	120.89%	107.81%	124.09%	94.21%						
40%	114.84%	109.50%	89.88%	84.11%	69.84%	79.33%					
30%	90.50%	84.35%	83.68%	86.12%	97.59%	90.26%	74.82%				
20%	97.50%	100.41%	101.61%	82.02%	77.22%	60.35%	65.72%	61.27%			
10%	60.80%	61.81%	62.55%	61.68%	52.65%	51.55%	46.91%	53.92%	61.00%		
0%	91.28%	91.28%	91.28%	91.28%	88.46%	88.46%	88.46%	85.71%	87.27%	84.84%	90.56%

Table B.5.4. Percentage of Time in Cash

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	18.93%										
80%	19.82%	19.53%									
70%	19.82%	20.41%	21.30%								
60%	20.71%	21.60%	22.19%	21.60%							
50%	21.01%	21.30%	21.30%	22.78%	21.89%						
40%	19.23%	20.41%	21.60%	21.01%	20.12%	21.60%					
30%	20.71%	20.71%	20.12%	20.41%	21.01%	20.71%	21.30%				
20%	18.05%	18.64%	19.53%	19.23%	19.23%	20.12%	19.53%	19.53%			
10%	15.38%	15.68%	15.09%	15.68%	15.98%	15.98%	15.68%	14.79%	13.02%		
0%	7.69%	7.69%	7.69%	7.69%	7.99%	7.99%	7.99%	8.28%	8.58%	9.76%	0.00%

B:6 Financials Sector

Table B.6.1. Annualised Return

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	11.93%										
90%	14.24%										
80%	14.34%	14.23%									
70%	14.03%	11.51%	10.15%								
60%	11.20%	11.55%	11.11%	13.13%							
50%	11.70%	11.63%	13.03%	12.93%	11.22%						
40%	13.58%	14.46%	11.43%	11.22%	10.10%	11.81%					
30%	12.44%	11.29%	11.02%	11.50%	11.07%	7.90%	7.69%				
20%	10.08%	9.21%	8.73%	5.85%	7.07%	6.32%	5.90%	7.87%			
10%	9.36%	10.68%	10.48%	8.94%	8.72%	8.86%	9.49%	9.39%	6.96%		
0%	2.83%	1.78%	2.41%	3.97%	3.97%	5.45%	5.36%	8.57%	8.04%	6.68%	11.93%

Table B.6.2. Annualised Standard Deviation

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	26.57%										
90%	16.20%										
80%	16.07%	16.44%									
70%	16.43%	16.60%	16.69%								
60%	16.60%	16.55%	16.82%	16.03%							
50%	16.58%	16.33%	16.03%	16.25%	15.79%						
40%	15.91%	16.12%	15.78%	15.79%	15.77%	15.95%					
30%	15.64%	15.60%	15.61%	15.98%	15.87%	16.23%	16.16%				
20%	15.83%	15.52%	15.54%	16.31%	16.21%	15.95%	16.28%	16.30%			
10%	16.35%	16.42%	16.44%	16.33%	16.10%	16.15%	16.17%	16.15%	16.31%		
0%	19.12%	19.29%	19.35%	19.70%	19.70%	19.38%	19.37%	20.04%	20.02%	19.36%	26.57%

Table B.6.3. Annualised Sharpe Ratio

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	39.82%										
90%	79.58%										
80%	81.11%	78.37%									
70%	77.18%	61.27%	52.76%								
60%	59.40%	61.66%	58.08%	73.47%							
50%	62.47%	62.96%	72.90%	71.29%	62.54%						
40%	76.91%	81.36%	63.90%	62.54%	55.51%	65.61%					
30%	70.93%	63.75%	61.96%	63.55%	61.25%	40.36%	39.26%				
20%	55.16%	50.64%	47.48%	27.59%	35.30%	31.17%	27.99%	39.99%			
10%	49.00%	56.82%	55.57%	46.52%	45.78%	46.50%	50.39%	49.83%	34.41%		
0%	7.74%	2.25%	5.51%	13.30%	13.30%	21.17%	20.73%	36.05%	33.46%	27.53%	39.82%

Table B.6.4. Percentage of Time in Cash

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	21.89%										
80%	22.19%	22.19%									
70%	22.19%	22.19%	22.19%								
60%	22.19%	22.78%	23.37%	24.56%							
50%	23.08%	23.96%	24.26%	24.85%	25.44%						
40%	23.67%	23.96%	25.15%	25.44%	25.15%	26.33%					
30%	24.26%	25.44%	24.85%	25.15%	26.63%	27.51%	27.51%				
20%	23.37%	24.56%	26.33%	25.44%	26.04%	26.63%	26.33%	25.74%			
10%	23.67%	24.85%	24.85%	25.15%	26.04%	25.44%	25.44%	26.63%	27.22%		
0%	5.62%	5.33%	5.33%	5.33%	5.33%	5.92%	5.92%	5.62%	6.21%	8.28%	0.00%

Appendix B: Exponential Moving Average Trend Timing Strategy (2009 to 2015)

B:7 Materials Sector

Table B.7.1. Annualised Return

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	9.62%										
90%	7.79%										
80%	7.62%	6.62%									
70%	6.13%	6.69%	5.91%								
60%	6.89%	4.53%	8.40%	8.16%							
50%	6.17%	7.73%	6.67%	5.19%	4.47%						
40%	5.61%	3.99%	3.33%	4.27%	4.40%	3.47%					
30%	5.08%	4.66%	5.28%	4.69%	3.87%	10.17%	4.96%				
20%	7.08%	7.78%	9.41%	8.67%	6.26%	5.50%	5.28%	7.52%			
10%	5.43%	5.39%	6.20%	7.93%	6.94%	6.61%	6.23%	7.55%	4.76%		
0%	8.61%	8.75%	8.75%	8.75%	8.75%	8.75%	8.46%	8.09%	6.57%	6.35%	9.62%

Table B.7.2. Annualised Standard Deviation

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	24.07%										
90%	16.04%										
80%	15.37%	15.30%									
70%	15.33%	15.79%	16.59%								
60%	15.71%	16.46%	15.94%	16.19%							
50%	16.11%	15.78%	15.96%	15.95%	15.47%						
40%	15.44%	15.71%	15.56%	15.57%	15.24%	14.88%					
30%	15.27%	15.34%	15.38%	15.16%	14.72%	14.64%	15.95%				
20%	14.37%	14.29%	14.64%	14.73%	15.44%	16.28%	16.31%	16.48%			
10%	15.44%	15.44%	15.33%	15.75%	16.44%	16.41%	16.35%	16.64%	16.68%		
0%	25.11%	25.11%	25.11%	25.11%	25.13%	25.13%	25.13%	25.13%	25.02%	24.97%	26.35%

Table B.7.3. Annualised Sharpe Ratio

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	34.36%										
90%	40.16%										
80%	40.80%	34.47%									
70%	31.17%	33.85%	27.53%								
60%	35.27%	19.32%	44.26%	42.06%							
50%	29.93%	40.45%	33.36%	24.08%	20.19%						
40%	27.63%	16.80%	12.75%	18.80%	20.05%	14.29%					
30%	24.48%	21.59%	25.57%	22.04%	17.12%	60.26%	22.64%				
20%	39.87%	45.00%	55.09%	49.70%	31.79%	25.53%	24.10%	37.46%			
10%	26.48%	26.23%	31.66%	41.76%	34.03%	32.10%	29.85%	37.26%	20.49%		
0%	32.44%	33.08%	33.08%	33.08%	33.08%	33.08%	31.77%	30.16%	23.62%	22.87%	34.36%

Table B.7.4. Percentage of Time in Cash

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	22.19%										
80%	23.37%	24.26%									
70%	23.37%	24.85%	25.15%								
60%	25.44%	24.85%	26.04%	26.33%							
50%	24.85%	26.04%	28.40%	29.59%	30.77%						
40%	26.63%	28.99%	29.88%	30.47%	33.43%	33.43%					
30%	30.18%	31.07%	31.95%	33.73%	34.02%	35.50%	35.21%				
20%	31.66%	33.43%	34.62%	35.21%	36.09%	36.39%	34.91%	36.09%			
10%	32.54%	31.95%	32.25%	33.43%	33.43%	33.73%	34.02%	32.25%	33.43%		
0%	3.25%	3.85%	3.85%	3.85%	3.85%	3.85%	4.14%	4.44%	4.73%	5.33%	0.00%

B:8 Consumer Discretionary Sector

Table B.8.1. Annualised Return

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	19.22%										
90%	15.24%										
80%	14.58%	16.00%									
70%	16.60%	17.36%	17.09%								
60%	16.62%	17.09%	16.67%	15.23%							
50%	16.95%	16.83%	15.07%	15.20%	15.05%						
40%	16.07%	15.14%	15.15%	16.00%	17.27%	19.37%					
30%	13.82%	15.45%	14.94%	18.17%	18.56%	15.42%	15.66%				
20%	17.40%	17.16%	17.96%	16.53%	16.18%	15.47%	14.26%	13.72%			
10%	14.16%	17.19%	18.04%	17.09%	16.75%	16.64%	13.50%	9.69%	9.61%		
0%	7.33%	7.33%	6.88%	6.88%	6.88%	6.88%	6.57%	6.37%	5.66%	5.66%	19.22%

Table B.8.2. Annualised Standard Deviation

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	18.17%										
90%	12.18%										
80%	12.20%	11.93%									
70%	11.96%	12.06%	12.10%								
60%	12.08%	12.10%	12.23%	11.97%							
50%	12.11%	12.22%	11.68%	11.70%	11.51%						
40%	12.10%	11.77%	11.76%	11.59%	11.50%	11.21%					
30%	11.83%	11.69%	11.77%	11.33%	11.25%	11.97%	11.96%				
20%	11.62%	11.68%	11.60%	12.18%	12.07%	12.06%	11.80%	12.18%			
10%	12.83%	12.89%	12.77%	12.28%	12.03%	12.03%	11.80%	10.43%	9.52%		
0%	7.18%	7.18%	7.12%	7.12%	7.12%	7.12%	7.08%	7.07%	6.88%	6.25%	18.17%

Table B.8.3. Annualised Sharpe Ratio

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	98.37%										
90%	114.02%										
80%	108.46%	122.84%									
70%	127.52%	132.79%	130.09%								
60%	126.49%	130.09%	125.32%	115.97%							
50%	128.87%	126.68%	117.50%	118.48%	119.02%						
40%	121.69%	117.27%	117.32%	126.36%	138.42%	160.73%					
30%	105.43%	120.58%	115.52%	148.50%	153.02%	117.61%	119.68%				
20%	138.14%	135.40%	143.20%	124.69%	122.93%	117.06%	109.44%	101.54%			
10%	99.86%	122.91%	130.75%	128.25%	128.08%	127.07%	102.91%	79.94%	86.86%		
0%	83.24%	83.24%	77.82%	77.82%	77.82%	77.82%	73.74%	71.06%	62.69%	69.02%	98.37%

Table B.8.4. Percentage of Time in Cash

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	17.75%										
80%	18.64%	20.71%									
70%	20.41%	20.71%	20.41%								
60%	20.12%	20.41%	21.30%	21.89%							
50%	20.41%	21.30%	22.49%	23.08%	23.67%						
40%	21.01%	21.89%	22.19%	23.96%	24.26%	25.74%					
30%	21.01%	21.60%	21.89%	25.15%	25.44%	23.96%	25.74%				
20%	22.19%	21.89%	22.49%	22.49%	23.96%	25.15%	26.63%	26.04%			
10%	19.82%	22.49%	23.67%	24.56%	28.70%	28.40%	32.84%	53.85%	55.92%		
0%	11.07%	11.07%	11.36%	11.36%	11.36%	10.36%	10.66%	11.95%	12.25%	13.43%	0.00%

Appendix B: Exponential Moving Average Trend Timing Strategy (2009 to 2015)

B:9 Information Technology Sector

Table B.9.1. Annualised Return

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	18.19%										
90%	15.14%										
80%	16.47%	16.53%									
70%	16.23%	16.33%	15.54%								
60%	15.83%	14.84%	15.14%	16.01%							
50%	14.86%	15.32%	15.60%	15.73%	15.55%						
40%	15.99%	16.58%	15.99%	16.71%	14.20%	14.10%					
30%	15.76%	16.39%	15.28%	13.41%	14.00%	12.30%	15.50%				
20%	15.61%	14.61%	14.58%	15.40%	16.33%	15.61%	12.82%	12.60%			
10%	15.74%	14.51%	14.50%	13.63%	14.59%	12.40%	13.70%	12.59%	13.90%		
0%	9.58%	8.63%	9.25%	9.25%	9.25%	9.25%	9.08%	9.08%	8.83%	8.25%	18.19%

Table B.9.2. Annualised Standard Deviation

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	17.81%										
90%	11.02%										
80%	11.02%	11.08%									
70%	11.00%	11.01%	10.95%								
60%	10.97%	11.02%	11.03%	11.16%							
50%	10.99%	11.09%	11.14%	11.16%	11.08%						
40%	11.08%	11.19%	11.13%	11.19%	11.12%	11.33%					
30%	11.26%	11.38%	10.95%	11.27%	11.08%	10.80%	10.69%				
20%	10.94%	10.95%	11.18%	11.07%	11.06%	11.00%	11.34%	11.06%			
10%	11.17%	10.72%	10.78%	11.51%	11.44%	10.99%	10.50%	10.28%	9.32%		
0%	7.05%	6.73%	6.57%	6.57%	6.57%	6.57%	6.56%	6.56%	6.54%	6.49%	17.81%

Table B.9.3. Annualised Sharpe Ratio

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	94.57%										
90%	125.09%										
80%	137.22%	137.09%									
70%	135.35%	136.04%	129.52%								
60%	132.01%	122.37%	125.08%	131.44%							
50%	123.00%	126.06%	127.94%	128.88%	128.22%						
40%	132.13%	136.21%	131.52%	137.34%	115.62%	112.58%					
30%	128.04%	132.17%	127.26%	107.03%	114.20%	101.43%	132.43%				
20%	130.39%	121.07%	118.34%	126.98%	135.49%	129.64%	101.15%	101.73%			
10%	128.84%	122.80%	122.02%	106.73%	115.78%	100.50%	117.67%	109.40%	134.63%		
0%	116.72%	108.18%	120.26%	120.26%	120.26%	120.26%	117.76%	117.76%	114.36%	106.38%	94.57%

Table B.9.4. Percentage of Time in Cash

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	20.12%										
80%	21.30%	21.30%									
70%	21.30%	21.30%	21.01%								
60%	20.71%	19.82%	20.12%	20.41%							
50%	20.12%	19.82%	20.12%	21.01%	23.08%						
40%	20.12%	20.12%	21.60%	23.08%	24.85%	24.85%					
30%	20.12%	21.30%	23.37%	24.56%	26.04%	26.04%	28.99%				
20%	22.49%	23.67%	25.15%	26.33%	26.63%	26.92%	26.92%	34.02%			
10%	22.78%	30.77%	30.77%	30.18%	30.47%	41.72%	43.49%	44.67%	50.00%		
0%	5.74%	6.04%	6.63%	6.63%	6.63%	6.63%	6.92%	6.92%	7.22%	7.81%	0.00%

B:10 Utilities Sector

Table B.10.1. Annualised Return

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	1.87%										
90%	1.06%										
80%	1.83%	1.81%									
70%	2.20%	2.74%	4.00%								
60%	3.03%	4.44%	4.00%	4.02%							
50%	3.37%	3.92%	4.82%	4.12%	4.41%						
40%	3.45%	4.60%	4.79%	4.42%	4.61%	5.10%					
30%	4.36%	4.35%	3.91%	5.88%	4.67%	5.07%	3.31%				
20%	3.98%	4.02%	3.33%	3.06%	3.52%	3.82%	4.46%	3.14%			
10%	1.92%	2.27%	2.91%	3.09%	2.03%	3.22%	2.19%	3.76%	2.78%		
0%	1.14%	1.58%	1.41%	1.40%	1.25%	1.25%	1.30%	1.08%	1.46%	2.13%	1.87%

Table B.10.2. Annualised Standard Deviation

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	14.42%										
90%	8.86%										
80%	8.76%	8.74%									
70%	8.63%	8.67%	8.55%								
60%	8.73%	8.59%	8.73%	8.76%							
50%	8.71%	8.79%	8.96%	8.71%	8.61%						
40%	8.78%	8.49%	8.59%	8.61%	8.59%	8.59%					
30%	8.53%	8.51%	8.69%	8.58%	8.58%	8.44%	8.29%				
20%	8.32%	8.44%	8.36%	8.38%	8.30%	8.11%	8.14%	8.21%			
10%	8.02%	8.01%	7.77%	7.74%	7.96%	8.09%	8.00%	7.76%	6.90%		
0%	4.49%	4.37%	4.46%	4.46%	4.44%	4.43%	4.40%	4.70%	4.21%	3.86%	14.42%

Table B.10.3. Annualised Sharpe Ratio

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	3.61%										
90%	-3.24%										
80%	5.52%	5.27%									
70%	9.91%	16.05%	31.00%								
60%	19.26%	36.04%	30.37%	30.52%							
50%	23.22%	29.25%	38.80%	31.88%	35.59%						
40%	23.92%	38.34%	40.14%	35.71%	38.03%	43.72%					
30%	35.33%	35.33%	29.49%	52.84%	38.70%	44.13%	23.64%				
20%	31.64%	31.63%	23.72%	20.47%	26.19%	30.46%	38.25%	21.84%			
10%	7.17%	11.55%	20.10%	22.48%	8.55%	23.08%	10.54%	31.03%	20.77%		
0%	-4.69%	5.37%	1.51%	1.19%	-2.12%	-2.08%	-1.07%	-5.61%	2.58%	20.34%	3.61%

Table B.10.4. Percentage of Time in Cash

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	20.71%										
80%	21.89%	23.08%									
70%	23.37%	23.67%	26.33%								
60%	24.56%	26.33%	26.04%	27.22%							
50%	25.74%	26.33%	26.33%	26.63%	28.11%						
40%	26.63%	27.22%	27.81%	28.11%	29.59%	30.47%					
30%	28.40%	29.88%	29.29%	30.18%	30.47%	32.54%	35.50%				
20%	31.66%	31.36%	31.95%	32.54%	34.91%	37.57%	39.35%	40.53%			
10%	32.84%	34.91%	36.69%	37.28%	37.87%	38.17%	39.64%	42.60%	57.40%		
0%	4.26%	5.15%	5.44%	5.74%	6.04%	6.63%	7.22%	8.11%	9.88%	12.54%	0.00%

Appendix C: Exponential Moving Average Trend Timing Strategy (2002 to 2015)

C:1 Healthcare Sector

Table C.1.1. Annualised Return

Fast Moving Average (columns); Slow Moving Average (rows)

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	8.63%										
90%	4.46%										
80%	5.20%	6.42%									
70%	6.72%	8.09%	7.46%								
60%	8.43%	7.96%	7.33%	7.48%							
50%	8.49%	7.86%	8.03%	7.86%	6.75%						
40%	7.55%	7.91%	7.66%	6.58%	5.30%	4.40%					
30%	7.12%	6.71%	6.28%	4.76%	3.54%	3.55%	2.55%				
20%	5.45%	4.68%	4.95%	3.84%	3.65%	2.20%	2.16%	3.74%			
10%	5.43%	5.56%	5.08%	5.11%	4.65%	4.92%	5.05%	6.22%	6.34%		
0%	4.02%	4.69%	4.69%	5.78%	5.07%	5.09%	5.15%	6.18%	6.18%	5.70%	8.63%

Table C.1.2. Annualised Standard Deviation

Fast Moving Average (columns); Slow Moving Average (rows)

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	15.62%										
90%	8.98%										
80%	8.85%	8.91%									
70%	8.92%	8.83%	8.78%								
60%	8.71%	8.84%	8.77%	8.82%							
50%	8.83%	8.81%	8.86%	8.90%	8.97%						
40%	8.80%	8.90%	8.88%	9.01%	8.87%	8.94%					
30%	8.89%	8.85%	8.82%	8.97%	8.90%	8.81%	9.03%				
20%	9.12%	8.96%	9.04%	8.99%	8.99%	9.33%	9.41%	9.56%			
10%	9.40%	9.44%	9.54%	9.58%	9.56%	9.64%	9.89%	9.83%	10.05%		
0%	13.36%	13.46%	13.46%	13.75%	14.05%	14.07%	14.07%	14.20%	14.17%	14.30%	15.62%

Table C.1.3. Annualised Sharpe Ratio

Fast Moving Average (columns); Slow Moving Average (rows)

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	46.60%										
90%	34.64%										
80%	43.51%	57.00%									
70%	60.18%	76.32%	69.65%								
60%	81.33%	74.80%	68.21%	69.58%							
50%	80.90%	73.95%	75.47%	73.17%	60.18%						
40%	70.50%	73.77%	71.08%	58.08%	44.59%	34.16%					
30%	64.97%	60.60%	55.92%	38.07%	24.66%	25.01%	13.31%				
20%	44.98%	37.20%	39.88%	27.73%	25.66%	9.19%	8.62%	25.02%			
10%	43.44%	44.58%	39.16%	39.24%	34.55%	37.07%	37.40%	49.59%	49.68%		
0%	19.99%	24.85%	24.85%	32.25%	26.51%	26.60%	27.02%	34.05%	34.11%	30.45%	46.60%

Table C.1.4. Percentage of Time in Cash

Fast Moving Average (columns); Slow Moving Average (rows)

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100 %	0.00%										
90%	20.70%										
80%	22.22%	23.29%									
70%	23.44%	25.27%	25.57%								
60%	25.72%	25.27%	25.57%	26.33%							
50%	25.42%	25.88%	26.48%	26.48%	25.88%						
40%	26.18%	26.48%	26.33%	25.72%	26.18%	26.48%					
30%	24.96%	25.57%	25.88%	25.88%	26.03%	27.40%	26.48%				
20%	23.14%	24.81%	25.11%	26.18%	26.18%	26.03%	24.81%	24.81%			
10%	22.68%	22.83%	22.98%	22.53%	22.98%	23.90%	23.74%	24.81%	25.11%		
0%	8.07%	8.52%	8.52%	8.98%	9.13%	9.44%	9.28%	9.28%	9.89%	10.05%	0.00%

C:2 Energy Sector

Table C.2.1. Annualised Return

Fast Moving Average (columns); Slow Moving Average (rows)

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	8.82%										
90%	5.02%										
80%	4.12%	3.75%									
70%	3.14%	2.22%	2.29%								
60%	2.85%	2.15%	3.53%	2.79%							
50%	1.73%	3.68%	2.19%	2.55%	2.09%						
40%	2.52%	2.21%	3.06%	2.94%	2.55%	3.75%					
30%	3.24%	4.03%	2.61%	4.10%	4.72%	5.32%	5.49%				
20%	6.68%	5.91%	4.82%	5.18%	4.95%	5.76%	5.51%	4.60%			
10%	6.94%	6.36%	6.28%	7.31%	5.28%	5.58%	3.67%	4.30%	6.53%		
0%	7.74%	7.74%	7.74%	7.74%	7.74%	7.74%	7.70%	7.49%	7.60%	7.52%	8.82%

Table C.2.2. Annualised Standard Deviation

Fast Moving Average (columns); Slow Moving Average (rows)

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	24.00%										
90%	14.88%										
80%	15.17%	15.03%									
70%	15.12%	14.97%	15.09%								
60%	14.95%	15.14%	15.13%	15.08%							
50%	15.10%	15.19%	14.87%	14.65%	14.81%						
40%	15.16%	14.73%	14.75%	14.46%	14.90%	14.66%					
30%	14.45%	14.44%	14.97%	14.36%	14.47%	14.30%	14.58%				
20%	14.08%	14.09%	14.56%	14.65%	14.48%	14.69%	14.97%	14.74%			
10%	14.62%	15.01%	15.10%	14.66%	14.91%	14.93%	15.15%	15.59%	14.85%		
0%	23.33%	23.33%	23.33%	23.33%	23.33%	23.33%	23.33%	23.32%	23.32%	23.29%	24.00%

Table C.2.3. Annualised Sharpe Ratio

Fast Moving Average (columns); Slow Moving Average (rows)

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	31.13%										
90%	24.67%										
80%	18.27%	15.99%									
70%	11.87%	5.86%	6.26%								
60%	10.04%	5.33%	14.44%	9.57%							
50%	2.53%	15.37%	5.69%	8.22%	5.03%						
40%	7.73%	5.84%	11.60%	11.00%	8.11%	16.40%					
30%	13.12%	18.61%	8.47%	19.19%	23.30%	27.76%	28.44%				
20%	37.88%	32.36%	23.88%	26.13%	24.85%	30.08%	27.84%	22.07%			
10%	38.29%	33.40%	32.64%	40.65%	26.37%	28.38%	15.32%	18.95%	34.90%		
0%	27.42%	27.42%	27.42%	27.42%	27.42%	27.42%	27.21%	26.33%	26.81%	26.53%	31.13%

Table C.2.4. Percentage of Time in Cash

Fast Moving Average (columns); Slow Moving Average (rows)

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	22.37%										
80%	21.92%	24.66%									
70%	24.05%	24.35%	24.96%								
60%	24.35%	24.51%	25.72%	26.94%							
50%	24.51%	25.27%	27.40%	28.16%	28.77%						
40%	26.03%	27.70%	28.31%	29.22%	29.83%	30.29%					
30%	27.85%	28.92%	29.22%	30.14%	30.90%	31.96%	31.96%				
20%	29.22%	29.22%	29.68%	30.29%	30.29%	31.05%	31.96%	35.01%			
10%	28.16%	28.46%	28.31%	29.83%	29.38%	29.53%	29.68%	29.22%	29.53%		
0%	11.26%	11.26%	11.26%	11.26%	11.26%	11.26%	11.42%	11.57%	11.72%	12.48%	0.00%

Appendix C: Exponential Moving Average Trend Timing Strategy (2002 to 2015) C

C:3 Industrial Sector

Table C.3.1. Annualised Return

Slow Moving Average \ Fast Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	8.01%										
90%	6.44%										
80%	4.76%	4.26%									
70%	4.18%	2.62%	4.05%								
60%	3.33%	4.89%	5.10%	5.98%							
50%	5.64%	5.14%	5.85%	6.03%	6.18%						
40%	5.65%	5.61%	6.08%	8.18%	6.71%	7.54%					
30%	7.30%	7.27%	7.41%	7.62%	9.18%	8.65%	8.18%				
20%	7.01%	7.70%	8.47%	7.93%	8.26%	6.87%	7.18%	8.11%			
10%	8.71%	9.19%	8.99%	8.75%	8.73%	8.82%	8.96%	8.98%	8.88%		
0%	3.88%	3.88%	3.88%	3.82%	3.91%	4.98%	4.68%	4.89%	5.66%	3.48%	8.01%

Table C.3.2. Annualised Standard Deviation

Slow Moving Average \ Fast Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	19.52%										
90%	12.13%										
80%	12.04%	11.80%									
70%	11.84%	12.08%	12.03%								
60%	12.01%	11.93%	12.15%	11.89%							
50%	12.05%	12.05%	11.97%	12.27%	12.48%						
40%	12.04%	12.21%	12.33%	12.19%	11.98%	11.78%					
30%	12.08%	11.99%	11.82%	11.88%	11.97%	11.86%	12.02%				
20%	11.71%	11.75%	11.82%	11.86%	11.86%	12.10%	11.99%	12.17%			
10%	11.76%	11.78%	11.79%	11.77%	11.83%	11.86%	12.06%	12.18%	12.08%		
0%	16.66%	16.66%	16.66%	16.66%	16.84%	17.15%	17.25%	17.18%	17.60%	18.03%	19.52%

Table C.3.3. Annualised Sharpe Ratio

Slow Moving Average \ Fast Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	34.14%										
90%	42.01%										
80%	28.36%	24.71%									
70%	23.93%	10.55%	22.47%								
60%	16.47%	29.72%	30.86%	39.00%							
50%	35.60%	31.47%	37.62%	38.16%	38.76%						
40%	35.72%	34.95%	38.40%	56.05%	44.78%	52.57%					
30%	49.33%	49.40%	51.30%	52.83%	65.47%	61.57%	56.83%				
20%	48.39%	54.04%	60.26%	55.55%	58.26%	45.68%	48.68%	55.58%			
10%	62.65%	66.55%	64.84%	62.91%	62.37%	63.00%	64.31%	65.89%	62.34%		
0%	15.24%	15.24%	15.24%	14.86%	15.22%	21.17%	19.35%	20.64%	24.50%	11.82%	34.14%

Table C.3.4. Percentage of Time in Cash

Slow Moving Average \ Fast Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	19.18%										
80%	19.63%	20.70%									
70%	21.00%	20.55%	21.92%								
60%	20.55%	21.77%	21.92%	24.20%							
50%	22.07%	22.07%	23.90%	23.74%	24.05%						
40%	22.83%	23.44%	24.05%	24.51%	25.42%	27.85%					
30%	23.90%	24.51%	26.33%	26.33%	27.40%	28.61%	27.85%				
20%	26.18%	27.09%	27.40%	27.09%	27.85%	28.01%	28.61%	29.07%			
10%	25.72%	26.33%	26.79%	27.40%	27.85%	28.31%	28.77%	28.92%	27.70%		
0%	12.18%	12.18%	12.18%	12.33%	12.18%	12.33%	12.48%	12.94%	12.79%	13.09%	0.00%

C:4 Telecommunication Services Sector

Table C.4.1. Annualised Return

Slow Moving Average \ Fast Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	6.49%										
90%	3.02%										
80%	3.81%	4.61%									
70%	4.38%	5.66%	4.76%								
60%	5.21%	4.07%	4.42%	4.62%							
50%	3.79%	4.35%	5.18%	6.01%	5.87%						
40%	5.21%	6.18%	6.98%	6.46%	5.82%	4.71%					
30%	5.82%	6.25%	5.74%	4.44%	4.68%	4.67%	6.04%				
20%	4.26%	4.54%	5.39%	5.30%	5.20%	6.62%	6.11%	4.86%			
10%	5.21%	4.87%	5.58%	5.04%	5.86%	4.91%	4.15%	4.19%	3.00%		
0%	6.13%	5.92%	5.92%	5.63%	5.63%	5.63%	5.30%	5.03%	4.62%	4.41%	6.49%

Table C.4.2. Annualised Standard Deviation

Slow Moving Average \ Fast Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	16.59%										
90%	10.35%										
80%	10.66%	10.71%									
70%	10.66%	10.22%	10.38%								
60%	10.28%	10.43%	10.20%	10.25%							
50%	10.29%	10.23%	10.19%	10.11%	10.23%						
40%	9.95%	9.92%	9.83%	10.07%	10.08%	10.11%					
30%	9.93%	10.07%	10.03%	10.15%	10.22%	10.22%	10.19%				
20%	10.03%	10.04%	10.20%	10.18%	10.16%	10.16%	10.15%	10.09%			
10%	9.90%	10.00%	9.84%	9.82%	9.86%	9.92%	9.92%	9.75%	10.34%		
0%	15.89%	15.87%	15.87%	15.85%	15.85%	15.85%	15.81%	15.83%	15.83%	15.67%	16.59%

Table C.4.3. Annualised Sharpe Ratio

Slow Moving Average \ Fast Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	30.98%										
90%	16.21%										
80%	23.11%	30.48%									
70%	28.45%	42.16%	32.91%								
60%	37.54%	26.12%	30.14%	31.91%							
50%	23.79%	29.38%	37.59%	46.11%	44.23%						
40%	38.80%	48.77%	57.30%	50.78%	44.32%	33.27%					
30%	45.07%	48.72%	43.76%	30.43%	32.61%	32.50%	46.00%				
20%	29.04%	31.80%	39.62%	38.87%	37.94%	51.96%	46.91%	34.80%			
10%	39.03%	35.19%	42.99%	37.57%	45.77%	35.87%	28.22%	29.14%	15.96%		
0%	30.14%	28.81%	28.81%	27.01%	27.01%	27.01%	25.00%	23.26%	20.70%	19.55%	30.98%

Table C.4.4. Percentage of Time in Cash

Slow Moving Average \ Fast Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	19.33%										
80%	20.09%	22.53%									
70%	22.07%	24.81%	24.51%								
60%	23.74%	24.35%	26.48%	26.94%							
50%	24.51%	26.03%	27.40%	29.07%	29.68%						
40%	27.55%	28.77%	29.83%	29.38%	29.83%	31.05%					
30%	28.46%	28.61%	29.07%	29.98%	30.75%	31.81%	33.79%				
20%	29.38%	30.44%	31.66%	32.12%	33.03%	34.25%	35.01%	35.31%			
10%	30.29%	30.29%	31.81%	32.12%	33.33%	33.94%	34.09%	35.31%	33.94%		
0%	4.11%	4.26%	4.26%	4.26%	4.26%	4.26%	4.26%	4.26%	4.41%	5.48%	0.00%

Appendix C: Exponential Moving Average Trend Timing Strategy (2002 to 2015)

C:5 Consumer Staples Sector

Table C.5.1. Annualised Return

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	7.87%										
90%	6.11%										
80%	6.62%	7.17%									
70%	6.84%	7.44%	6.75%								
60%	7.15%	6.51%	5.78%	6.23%							
50%	6.67%	6.26%	6.04%	6.78%	5.64%						
40%	6.48%	6.48%	5.86%	5.16%	5.11%	5.18%					
30%	5.56%	5.49%	5.69%	5.72%	5.92%	5.98%	5.76%				
20%	5.81%	6.18%	6.38%	5.84%	6.19%	5.10%	5.71%	5.97%			
10%	6.02%	6.05%	6.42%	6.46%	5.93%	5.83%	5.64%	6.40%	6.49%		
0%	6.80%	6.66%	6.66%	6.64%	7.12%	7.12%	7.32%	7.21%	7.21%	6.76%	7.87%

Table C.5.2. Annualised Standard Deviation

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	12.92%										
90%	7.93%										
80%	7.97%	7.75%									
70%	7.70%	7.68%	7.56%								
60%	7.69%	7.51%	7.67%	7.75%							
50%	7.58%	7.75%	7.79%	7.72%	7.57%						
40%	7.86%	7.91%	7.65%	7.61%	7.68%	7.71%					
30%	7.59%	7.57%	7.75%	7.74%	7.83%	7.87%	7.98%				
20%	7.71%	7.78%	7.76%	7.87%	7.96%	8.04%	8.08%	8.11%			
10%	8.00%	8.03%	8.12%	8.11%	8.19%	8.21%	8.24%	8.40%	8.64%		
0%	12.09%	12.08%	12.08%	12.08%	12.15%	12.15%	12.15%	12.15%	12.15%	12.12%	12.92%

Table C.5.3. Annualised Sharpe Ratio

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	50.46%										
90%	60.12%										
80%	66.20%	75.08%									
70%	71.28%	79.23%	71.38%								
60%	75.51%	68.77%	57.83%	62.91%							
50%	70.25%	63.40%	60.23%	70.43%	56.73%						
40%	65.28%	64.85%	58.98%	50.13%	49.03%	49.70%					
30%	55.52%	54.68%	56.05%	56.43%	58.43%	58.87%	55.31%				
20%	57.80%	62.14%	64.89%	57.04%	60.86%	46.65%	54.07%	56.96%			
10%	58.42%	58.55%	62.49%	63.01%	55.97%	54.65%	52.09%	60.19%	59.56%		
0%	45.07%	43.98%	43.98%	43.83%	47.53%	47.53%	49.19%	48.25%	48.27%	44.69%	50.46%

Table C.5.4. Percentage of Time in Cash

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	19.18%										
80%	20.24%	20.70%									
70%	20.85%	22.22%	23.29%								
60%	21.77%	23.29%	24.35%	24.20%							
50%	22.53%	23.90%	23.59%	24.96%	25.11%						
40%	22.22%	23.14%	24.05%	24.51%	24.35%	25.11%					
30%	24.51%	24.66%	24.35%	24.51%	24.81%	25.88%	26.03%				
20%	23.59%	23.90%	24.35%	24.51%	25.27%	25.72%	25.88%	26.48%			
10%	22.68%	23.44%	23.74%	23.90%	24.05%	23.90%	23.59%	22.98%	21.46%		
0%	11.72%	11.87%	11.87%	11.72%	11.87%	11.87%	11.87%	12.02%	12.18%	12.79%	0.00%

C:6 Financials Sector

Table C.6.1. Annualised Return

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	4.21%										
90%	6.11%										
80%	6.33%	6.10%									
70%	5.53%	5.67%	4.86%								
60%	5.73%	6.27%	5.44%	5.89%							
50%	6.02%	6.63%	6.29%	6.88%	6.58%						
40%	6.66%	7.48%	5.72%	5.76%	5.89%	7.53%					
30%	7.22%	7.00%	8.01%	7.70%	8.06%	7.71%	8.17%				
20%	7.98%	7.36%	7.82%	6.76%	7.86%	7.53%	7.34%	7.39%			
10%	7.85%	9.09%	8.28%	5.94%	6.38%	6.01%	6.77%	7.66%	6.10%		
0%	-0.91%	-0.91%	-0.94%	-0.98%	-1.14%	-1.14%	-1.25%	-1.07%	-1.46%	-2.20%	4.21%

Table C.6.2. Annualised Standard Deviation

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	25.39%										
90%	14.18%										
80%	14.19%	14.39%									
70%	14.34%	14.26%	14.24%								
60%	14.23%	14.09%	14.35%	14.34%							
50%	14.12%	14.09%	14.27%	14.44%	14.28%						
40%	13.77%	13.84%	14.25%	14.25%	14.12%	14.20%					
30%	13.51%	13.53%	13.39%	14.20%	13.47%	13.55%	13.44%				
20%	13.39%	13.23%	13.12%	13.55%	13.47%	13.33%	13.54%	13.44%			
10%	13.56%	13.55%	13.50%	13.50%	13.32%	13.34%	13.43%	13.35%	12.50%		
0%	13.10%	13.10%	13.07%	13.07%	13.06%	13.06%	13.05%	13.08%	13.51%	14.05%	25.39%

Table C.6.3. Annualised Sharpe Ratio

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	11.30%										
90%	33.56%										
80%	35.10%	33.01%									
70%	29.19%	30.31%	24.68%								
60%	30.80%	34.97%	28.54%	31.68%							
50%	33.13%	37.46%	34.65%	38.35%	36.63%						
40%	38.59%	44.35%	30.70%	30.97%	32.17%	43.50%					
30%	43.46%	41.77%	49.74%	44.74%	49.81%	46.93%	50.74%				
20%	49.52%	45.43%	49.31%	39.92%	48.38%	46.38%	44.26%	44.95%			
10%	47.98%	57.18%	51.37%	34.01%	37.78%	34.92%	40.38%	47.28%	38.03%		
0%	-17.26%	-17.26%	-17.46%	-17.80%	-19.03%	-19.03%	-19.92%	-18.47%	-20.76%	-25.26%	11.30%

Table C.6.4. Percentage of Time in Cash

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	22.98%										
80%	23.29%	23.29%									
70%	22.98%	24.51%	25.11%								
60%	24.51%	25.57%	26.18%	27.40%							
50%	26.18%	27.09%	27.40%	28.16%	28.77%						
40%	26.79%	27.25%	28.01%	28.61%	28.77%	30.44%					
30%	28.16%	29.07%	29.68%	29.98%	31.20%	32.57%	33.33%				
20%	29.22%	29.68%	31.35%	31.51%	32.72%	33.03%	32.72%	33.03%			
10%	30.44%	31.96%	32.12%	32.27%	32.88%	32.57%	32.57%	35.16%	36.23%		
0%	45.36%	45.36%	45.81%	46.12%	46.12%	46.12%	46.27%	46.27%	47.03%	47.79%	0.00%

Appendix C: Exponential Moving Average Trend Timing Strategy (2002 to 2015) C

C:7 Materials Sector

Table C.7.1. Annualised Return

Fast Moving Average (columns) / Slow Moving Average (rows)

	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	9.74%										
90%	5.89%										
80%	6.07%	5.64%									
70%	6.65%	6.34%	5.90%								
60%	6.05%	5.67%	7.42%	9.44%							
50%	7.64%	8.35%	8.55%	9.17%	9.09%						
40%	8.53%	8.76%	8.20%	9.48%	8.99%	8.83%					
30%	8.98%	9.93%	10.27%	9.90%	8.64%	11.42%	9.23%				
20%	9.90%	10.27%	11.61%	11.45%	10.37%	8.82%	7.59%	9.58%			
10%	8.20%	7.99%	7.76%	8.20%	7.41%	7.39%	7.50%	9.06%	8.33%		
0%	9.02%	9.00%	9.00%	9.00%	9.15%	9.15%	9.15%	9.06%	8.93%	8.57%	9.74%

Table C.7.2. Annualised Standard Deviation

Fast Moving Average (columns) / Slow Moving Average (rows)

	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	25.33%										
90%	16.16%										
80%	15.72%	15.90%									
70%	15.64%	15.94%	16.38%								
60%	15.59%	16.42%	16.16%	16.17%							
50%	16.13%	15.99%	16.07%	15.73%	15.07%						
40%	15.68%	15.59%	15.54%	15.18%	15.13%	14.93%					
30%	15.32%	15.22%	15.27%	15.06%	14.83%	15.00%	15.45%				
20%	14.71%	14.73%	14.79%	14.79%	15.25%	15.59%	15.74%	15.86%			
10%	15.40%	15.27%	15.21%	15.25%	16.02%	16.08%	15.96%	16.35%	16.55%		
0%	24.67%	24.67%	24.67%	24.67%	24.69%	24.69%	24.69%	24.69%	24.63%	24.60%	25.33%

Table C.7.3. Annualised Sharpe Ratio

Fast Moving Average (columns) / Slow Moving Average (rows)

	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	33.15%										
90%	28.12%										
80%	30.05%	27.01%									
70%	33.93%	31.36%	27.82%								
60%	30.19%	26.32%	37.58%	50.04%							
50%	39.01%	43.80%	44.83%	49.73%	51.41%						
40%	45.79%	47.55%	44.08%	53.55%	50.51%	50.08%					
30%	49.82%	56.38%	58.42%	56.82%	49.19%	67.14%	51.00%				
20%	58.17%	60.61%	69.38%	68.28%	59.19%	47.97%	39.67%	51.93%			
10%	44.54%	43.47%	42.19%	44.97%	37.82%	37.61%	38.53%	47.18%	42.17%		
0%	31.09%	31.01%	31.01%	31.01%	31.61%	31.61%	31.61%	31.23%	30.78%	29.37%	33.15%

Table C.7.4. Percentage of Time in Cash

Fast Moving Average (columns) / Slow Moving Average (rows)

	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	20.40%										
80%	22.37%	22.68%									
70%	22.68%	23.90%	24.96%								
60%	25.11%	24.66%	26.18%	27.09%							
50%	24.81%	26.03%	28.01%	28.92%	29.98%						
40%	26.18%	28.01%	28.61%	29.68%	30.44%	31.05%					
30%	28.01%	28.61%	29.07%	30.90%	31.66%	33.03%	33.18%				
20%	29.98%	30.90%	32.42%	33.18%	32.72%	34.09%	32.72%	33.49%			
10%	29.53%	29.83%	30.44%	31.20%	30.90%	31.05%	31.51%	30.14%	30.59%		
0%	8.68%	8.83%	8.83%	8.83%	8.98%	8.98%	9.13%	9.28%	9.74%	10.35%	0.00%

C:8 Consumer Discretionary Sector

Table C.8.1. Annualised Return

Fast Moving Average (columns) / Slow Moving Average (rows)

	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	9.11%										
90%	6.29%										
80%	4.96%	5.58%									
70%	5.45%	5.52%	7.04%								
60%	5.58%	7.04%	7.72%	6.84%							
50%	7.81%	7.20%	6.76%	6.67%	7.01%						
40%	7.17%	7.24%	6.83%	7.06%	8.49%	10.33%					
30%	6.07%	6.99%	8.15%	9.42%	9.58%	8.55%	8.38%				
20%	8.60%	8.96%	9.15%	8.36%	8.06%	8.25%	8.82%	6.41%			
10%	6.68%	7.57%	8.26%	8.60%	8.09%	8.18%	7.02%	8.35%	8.23%		
0%	6.48%	6.48%	6.36%	6.36%	6.36%	6.27%	6.27%	5.19%	5.86%	5.17%	9.11%

Table C.8.2. Annualised Standard Deviation

Fast Moving Average (columns) / Slow Moving Average (rows)

	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	19.45%										
90%	11.72%										
80%	11.61%	11.72%									
70%	11.62%	11.72%	11.25%								
60%	11.50%	11.25%	11.57%	11.81%							
50%	11.29%	11.71%	11.61%	11.77%	11.80%						
40%	11.68%	11.78%	11.80%	11.79%	11.70%	11.47%					
30%	11.75%	11.81%	11.72%	11.48%	11.49%	11.88%	11.79%				
20%	11.38%	11.41%	11.52%	11.80%	11.76%	11.71%	11.71%	11.84%			
10%	11.78%	11.75%	11.84%	11.80%	11.80%	11.81%	11.78%	11.69%	11.62%		
0%	15.44%	15.44%	15.44%	15.44%	15.44%	15.42%	15.42%	15.78%	16.61%	17.06%	19.45%

Table C.8.3. Annualised Sharpe Ratio

Fast Moving Average (columns) / Slow Moving Average (rows)

	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	39.92%										
90%	42.17%										
80%	31.15%	36.09%									
70%	35.36%	35.59%	50.58%								
60%	36.78%	50.58%	55.04%	46.48%							
50%	57.28%	49.95%	46.64%	45.23%	48.04%						
40%	49.81%	50.02%	46.49%	48.49%	61.09%	78.32%					
30%	40.18%	47.79%	58.02%	70.31%	71.69%	60.61%	59.62%				
20%	63.75%	66.73%	67.73%	59.43%	57.07%	58.96%	63.80%	42.77%			
10%	45.31%	52.93%	58.44%	61.51%	57.14%	57.86%	48.19%	59.94%	59.19%		
0%	33.27%	33.27%	32.46%	32.46%	32.46%	31.90%	31.90%	24.37%	27.15%	22.41%	39.92%

Table C.8.4. Percentage of Time in Cash

Fast Moving Average (columns) / Slow Moving Average (rows)

	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	19.63%										
80%	20.70%	21.92%									
70%	21.77%	22.53%	23.90%								
60%	22.22%	23.90%	24.81%	25.11%							
50%	23.90%	24.81%	25.72%	26.18%	25.42%						
40%	24.05%	24.66%	24.81%	25.72%	26.94%	28.77%					
30%	24.05%	24.51%	26.18%	28.16%	28.61%	27.85%	29.07%				
20%	27.09%	26.94%	27.40%	27.70%	28.31%	29.53%	30.29%	30.29%			
10%	27.09%	29.07%	29.53%	29.98%	30.29%	29.98%	30.59%	31.66%	31.81%		
0%	14.61%	14.61%	14.76%	14.76%	14.76%	14.76%	14.76%	14.76%	14.76%	15.68%	0.00%

C:9 Information Technology Sector

Table C.9.1. Annualised Return

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	10.00%										
90%	4.68%										
80%	4.72%	4.68%									
70%	4.51%	4.58%	4.64%								
60%	4.55%	4.46%	5.58%	7.74%							
50%	7.10%	6.91%	8.49%	9.46%	7.78%						
40%	7.43%	7.98%	8.76%	8.59%	7.43%	6.99%					
30%	6.39%	7.32%	7.09%	6.45%	6.32%	5.76%	7.83%				
20%	6.12%	6.05%	6.84%	8.23%	7.60%	7.60%	8.10%	8.65%			
10%	7.87%	7.99%	8.09%	7.67%	7.74%	5.52%	7.38%	6.87%	6.62%		
0%	2.63%	2.63%	2.72%	2.72%	2.07%	2.79%	3.54%	2.93%	3.21%	2.27%	10.00%

Table C.9.2. Annualised Standard Deviation

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	21.54%										
90%	13.56%										
80%	13.26%	13.33%									
70%	13.30%	13.33%	13.76%								
60%	13.35%	13.79%	13.62%	13.50%							
50%	13.77%	13.95%	13.50%	13.63%	13.56%						
40%	13.50%	13.50%	13.37%	13.65%	13.45%	13.71%					
30%	13.52%	13.58%	13.46%	13.50%	13.48%	13.35%	13.59%				
20%	13.71%	13.52%	13.54%	13.60%	13.58%	13.49%	13.23%	13.26%			
10%	13.66%	13.65%	13.58%	13.42%	13.36%	13.40%	13.30%	12.92%	12.55%		
0%	15.12%	15.12%	15.06%	15.06%	15.24%	15.49%	15.22%	15.31%	15.53%	15.97%	21.54%

Table C.9.3. Annualised Sharpe Ratio

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	40.17%										
90%	24.61%										
80%	25.48%	24.98%									
70%	23.77%	24.25%	23.93%								
60%	24.01%	22.62%	31.07%	47.38%							
50%	41.76%	39.92%	52.93%	59.52%	47.45%						
40%	45.04%	49.14%	55.46%	53.06%	45.22%	41.18%					
30%	37.31%	43.97%	42.66%	37.80%	36.91%	33.04%	47.74%				
20%	34.82%	34.75%	40.56%	50.62%	46.08%	46.40%	51.05%	55.10%			
10%	47.76%	48.70%	49.62%	47.14%	47.84%	31.13%	45.39%	42.77%	42.04%		
0%	8.51%	8.51%	9.13%	9.13%	4.74%	9.35%	14.40%	10.33%	12.01%	5.77%	40.17%

Table C.9.4. Percentage of Time in Cash

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	22.22%										
80%	23.59%	23.59%									
70%	23.14%	24.05%	23.59%								
60%	23.29%	22.98%	23.74%	26.33%							
50%	23.44%	23.90%	26.79%	27.25%	28.16%						
40%	25.11%	26.33%	27.40%	28.01%	28.77%	28.92%					
30%	25.88%	26.94%	27.85%	28.46%	29.22%	30.14%	31.35%				
20%	25.42%	26.94%	28.31%	29.53%	30.29%	30.75%	32.42%	33.03%			
10%	27.09%	27.40%	27.55%	28.46%	28.61%	38.81%	39.27%	40.03%	43.07%		
0%	7.44%	7.44%	7.90%	7.90%	7.75%	7.90%	8.36%	8.36%	8.51%	7.29%	0.00%

C:10 Utilities Sector

Table C.10.1. Annualised Return

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	5.68%										
90%	2.47%										
80%	3.13%	2.87%									
70%	3.29%	5.24%	5.43%								
60%	5.68%	5.66%	5.39%	5.29%							
50%	4.93%	5.01%	6.48%	5.52%	6.07%						
40%	5.52%	5.71%	5.58%	6.16%	6.39%	6.69%					
30%	5.12%	5.66%	6.05%	7.33%	6.69%	6.94%	6.16%				
20%	6.77%	6.22%	5.49%	4.87%	5.65%	5.10%	6.09%	5.67%			
10%	5.23%	5.78%	5.70%	5.94%	4.99%	5.00%	4.70%	5.15%	6.02%		
0%	5.07%	5.07%	5.07%	5.07%	5.07%	4.95%	4.95%	4.95%	4.77%	4.55%	5.68%

Table C.10.2. Annualised Standard Deviation

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	16.22%										
90%	9.64%										
80%	9.76%	9.81%									
70%	9.80%	9.67%	9.79%								
60%	9.72%	9.81%	9.80%	9.84%							
50%	9.79%	9.88%	9.75%	9.86%	9.76%						
40%	9.72%	9.82%	9.85%	9.46%	9.54%	9.53%					
30%	9.98%	9.66%	9.59%	9.54%	9.57%	9.59%	9.65%				
20%	9.49%	9.58%	9.63%	9.55%	9.56%	9.54%	9.55%	9.53%			
10%	9.34%	9.37%	9.29%	9.25%	9.48%	9.51%	9.65%	9.66%	9.64%		
0%	15.45%	15.45%	15.45%	15.45%	15.45%	15.44%	15.44%	15.44%	15.43%	15.42%	16.22%

Table C.10.3. Annualised Sharpe Ratio

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	26.74%										
90%	11.62%										
80%	18.28%	15.57%									
70%	19.81%	40.31%	41.74%								
60%	44.59%	44.03%	41.27%	40.07%							
50%	36.65%	37.12%	52.65%	42.37%	48.43%						
40%	42.91%	44.44%	42.97%	50.84%	52.85%	56.07%					
30%	37.81%	44.61%	49.10%	62.65%	55.88%	58.32%	49.83%				
20%	57.12%	50.86%	43.05%	36.94%	45.06%	39.32%	49.65%	45.35%			
10%	41.54%	47.27%	46.92%	49.69%	38.41%	38.45%	34.75%	39.42%	48.53%		
0%	24.09%	24.09%	24.09%	24.09%	24.09%	23.34%	23.34%	23.34%	22.21%	20.76%	26.74%

Table C.10.4. Percentage of Time in Cash

Fast Moving Average

Slow Moving Average	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
100%	0.00%										
90%	18.87%										
80%	19.48%	20.24%									
70%	20.40%	21.61%	24.20%								
60%	22.83%	24.35%	24.66%	25.27%							
50%	24.20%	24.05%	24.96%	25.57%	25.88%						
40%	24.05%	24.51%	25.11%	26.48%	26.79%	27.55%					
30%	24.05%	26.03%	26.48%	27.25%	26.94%	28.16%	29.53%				
20%	26.18%	26.64%	26.79%	27.40%	28.92%	29.98%	31.81%	32.42%			
10%	27.40%	28.77%	29.53%	30.29%	30.44%	30.44%	30.29%	29.98%	31.05%		
0%	10.96%	10.96%	10.96%	10.96%	10.96%	11.11%	11.11%	11.11%	11.26%	11.72%	0.00%

D:1 Healthcare Sector

Table D.1.1. Annualised Return

Bull Flag Fit Threshold (columns); Bear Flag Fit Threshold (rows)

Bear Flag Fit Threshold	0	1	2	3	4
0	3.85%	1.80%	2.59%	3.23%	4.51%
1	5.65%	4.06%	4.79%	5.12%	3.99%
2	6.19%	4.94%	5.33%	5.15%	4.66%
3	4.06%	3.07%	3.25%	3.98%	2.77%
4	2.76%	1.78%	1.94%	2.66%	1.47%

Table D.1.2. Annualised Standard Deviation

Bull Flag Fit Threshold (columns); Bear Flag Fit Threshold (rows)

Bear Flag Fit Threshold	0	1	2	3	4
0	7.46%	6.24%	5.81%	5.13%	4.52%
1	8.39%	7.21%	6.80%	6.26%	4.95%
2	8.94%	7.73%	7.51%	6.78%	5.39%
3	10.23%	9.28%	9.22%	8.75%	7.93%
4	10.59%	9.67%	9.45%	8.99%	8.20%

Table D.1.3. Annualised Sharpe Ratio

Bull Flag Fit Threshold (columns); Bear Flag Fit Threshold (rows)

Bear Flag Fit Threshold	0	1	2	3	4
0	33.60%	7.22%	21.45%	36.59%	69.96%
1	51.35%	37.56%	50.67%	60.24%	53.34%
2	54.17%	46.47%	52.97%	56.14%	61.40%
3	26.48%	18.55%	20.60%	30.08%	17.90%
4	13.35%	4.53%	6.28%	14.64%	1.48%

Table D.1.4. Percentage of Time in Cash

Bull Flag Fit Threshold (columns); Bear Flag Fit Threshold (rows)

Bear Flag Fit Threshold	0	1	2	3	4
0	34.84%	29.68%	24.19%	17.10%	12.90%
1	45.48%	38.39%	32.26%	25.81%	15.48%
2	53.23%	43.55%	39.03%	30.65%	20.00%
3	61.29%	53.55%	50.65%	42.90%	33.87%
4	65.81%	58.06%	52.58%	44.84%	35.81%

D:2 Energy Sector

Table D.2.1. Annualised Return

Bull Flag Fit Threshold (columns); Bear Flag Fit Threshold (rows)

Bear Flag Fit Threshold	0	1	2	3	4
0	13.61%	11.31%	8.78%	9.30%	6.26%
1	14.78%	10.62%	8.59%	9.29%	6.26%
2	19.30%	13.22%	10.34%	11.00%	7.64%
3	17.64%	11.64%	8.17%	8.82%	5.53%
4	17.15%	10.92%	6.55%	7.06%	4.14%

Table D.2.2. Annualised Standard Deviation

Bull Flag Fit Threshold (columns); Bear Flag Fit Threshold (rows)

Bear Flag Fit Threshold	0	1	2	3	4
0	17.03%	10.72%	8.50%	7.59%	4.90%
1	17.32%	11.02%	8.51%	7.59%	4.90%
2	18.03%	11.83%	8.71%	7.81%	5.22%
3	18.76%	12.91%	9.47%	8.65%	6.39%
4	20.05%	14.84%	10.10%	9.33%	7.23%

Table D.2.3. Annualised Sharpe Ratio

Bull Flag Fit Threshold (columns); Bear Flag Fit Threshold (rows)

Bear Flag Fit Threshold	0	1	2	3	4
0	72.04%	92.90%	87.43%	104.74%	100.32%
1	77.52%	84.11%	85.12%	104.66%	100.32%
2	99.60%	99.42%	103.19%	123.61%	120.73%
3	86.84%	79.78%	71.99%	86.34%	65.38%
4	78.81%	64.55%	51.54%	61.24%	38.60%

Table D.2.4. Percentage of Time in Cash

Bull Flag Fit Threshold (columns); Bear Flag Fit Threshold (rows)

Bear Flag Fit Threshold	0	1	2	3	4
0	54.84%	63.23%	79.03%	83.55%	93.55%
1	49.35%	59.03%	78.39%	83.23%	93.55%
2	38.71%	49.03%	76.45%	81.61%	92.26%
3	33.55%	43.87%	74.52%	79.68%	90.32%
4	24.19%	33.87%	72.26%	77.74%	88.71%

D:3 Industrials Sector

Table D.3.1. Annualised Return

	Bull Flag Fit Threshold				
Bear Flag Fit Threshold	0	1	2	3	4
0	7.64%	6.49%	6.51%	7.17%	6.37%
1	8.05%	6.64%	6.66%	6.54%	5.75%
2	8.78%	7.26%	7.28%	7.39%	6.60%
3	11.59%	9.92%	9.94%	9.53%	8.71%
4	9.92%	8.64%	8.66%	9.53%	8.71%

Table D.3.2. Annualised Standard Deviation

	Bull Flag Fit Threshold				
Bear Flag Fit Threshold	0	1	2	3	4
0	7.38%	5.87%	5.75%	5.16%	4.26%
1	7.71%	6.25%	6.14%	5.44%	4.60%
2	12.31%	6.40%	6.29%	5.58%	4.77%
3	13.76%	8.24%	8.16%	7.54%	6.96%
4	14.23%	8.61%	8.53%	7.54%	6.96%

Table D.3.3. Annualised Sharpe Ratio

	Bull Flag Fit Threshold				
Bear Flag Fit Threshold	0	1	2	3	4
0	85.27%	87.66%	89.78%	112.88%	117.90%
1	87.00%	84.70%	86.54%	95.48%	95.73%
2	60.40%	92.35%	94.23%	108.36%	110.13%
3	74.43%	104.00%	105.31%	108.55%	105.86%
4	60.23%	84.70%	85.73%	108.55%	105.86%

Table D.3.4. Percentage of Time in Cash

	Bull Flag Fit Threshold				
Bear Flag Fit Threshold	0	1	2	3	4
0	65.16%	77.74%	78.71%	82.90%	86.45%
1	60.97%	74.52%	75.48%	80.32%	83.87%
2	51.94%	70.97%	71.94%	77.10%	80.65%
3	33.23%	57.10%	58.06%	63.55%	67.10%
4	29.68%	55.48%	56.45%	63.55%	67.10%

D:4 Telecommunication Services Sector

Table D.4.1. Annualised Return

	Bull Flag Fit Threshold				
Bear Flag Fit Threshold	0	1	2	3	4
0	6.73%	6.71%	4.86%	6.99%	3.89%
1	10.50%	9.93%	7.21%	9.41%	4.05%
2	11.28%	10.70%	7.58%	9.77%	5.92%
3	8.94%	9.25%	6.17%	8.33%	5.16%
4	6.80%	7.11%	4.70%	5.49%	2.40%

Table D.4.2. Annualised Standard Deviation

	Bull Flag Fit Threshold				
Bear Flag Fit Threshold	0	1	2	3	4
0	14.15%	14.15%	13.85%	13.58%	12.44%
1	14.71%	14.66%	14.32%	14.05%	12.45%
2	14.82%	14.78%	14.34%	14.08%	12.81%
3	15.09%	14.95%	14.52%	14.26%	12.89%
4	15.51%	15.38%	14.81%	14.73%	13.40%

Table D.4.3. Annualised Sharpe Ratio

	Bull Flag Fit Threshold				
Bear Flag Fit Threshold	0	1	2	3	4
0	38.03%	37.93%	25.38%	41.58%	20.42%
1	62.22%	58.53%	40.95%	57.35%	21.69%
2	66.99%	63.31%	43.47%	59.82%	35.69%
3	50.29%	52.88%	33.24%	48.98%	29.57%
4	35.16%	37.49%	22.65%	28.11%	7.84%

Table D.4.4. Percentage of Time in Cash

	Bull Flag Fit Threshold				
Bear Flag Fit Threshold	0	1	2	3	4
0	58.71%	59.03%	63.87%	67.74%	86.77%
1	48.71%	49.35%	56.45%	60.65%	86.45%
2	43.87%	44.52%	56.13%	60.00%	80.00%
3	39.03%	41.61%	53.23%	57.10%	79.35%
4	33.87%	36.45%	49.68%	52.58%	74.84%

D:5 Consumer Staples Sector

Table D.5.1. Annualised Return

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	7.21%	6.71%	6.18%	5.90%	3.88%
1	7.92%	6.79%	6.25%	5.98%	3.95%
2	7.70%	6.58%	6.05%	5.77%	3.90%
3	7.09%	5.91%	5.12%	4.85%	3.49%
4	8.42%	6.23%	4.75%	4.48%	3.49%

Table D.5.2. Annualised Standard Deviation

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	5.69%	4.71%	3.33%	3.22%	2.25%
1	5.89%	5.07%	3.82%	3.72%	2.47%
2	5.98%	5.15%	3.92%	3.83%	2.49%
3	6.67%	5.37%	4.20%	4.11%	2.64%
4	7.53%	5.89%	4.29%	4.21%	2.64%

Table D.5.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	103.04%	113.81%	144.95%	141.35%	112.59%
1	111.50%	107.35%	128.48%	124.39%	105.39%
2	106.25%	101.62%	119.73%	115.48%	102.78%
3	86.12%	84.92%	89.88%	85.19%	81.43%
4	93.92%	82.92%	79.27%	74.46%	81.43%

Table D.5.4. Percentage of Time in Cash

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	65.16%	75.81%	83.23%	84.19%	93.55%
1	60.97%	70.97%	78.39%	79.35%	92.90%
2	58.71%	69.35%	76.77%	77.74%	92.26%
3	48.06%	67.10%	75.48%	76.45%	91.29%
4	30.97%	57.74%	72.90%	73.87%	91.29%

D:6 Financials Sector

Table D.6.1. Annualised Return

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	6.49%	5.13%	6.19%	6.96%	7.63%
1	6.82%	4.97%	6.57%	7.81%	8.48%
2	8.76%	6.50%	8.13%	8.43%	9.10%
3	11.99%	9.17%	10.84%	10.96%	11.65%
4	-1.28%	-4.36%	-3.50%	-0.43%	0.18%

Table D.6.2. Annualised Standard Deviation

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	10.20%	8.74%	8.00%	6.25%	6.05%
1	10.46%	9.18%	8.32%	6.56%	6.37%
2	10.72%	9.47%	8.63%	6.61%	6.43%
3	12.07%	10.81%	10.08%	8.41%	8.26%
4	22.62%	22.15%	22.09%	20.71%	20.65%

Table D.6.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	50.40%	43.26%	60.58%	89.89%	103.75%
1	52.30%	39.44%	62.80%	98.56%	111.95%
2	69.13%	54.45%	78.58%	107.06%	120.62%
3	88.20%	72.37%	94.16%	114.30%	124.68%
4	-11.62%	-25.78%	-21.96%	-8.60%	-5.63%

Table D.6.4. Percentage of Time in Cash

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	67.10%	74.52%	75.81%	80.97%	81.29%
1	61.94%	67.10%	71.29%	76.77%	77.10%
2	58.06%	63.87%	68.06%	73.87%	74.19%
3	37.74%	45.16%	49.35%	55.48%	55.81%
4	26.45%	33.23%	36.77%	45.81%	46.13%

D:7 Materials Sector

Table D.7.1. Annualised Return

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	5.23%	3.44%	7.75%	7.36%	7.16%
1	8.01%	5.33%	9.72%	9.32%	9.12%
2	7.41%	6.60%	9.76%	9.36%	9.16%
3	15.09%	12.62%	16.75%	16.33%	16.12%
4	16.25%	12.39%	16.52%	16.10%	15.88%

Table D.7.2. Annualised Standard Deviation

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	19.30%	18.92%	8.05%	7.84%	7.73%
1	19.93%	19.51%	9.33%	9.16%	9.06%
2	20.40%	19.65%	9.39%	9.22%	9.12%
3	21.76%	20.64%	11.60%	11.46%	11.39%
4	21.94%	20.64%	11.61%	11.48%	11.40%

Table D.7.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	20.14%	11.05%	79.57%	76.68%	75.26%
1	33.42%	20.41%	89.72%	87.10%	85.82%
2	29.71%	26.74%	89.59%	86.98%	85.69%
3	63.16%	54.61%	132.86%	130.76%	129.75%
4	67.92%	53.48%	130.65%	128.53%	127.51%

Table D.7.4. Percentage of Time in Cash

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	66.77%	71.29%	80.97%	82.58%	83.87%
1	58.06%	63.55%	73.23%	74.84%	76.13%
2	52.26%	60.97%	71.29%	72.90%	74.19%
3	36.13%	46.13%	53.23%	54.84%	56.13%
4	35.16%	45.81%	52.90%	54.52%	55.81%

D:8 Consumer Discretionary Sector

Table D.8.1. Annualised Return

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	4.77%	4.88%	4.10%	4.00%	6.54%
1	4.14%	4.43%	3.47%	3.19%	6.41%
2	4.74%	5.04%	4.07%	3.80%	7.12%
3	6.34%	6.63%	5.65%	5.37%	8.77%
4	4.66%	4.36%	3.40%	3.13%	7.83%

Table D.8.2. Annualised Standard Deviation

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	11.90%	11.80%	11.31%	10.99%	5.98%
1	12.23%	12.13%	11.68%	11.13%	6.08%
2	12.41%	12.31%	11.86%	11.32%	6.42%
3	17.26%	17.19%	16.88%	16.50%	7.49%
4	18.83%	18.82%	18.53%	18.19%	10.56%

Table D.8.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	28.80%	29.95%	24.37%	24.18%	86.87%
1	22.80%	25.37%	18.16%	16.60%	83.27%
2	27.39%	29.97%	22.98%	21.65%	89.90%
3	28.90%	30.74%	25.52%	24.41%	99.08%
4	17.59%	15.99%	11.08%	9.79%	61.34%

Table D.8.4. Percentage of Time in Cash

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	63.87%	66.45%	67.74%	71.29%	80.32%
1	58.71%	60.97%	61.94%	68.06%	78.06%
2	54.52%	56.77%	57.74%	63.87%	74.19%
3	41.61%	43.87%	44.84%	50.97%	64.84%
4	18.39%	19.35%	20.32%	26.45%	44.19%

D:9 Information Technology Sector

Table D.9.1. Annualised Return

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	8.12%	7.61%	9.79%	9.28%	11.88%
1	7.60%	7.21%	10.58%	10.33%	11.39%
2	6.98%	6.27%	9.72%	9.46%	10.08%
3	4.92%	3.98%	7.35%	7.10%	8.44%
4	9.87%	8.65%	12.39%	12.39%	13.15%

Table D.9.2. Annualised Standard Deviation

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	12.88%	12.06%	10.50%	10.30%	6.92%
1	15.93%	15.24%	10.93%	10.92%	7.39%
2	16.09%	15.39%	11.15%	11.14%	7.66%
3	16.32%	15.62%	11.47%	11.46%	7.98%
4	17.82%	17.27%	13.62%	13.62%	10.57%

Table D.9.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	52.59%	51.94%	80.39%	76.98%	152.16%
1	39.24%	38.50%	84.44%	82.22%	135.90%
2	35.04%	32.00%	75.06%	72.89%	114.01%
3	21.92%	16.85%	52.32%	50.23%	88.80%
4	47.82%	42.28%	81.10%	81.10%	111.70%

Table D.9.4. Percentage of Time in Cash

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	58.06%	64.19%	65.16%	70.00%	83.23%
1	51.29%	58.06%	62.58%	62.90%	82.26%
2	49.03%	56.13%	60.97%	61.29%	81.29%
3	46.45%	53.87%	58.71%	59.03%	79.68%
4	30.32%	34.84%	39.35%	39.35%	63.23%

D:10 Utilities Sector

Table D.10.1. Annualised Return

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	12.86%	9.57%	8.73%	5.91%	4.34%
1	12.69%	9.32%	8.57%	5.91%	4.34%
2	9.89%	7.16%	6.53%	4.04%	2.50%
3	12.43%	9.64%	8.68%	6.90%	5.31%
4	18.40%	15.54%	12.37%	11.12%	5.25%

Table D.10.2. Annualised Standard Deviation

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	9.14%	5.20%	4.95%	4.21%	3.12%
1	9.16%	5.22%	4.97%	4.21%	3.12%
2	10.18%	6.71%	6.01%	5.18%	4.33%
3	10.97%	7.87%	7.17%	6.53%	5.89%
4	11.97%	9.24%	8.58%	8.44%	5.90%

Table D.10.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	125.88%	158.05%	149.17%	108.50%	95.94%
1	123.86%	152.82%	145.49%	108.50%	95.94%
2	83.95%	86.62%	86.37%	52.04%	26.56%
3	101.06%	105.35%	102.22%	85.13%	67.39%
4	142.42%	153.54%	128.54%	115.78%	66.24%

Table D.10.4. Percentage of Time in Cash

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	66.45%	71.29%	77.10%	81.29%	89.03%
1	65.48%	70.65%	76.77%	81.29%	89.03%
2	59.68%	65.16%	74.52%	80.00%	87.74%
3	48.39%	53.87%	64.84%	70.65%	78.39%
4	26.13%	31.29%	42.26%	43.23%	77.74%

Appendix E: Technical Charting Heuristics Trend Timing Strategy (2009 to 2015) E

E:1 Healthcare Sector

Table E.1.1. Annualised Return

Bear Flag Fit Threshold	Bull Flag Fit Threshold 0	1	2	3	4
0	7.16%	6.22%	4.92%	2.84%	3.16%
1	5.83%	5.97%	4.92%	2.84%	3.16%
2	12.31%	10.96%	10.48%	7.57%	7.90%
3	9.95%	8.33%	7.25%	4.75%	5.07%
4	10.64%	9.01%	7.25%	4.75%	5.07%

Table E.1.2. Annualised Standard Deviation

Bear Flag Fit Threshold	Bull Flag Fit Threshold 0	1	2	3	4
0	7.61%	7.25%	6.55%	6.27%	6.23%
1	8.08%	7.27%	6.55%	6.27%	6.23%
2	10.05%	8.73%	8.45%	7.77%	7.73%
3	9.45%	8.01%	7.36%	6.50%	6.46%
4	9.50%	8.07%	7.36%	6.50%	6.46%

Table E.1.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold	Bull Flag Fit Threshold 0	1	2	3	4
0	76.31%	67.27%	54.49%	23.86%	29.07%
1	55.50%	63.63%	54.49%	23.86%	29.07%
2	109.05%	110.04%	108.14%	80.13%	84.79%
3	91.03%	87.17%	80.11%	52.38%	57.70%
4	97.81%	94.94%	80.11%	52.38%	57.70%

Table E.1.4. Percentage of Time in Cash

Bear Flag Fit Threshold	Bull Flag Fit Threshold 0	1	2	3	4
0	71.29%	76.13%	81.61%	86.77%	87.10%
1	69.35%	75.81%	81.61%	86.77%	87.10%
2	40.32%	53.87%	58.71%	70.65%	70.97%
3	44.84%	58.71%	64.52%	76.77%	77.10%
4	44.19%	58.06%	64.52%	76.77%	77.10%

E:2 Energy Sector

Table E.2.1. Annualised Return

Bear Flag Fit Threshold	Bull Flag Fit Threshold 0	1	2	3	4
0	5.08%	2.88%	2.91%	-2.69%	-2.15%
1	7.52%	8.79%	8.82%	2.90%	4.48%
2	10.96%	12.07%	12.10%	6.01%	7.63%
3	11.66%	12.71%	12.74%	6.61%	7.30%
4	11.90%	12.84%	12.89%	7.94%	7.84%

Table E.2.2. Annualised Standard Deviation

Bear Flag Fit Threshold	Bull Flag Fit Threshold 0	1	2	3	4
0	14.13%	11.87%	11.87%	12.11%	11.70%
1	14.85%	14.60%	14.60%	14.84%	14.68%
2	15.35%	15.03%	15.03%	15.29%	15.13%
3	16.25%	16.09%	16.09%	16.33%	15.93%
4	17.62%	16.97%	16.97%	17.12%	16.84%

Table E.2.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold	Bull Flag Fit Threshold 0	1	2	3	4
0	26.39%	12.93%	13.17%	-33.34%	-29.86%
1	41.58%	50.98%	51.19%	10.48%	21.35%
2	62.66%	71.30%	71.51%	30.47%	41.53%
3	63.49%	70.62%	70.81%	32.25%	37.38%
4	59.91%	67.71%	68.06%	38.53%	38.54%

Table E.2.4. Percentage of Time in Cash

Bear Flag Fit Threshold	Bull Flag Fit Threshold 0	1	2	3	4
0	60.65%	72.26%	73.23%	79.03%	81.61%
1	56.77%	63.23%	64.19%	70.00%	72.26%
2	50.00%	57.74%	58.71%	64.52%	66.77%
3	39.35%	42.58%	43.55%	49.35%	60.00%
4	30.00%	37.10%	37.74%	45.48%	55.81%

E:3 Industrials Sector

Table E.3.1. Annualised Return

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	2.84%	4.49%	4.07%	2.97%	2.71%
1	9.22%	13.20%	12.52%	11.33%	11.05%
2	11.72%	16.12%	13.69%	12.49%	12.20%
3	14.54%	18.93%	15.54%	14.33%	14.03%
4	13.98%	17.54%	14.32%	13.12%	12.83%

Table E.3.2. Annualised Standard Deviation

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	13.87%	10.54%	9.91%	9.57%	9.52%
1	15.77%	12.99%	12.10%	11.84%	11.81%
2	16.60%	13.91%	12.96%	12.72%	12.69%
3	16.90%	14.26%	13.20%	12.96%	12.93%
4	17.27%	14.82%	13.68%	13.46%	13.43%

Table E.3.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	10.75%	29.86%	27.47%	16.99%	14.30%
1	49.92%	91.27%	92.29%	84.33%	82.15%
2	62.50%	106.17%	95.18%	87.59%	85.53%
3	78.06%	123.31%	107.55%	100.13%	98.09%
4	73.15%	109.32%	94.82%	87.50%	85.53%

Table E.3.4. Percentage of Time in Cash

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	63.23%	76.45%	85.81%	86.13%	87.10%
1	51.61%	61.94%	73.87%	74.19%	75.16%
2	42.90%	55.16%	69.68%	70.00%	70.97%
3	32.90%	45.48%	63.55%	63.87%	64.84%
4	27.10%	39.68%	59.03%	59.35%	60.32%

E:4 Telecommunication Services Sector

Table E.4.1. Annualised Return

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	1.32%	2.76%	3.61%	-0.71%	-2.10%
1	5.19%	6.12%	6.68%	1.90%	0.00%
2	6.57%	7.51%	8.08%	3.03%	1.35%
3	7.64%	8.58%	8.95%	4.23%	3.95%
4	7.62%	8.56%	8.93%	4.18%	3.89%

Table E.4.2. Annualised Standard Deviation

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	9.39%	8.30%	7.58%	6.45%	5.92%
1	10.50%	9.59%	8.62%	7.64%	7.11%
2	11.35%	10.51%	9.63%	8.55%	7.96%
3	12.54%	11.78%	11.10%	9.95%	9.44%
4	12.54%	11.78%	11.10%	9.95%	9.44%

Table E.4.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	-0.28%	16.98%	29.82%	-31.94%	-58.13%
1	36.63%	49.74%	61.81%	7.29%	-18.92%
2	46.08%	58.66%	69.89%	19.74%	0.02%
3	50.17%	61.41%	68.50%	29.01%	27.54%
4	50.02%	61.25%	68.33%	28.49%	26.96%

Table E.4.4. Percentage of Time in Cash

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	55.48%	61.29%	67.42%	78.39%	87.74%
1	49.35%	54.52%	63.55%	74.84%	84.52%
2	38.71%	43.87%	52.90%	67.42%	78.39%
3	17.74%	22.90%	30.32%	49.35%	59.03%
4	16.77%	21.94%	29.35%	48.71%	58.71%

E:5 Consumer Staples Sector

Table E.5.1. Annualised Return

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	8.15%	6.90%	6.96%	5.91%	4.39%
1	8.70%	7.31%	7.09%	7.59%	6.11%
2	11.18%	9.47%	9.13%	9.63%	7.96%
3	11.11%	9.69%	9.34%	10.06%	9.03%
4	10.78%	8.83%	8.48%	9.67%	8.67%

Table E.5.2. Annualised Standard Deviation

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	7.10%	6.83%	6.67%	5.90%	5.74%
1	8.06%	7.79%	7.68%	6.50%	6.37%
2	8.68%	8.22%	8.12%	7.01%	6.83%
3	9.32%	8.87%	8.77%	7.68%	7.41%
4	9.69%	9.18%	9.09%	7.75%	7.48%

Table E.5.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	95.83%	81.36%	84.20%	77.37%	53.06%
1	91.14%	76.57%	74.81%	95.99%	74.70%
2	113.31%	98.86%	95.85%	118.19%	96.93%
3	104.75%	94.06%	91.12%	113.43%	103.69%
4	97.31%	81.51%	78.55%	107.40%	97.91%

Table E.5.4. Percentage of Time in Cash

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	60.00%	67.10%	69.35%	81.29%	85.48%
1	52.26%	60.32%	61.94%	76.13%	80.65%
2	38.06%	50.00%	51.94%	66.13%	71.94%
3	27.10%	39.68%	41.61%	57.42%	64.19%
4	20.97%	33.55%	35.48%	55.16%	62.26%

E:6 Financials Sector

Table E.6.1. Annualised Return

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	9.67%	11.02%	8.26%	5.66%	5.29%
1	8.26%	7.60%	6.65%	4.09%	3.73%
2	19.96%	17.46%	16.70%	13.90%	13.51%
3	20.78%	20.18%	19.10%	16.24%	15.84%
4	19.08%	17.39%	17.67%	17.27%	17.48%

Table E.6.2. Annualised Standard Deviation

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	20.28%	18.20%	17.61%	19.37%	19.33%
1	20.90%	18.65%	17.81%	19.55%	19.51%
2	22.48%	20.22%	19.69%	21.30%	21.26%
3	22.96%	20.77%	20.17%	21.74%	21.71%
4	24.14%	23.19%	23.00%	22.99%	22.98%

Table E.6.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	41.06%	53.14%	39.26%	22.25%	20.43%
1	33.09%	33.53%	29.80%	14.02%	12.22%
2	82.78%	79.66%	77.98%	58.92%	57.20%
3	84.66%	90.66%	88.04%	68.50%	66.78%
4	73.45%	69.15%	70.95%	69.28%	70.20%

Table E.6.4. Percentage of Time in Cash

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	65.16%	74.19%	80.00%	76.13%	76.77%
1	51.61%	69.03%	79.35%	75.48%	76.13%
2	35.81%	58.39%	65.16%	61.29%	61.94%
3	28.06%	49.68%	57.10%	53.23%	53.87%
4	10.00%	34.52%	38.39%	38.71%	39.03%

E:7 Materials Sector

Table E.7.1. Annualised Return

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	3.84%	0.44%	-0.72%	-1.94%	2.71%
1	5.03%	3.20%	2.11%	0.85%	4.39%
2	10.13%	8.07%	7.81%	7.68%	11.46%
3	9.07%	7.02%	6.76%	6.64%	11.60%
4	8.59%	7.63%	7.98%	8.33%	12.37%

Table E.7.2. Annualised Standard Deviation

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	15.17%	14.33%	13.99%	12.31%	9.08%
1	17.27%	17.04%	16.75%	15.39%	9.97%
2	18.16%	17.96%	17.75%	17.38%	12.80%
3	18.70%	18.50%	18.30%	17.94%	13.27%
4	19.73%	19.69%	19.66%	19.29%	13.97%

Table E.7.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	16.46%	-6.34%	-14.75%	-26.72%	15.01%
1	21.33%	10.86%	4.57%	-3.22%	30.58%
2	48.37%	37.45%	36.41%	36.46%	79.04%
3	41.27%	30.69%	29.61%	29.51%	77.32%
4	36.68%	31.94%	33.75%	36.18%	78.90%

Table E.7.4. Percentage of Time in Cash

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	60.97%	62.58%	64.84%	72.26%	87.10%
1	52.90%	54.52%	57.10%	64.52%	83.55%
2	45.16%	46.45%	48.39%	58.39%	77.42%
3	40.00%	41.29%	43.23%	53.23%	72.58%
4	32.26%	33.23%	34.52%	46.77%	71.94%

E:8 Consumer Discretionary Sector

Table E.8.1. Annualised Return

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	10.78%	4.49%	3.25%	3.32%	0.67%
1	12.58%	7.45%	6.92%	7.29%	4.53%
2	13.35%	8.64%	9.18%	9.55%	6.74%
3	13.30%	8.83%	9.18%	9.56%	5.80%
4	17.79%	12.52%	12.88%	13.27%	10.50%

Table E.8.2. Annualised Standard Deviation

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	11.06%	9.35%	8.32%	8.08%	7.05%
1	12.53%	11.18%	10.19%	10.02%	9.23%
2	12.87%	11.58%	10.78%	10.61%	9.88%
3	13.68%	12.00%	11.22%	11.06%	10.24%
4	14.70%	13.64%	12.95%	12.82%	11.97%

Table E.8.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	85.27%	33.63%	22.91%	24.40%	-9.66%
1	89.64%	54.65%	54.65%	59.26%	34.53%
2	93.27%	62.96%	72.64%	77.31%	54.62%
3	87.37%	62.39%	69.86%	74.25%	43.47%
4	111.85%	81.91%	89.03%	93.01%	76.43%

Table E.8.4. Percentage of Time in Cash

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	63.23%	71.61%	78.39%	80.32%	87.10%
1	58.39%	68.06%	75.16%	76.77%	83.55%
2	55.16%	64.84%	68.39%	70.00%	76.77%
3	45.16%	60.00%	63.87%	65.48%	75.16%
4	36.45%	47.74%	51.61%	53.23%	64.52%

E:9 Information Technology Sector

Table E.9.1. Annualised Return

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	3.06%	5.01%	3.64%	4.48%	0.18%
1	3.61%	5.37%	4.14%	5.49%	-0.05%
2	7.44%	10.21%	8.60%	8.25%	1.56%
3	12.22%	15.08%	13.59%	12.25%	7.43%
4	12.83%	14.93%	13.86%	12.32%	7.49%

Table E.9.2. Annualised Standard Deviation

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	11.24%	10.33%	7.70%	5.31%	3.43%
1	11.78%	10.71%	8.19%	5.65%	3.48%
2	13.07%	12.08%	11.78%	6.94%	5.23%
3	14.00%	13.07%	12.80%	8.44%	7.60%
4	14.70%	13.90%	13.67%	9.04%	8.26%

Table E.9.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	15.25%	35.41%	29.82%	59.03%	-34.04%
1	19.19%	37.60%	34.12%	73.43%	-40.32%
2	46.61%	73.37%	61.55%	99.49%	4.06%
3	77.69%	105.12%	95.64%	129.15%	80.00%
4	78.14%	97.73%	91.52%	121.45%	74.47%

Table E.9.4. Percentage of Time in Cash

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	62.58%	65.81%	73.55%	84.84%	92.58%
1	56.45%	62.26%	70.65%	83.55%	92.26%
2	47.74%	53.23%	62.26%	81.29%	91.94%
3	43.87%	49.68%	58.39%	78.06%	85.81%
4	35.48%	39.35%	47.74%	73.23%	80.97%

E:10 Utilities Sector

Table E.10.1. Annualised Return

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	2.55%	2.67%	2.23%	0.98%	1.07%
1	3.54%	3.13%	3.01%	1.76%	1.78%
2	5.89%	5.48%	5.35%	3.92%	3.95%
3	5.45%	6.11%	6.07%	5.18%	4.07%
4	6.10%	3.94%	3.67%	4.24%	3.85%

Table E.10.2. Annualised Standard Deviation

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	9.90%	9.13%	8.95%	8.18%	7.90%
1	10.05%	9.39%	9.16%	8.41%	8.03%
2	10.52%	9.81%	9.59%	8.88%	8.52%
3	10.78%	9.90%	9.69%	9.07%	8.52%
4	12.29%	11.91%	11.84%	11.18%	10.78%

Table E.10.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	12.16%	14.53%	9.84%	-4.44%	-3.44%
1	21.79%	19.02%	18.15%	4.88%	5.43%
2	43.24%	42.12%	41.78%	29.03%	30.56%
3	38.09%	48.07%	48.72%	42.25%	31.94%
4	38.72%	21.73%	19.59%	25.92%	23.23%

Table E.10.4. Percentage of Time in Cash

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	54.19%	62.26%	64.84%	73.87%	79.03%
1	48.39%	54.19%	57.74%	66.77%	75.81%
2	43.23%	50.32%	53.87%	63.23%	72.26%
3	39.03%	46.77%	50.00%	59.03%	71.94%
4	19.35%	23.55%	24.84%	36.77%	46.13%

Appendix F: Technical Charting Heuristics Trend Timing Strategy (2002 to 2015)

F:1 Healthcare Sector

Table F.1.1. Annualised Return

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	4.67%	3.20%	2.96%	2.27%	3.04%
1	4.91%	4.20%	4.05%	3.18%	2.79%
2	6.89%	6.00%	5.67%	4.20%	4.12%
3	6.20%	5.44%	5.01%	4.16%	3.72%
4	5.41%	4.79%	4.33%	3.48%	3.04%

Table F.1.2. Annualised Standard Deviation

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	7.17%	6.37%	5.76%	5.27%	4.96%
1	7.89%	6.86%	6.27%	5.84%	5.16%
2	9.08%	7.82%	7.39%	6.62%	5.93%
3	9.84%	8.74%	8.42%	7.79%	7.33%
4	10.80%	9.81%	9.55%	9.00%	8.61%

Table F.1.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	46.34%	29.07%	28.09%	17.44%	34.25%
1	45.23%	41.56%	43.04%	31.47%	28.03%
2	61.06%	59.55%	58.53%	43.17%	46.71%
3	49.37%	46.87%	43.54%	36.13%	32.34%
4	37.60%	35.11%	31.20%	23.74%	19.70%

Table F.1.4. Percentage of Time in Cash

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	68.84%	73.77%	79.17%	85.21%	87.44%
1	62.64%	69.32%	75.20%	80.92%	86.17%
2	49.92%	60.25%	65.34%	75.36%	80.76%
3	42.93%	52.31%	56.60%	66.45%	71.07%
4	39.27%	48.49%	53.90%	63.75%	68.36%

F:2 Energy Sector

Table F.2.1. Annualised Return

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	8.94%	5.85%	4.67%	2.87%	1.97%
1	8.83%	6.34%	5.39%	3.66%	3.26%
2	12.16%	8.52%	7.16%	5.38%	4.83%
3	12.25%	8.58%	6.91%	5.14%	4.14%
4	12.39%	8.62%	6.50%	4.93%	4.09%

Table F.2.2. Annualised Standard Deviation

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	16.31%	11.95%	11.03%	10.23%	9.06%
1	17.37%	13.41%	12.48%	11.78%	10.91%
2	18.07%	14.17%	13.00%	12.34%	11.50%
3	18.65%	14.98%	13.66%	13.02%	12.07%
4	19.72%	16.34%	14.45%	13.77%	12.86%

Table F.2.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	46.58%	37.67%	30.14%	14.88%	6.92%
1	43.11%	37.24%	32.42%	19.67%	17.50%
2	59.87%	50.63%	44.73%	32.73%	30.33%
3	58.48%	48.28%	40.76%	29.13%	23.13%
4	55.99%	44.49%	35.66%	26.06%	21.35%

Table F.2.4. Percentage of Time in Cash

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	57.07%	67.09%	75.36%	81.08%	87.44%
1	51.35%	61.21%	71.22%	77.11%	83.47%
2	43.88%	54.53%	68.52%	74.56%	81.08%
3	36.72%	45.15%	60.73%	66.77%	77.42%
4	27.50%	35.77%	55.17%	62.48%	73.29%

F:3 Industrials Sector

Table F.3.1. Annualised Return

Bull Flag Fit Threshold

Bear Flag Fit Threshold	0	1	2	3	4
0	4.11%	4.38%	4.05%	3.82%	3.31%
1	6.02%	7.21%	6.97%	6.35%	5.83%
2	7.99%	8.72%	7.82%	7.32%	6.79%
3	10.18%	10.81%	9.47%	8.70%	8.17%
4	9.65%	10.10%	8.83%	8.69%	8.15%

Table F.3.2. Annualised Standard Deviation

Bull Flag Fit Threshold

Bear Flag Fit Threshold	0	1	2	3	4
0	11.55%	9.13%	8.75%	8.37%	8.09%
1	13.12%	11.09%	10.54%	10.19%	9.96%
2	15.31%	11.69%	11.08%	10.74%	10.53%
3	16.00%	12.37%	11.71%	11.37%	11.17%
4	16.45%	12.88%	12.18%	11.72%	11.53%

Table F.3.3. Annualised Sharpe Ratio

Bull Flag Fit Threshold

Bear Flag Fit Threshold	0	1	2	3	4
0	23.96%	33.22%	30.86%	29.54%	24.23%
1	35.61%	52.88%	53.36%	49.13%	44.99%
2	43.43%	63.11%	58.46%	55.61%	51.71%
3	55.17%	76.53%	69.41%	64.74%	61.10%
4	50.46%	67.96%	61.40%	62.61%	59.02%

Table F.3.4. Percentage of Time in Cash

Bull Flag Fit Threshold

Bear Flag Fit Threshold	0	1	2	3	4
0	64.07%	76.79%	81.56%	83.78%	86.01%
1	55.96%	67.73%	73.93%	76.47%	78.70%
2	46.90%	62.48%	70.11%	72.81%	75.04%
3	34.82%	52.94%	62.32%	65.18%	67.41%
4	27.98%	47.06%	57.07%	60.73%	62.96%

F:4 Telecommunication Services Sector

Table F.4.1. Annualised Return

Bull Flag Fit Threshold

Bear Flag Fit Threshold	0	1	2	3	4
0	3.69%	4.40%	3.92%	2.78%	0.60%
1	5.99%	6.17%	5.29%	3.97%	0.49%
2	6.95%	7.14%	6.05%	4.62%	1.96%
3	6.60%	7.21%	6.03%	4.78%	3.11%
4	5.72%	6.33%	5.46%	3.55%	1.90%

Table F.4.2. Annualised Standard Deviation

Bull Flag Fit Threshold

Bear Flag Fit Threshold	0	1	2	3	4
0	12.14%	11.74%	11.31%	10.80%	9.94%
1	12.81%	12.43%	11.85%	11.36%	10.19%
2	13.13%	12.76%	12.14%	11.58%	10.60%
3	13.82%	13.41%	12.87%	12.24%	11.26%
4	14.13%	13.73%	13.12%	12.61%	11.65%

Table F.4.3. Annualised Sharpe Ratio

Bull Flag Fit Threshold

Bear Flag Fit Threshold	0	1	2	3	4
0	19.27%	26.01%	22.79%	13.27%	-7.52%
1	36.23%	38.85%	33.25%	23.12%	-8.40%
2	42.65%	45.38%	38.76%	28.25%	5.79%
3	38.00%	43.73%	36.41%	28.01%	15.69%
4	30.94%	36.27%	31.35%	17.46%	4.77%

Table F.4.4. Percentage of Time in Cash

Bull Flag Fit Threshold

Bear Flag Fit Threshold	0	1	2	3	4
0	57.39%	60.41%	65.82%	73.13%	87.12%
1	49.92%	52.78%	60.89%	68.52%	86.01%
2	44.04%	46.90%	57.23%	66.30%	81.56%
3	31.16%	34.98%	44.52%	55.80%	71.54%
4	26.07%	29.89%	40.22%	51.19%	67.09%

F:5 Consumer Staples Sector

Table F.5.1. Annualised Return

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	5.73%	5.22%	4.99%	5.15%	3.42%
1	6.34%	5.46%	5.09%	6.00%	4.28%
2	7.54%	6.50%	6.07%	6.82%	5.09%
3	6.37%	5.45%	4.90%	5.74%	4.58%
4	6.86%	5.20%	4.31%	5.37%	4.40%

Table F.5.2. Annualised Standard Deviation

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	6.26%	5.56%	4.94%	4.09%	3.63%
1	6.89%	6.29%	5.77%	4.71%	4.18%
2	7.69%	7.02%	6.56%	5.06%	4.49%
3	8.11%	7.26%	6.80%	5.33%	4.63%
4	8.68%	7.63%	7.02%	5.41%	4.67%

Table F.5.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	70.13%	69.62%	73.71%	92.98%	57.01%
1	72.44%	65.31%	64.88%	98.95%	70.25%
2	80.52%	73.43%	72.09%	108.10%	83.31%
3	61.88%	56.53%	52.18%	82.42%	69.77%
4	63.51%	50.46%	42.14%	74.35%	65.36%

Table F.5.4. Percentage of Time in Cash

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	63.12%	71.86%	76.63%	84.10%	90.78%
1	57.23%	66.14%	70.59%	79.17%	88.08%
2	48.81%	59.94%	64.55%	74.24%	84.26%
3	41.34%	56.92%	62.00%	72.50%	83.15%
4	29.89%	49.28%	57.71%	70.11%	82.19%

F:6 Financials Sector

Table F.6.1. Annualised Return

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	5.77%	4.48%	4.41%	6.13%	4.34%
1	5.26%	2.80%	3.82%	5.76%	3.98%
2	9.48%	5.96%	7.14%	8.67%	6.83%
3	11.17%	7.35%	8.41%	9.86%	8.01%
4	4.68%	1.53%	2.10%	3.52%	3.92%

Table F.6.2. Annualised Standard Deviation

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	17.01%	16.22%	15.87%	14.00%	9.89%
1	17.45%	16.58%	16.05%	14.20%	10.16%
2	18.15%	17.20%	16.83%	14.98%	11.25%
3	18.65%	17.65%	17.23%	15.43%	11.84%
4	24.35%	23.60%	23.47%	22.83%	22.81%

Table F.6.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	26.00%	19.32%	19.31%	34.18%	30.26%
1	22.41%	8.79%	15.43%	31.11%	25.87%
2	44.82%	26.84%	34.42%	48.86%	48.78%
3	52.68%	34.04%	40.98%	55.20%	56.29%
4	13.69%	0.78%	3.21%	9.50%	11.29%

Table F.6.4. Percentage of Time in Cash

Bear Flag Fit Threshold \ Bull Flag Fit Threshold	0	1	2	3	4
0	65.34%	71.54%	74.88%	80.13%	82.35%
1	56.12%	65.34%	72.34%	77.74%	79.97%
2	48.65%	60.57%	65.82%	71.38%	73.61%
3	36.72%	50.72%	56.28%	62.00%	64.23%
4	18.92%	36.57%	40.22%	44.83%	45.15%

F:7 Materials Sector

Table F.7.1. Annualised Return

Bear Flag Fit Threshold	Bull Flag Fit Threshold: 0	1	2	3	4
0	4.46%	1.89%	2.68%	1.87%	4.17%
1	5.60%	3.40%	4.25%	3.43%	5.15%
2	7.80%	6.40%	7.09%	6.84%	8.62%
3	11.00%	8.80%	9.88%	9.62%	12.05%
4	11.31%	8.99%	10.38%	10.36%	12.31%

Table F.7.2. Annualised Standard Deviation

Bear Flag Fit Threshold	Bull Flag Fit Threshold: 0	1	2	3	4
0	17.94%	17.39%	12.18%	11.19%	9.48%
1	19.27%	18.95%	14.31%	13.48%	10.63%
2	19.91%	19.43%	14.91%	14.64%	12.06%
3	20.85%	20.18%	15.98%	15.73%	13.21%
4	21.40%	20.73%	16.76%	16.50%	13.57%

Table F.7.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold	Bull Flag Fit Threshold: 0	1	2	3	4
0	17.37%	3.13%	10.96%	4.71%	29.80%
1	22.06%	10.81%	20.27%	15.44%	35.75%
2	32.41%	26.02%	38.56%	37.55%	60.31%
3	46.31%	36.93%	53.41%	52.61%	81.01%
4	46.55%	36.89%	53.93%	54.64%	80.83%

Table F.7.4. Percentage of Time in Cash

Bear Flag Fit Threshold	Bull Flag Fit Threshold: 0	1	2	3	4
0	63.28%	66.14%	72.18%	76.63%	84.74%
1	54.69%	58.03%	64.23%	68.68%	78.86%
2	48.01%	52.78%	58.98%	64.71%	74.88%
3	37.52%	42.93%	47.54%	53.26%	63.59%
4	33.23%	38.79%	43.08%	49.92%	63.12%

F:8 Consumer Discretionary Sector

Table F.8.1. Annualised Return

Bear Flag Fit Threshold	Bull Flag Fit Threshold: 0	1	2	3	4
0	6.64%	3.66%	2.68%	2.76%	2.67%
1	5.53%	2.62%	1.90%	1.90%	2.14%
2	7.19%	5.04%	4.82%	4.97%	5.25%
3	8.49%	6.43%	6.11%	6.16%	5.58%
4	9.02%	7.05%	6.73%	6.77%	7.41%

Table F.8.2. Annualised Standard Deviation

Bear Flag Fit Threshold	Bull Flag Fit Threshold: 0	1	2	3	4
0	11.81%	10.99%	10.31%	10.03%	7.16%
1	12.27%	11.32%	10.60%	10.21%	7.35%
2	13.06%	12.39%	11.81%	11.47%	9.01%
3	15.96%	15.23%	14.76%	14.49%	9.60%
4	17.10%	16.79%	16.36%	16.12%	11.77%

Table F.8.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold	Bull Flag Fit Threshold: 0	1	2	3	4
0	44.82%	21.06%	12.91%	14.11%	18.45%
1	34.11%	11.25%	5.25%	5.45%	10.80%
2	44.77%	29.81%	29.42%	31.56%	43.32%
3	44.75%	33.36%	32.30%	33.19%	44.14%
4	44.87%	33.96%	32.92%	33.67%	51.51%

Table F.8.4. Percentage of Time in Cash

Bear Flag Fit Threshold	Bull Flag Fit Threshold: 0	1	2	3	4
0	63.12%	68.36%	72.34%	75.20%	82.99%
1	58.66%	64.55%	68.52%	72.66%	80.92%
2	54.37%	59.94%	62.16%	66.14%	74.56%
3	42.93%	51.03%	53.42%	57.23%	69.16%
4	29.57%	32.91%	35.29%	39.11%	53.74%

Appendix F: Technical Charting Heuristics Trend Timing Strategy (2002 to 2015) F

F:9 Information Technology Sector

Table F.9.1. Annualised Return

Bear Flag Fit Threshold	Bull Flag Fit Threshold				
	0	1	2	3	4
0	5.42%	5.74%	6.10%	6.28%	6.18%
1	5.25%	5.63%	6.34%	6.90%	5.83%
2	6.54%	7.53%	8.14%	7.85%	5.21%
3	7.81%	8.67%	9.38%	8.62%	4.43%
4	10.24%	10.94%	11.98%	11.23%	6.65%

Table F.9.2. Annualised Standard Deviation

Bear Flag Fit Threshold	Bull Flag Fit Threshold				
	0	1	2	3	4
0	12.42%	11.31%	9.34%	8.36%	5.31%
1	14.43%	13.68%	9.87%	8.94%	5.62%
2	15.09%	14.31%	11.62%	9.50%	5.79%
3	15.62%	14.86%	12.29%	10.26%	5.99%
4	16.59%	15.91%	13.56%	11.49%	7.74%

Table F.9.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold	Bull Flag Fit Threshold				
	0	1	2	3	4
0	32.76%	38.87%	50.94%	59.04%	90.98%
1	27.04%	31.36%	50.58%	62.08%	79.64%
2	34.39%	43.20%	58.47%	68.43%	66.74%
3	41.39%	49.29%	65.36%	70.88%	51.51%
4	53.62%	60.31%	78.44%	86.05%	68.52%

Table F.9.4. Percentage of Time in Cash

Bear Flag Fit Threshold	Bull Flag Fit Threshold				
	0	1	2	3	4
0	60.25%	65.34%	69.63%	77.58%	88.24%
1	54.05%	59.30%	66.77%	73.29%	87.60%
2	47.69%	53.90%	61.84%	71.38%	87.12%
3	44.52%	51.03%	58.82%	68.68%	86.33%
4	33.70%	38.95%	46.42%	58.98%	78.22%

F:10 Utilities Sector

Table F.10.1. Annualised Return

Bear Flag Fit Threshold	Bull Flag Fit Threshold				
	0	1	2	3	4
0	6.45%	5.08%	4.03%	2.07%	1.41%
1	6.49%	4.86%	4.35%	2.45%	1.76%
2	5.88%	4.52%	4.07%	2.16%	1.47%
3	6.54%	5.70%	5.09%	3.54%	2.80%
4	9.62%	7.37%	5.30%	5.07%	2.66%

Table F.10.2. Annualised Standard Deviation

Bear Flag Fit Threshold	Bull Flag Fit Threshold				
	0	1	2	3	4
0	9.36%	7.22%	6.87%	6.10%	5.57%
1	9.98%	8.20%	7.01%	6.26%	5.66%
2	10.78%	9.07%	7.82%	7.07%	6.55%
3	11.76%	10.13%	8.97%	8.34%	7.89%
4	12.93%	11.67%	11.28%	10.25%	9.15%

Table F.10.3. Annualised Sharpe Ratio

Bear Flag Fit Threshold	Bull Flag Fit Threshold				
	0	1	2	3	4
0	54.56%	51.68%	39.07%	11.79%	1.08%
1	51.52%	42.78%	42.79%	17.64%	7.24%
2	42.05%	35.00%	34.82%	11.53%	1.88%
3	44.17%	42.98%	41.70%	26.30%	18.44%
4	64.00%	51.60%	35.03%	36.36%	14.41%

Table F.10.4. Percentage of Time in Cash

Bear Flag Fit Threshold	Bull Flag Fit Threshold				
	0	1	2	3	4
0	60.57%	67.09%	71.38%	77.90%	84.42%
1	55.33%	60.10%	67.73%	74.40%	82.83%
2	49.76%	55.33%	64.55%	71.86%	80.29%
3	42.13%	48.01%	58.03%	65.34%	74.09%
4	21.46%	25.44%	31.80%	41.02%	61.21%