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University of Cape Town

FACULTY OF COMMERCE

APPLICATIONS OF GLOBAL EQUITY STYLE INDICES IN

ACTIVE AND PASSIVE PORTFOLIO MANAGEMENT

BY

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Thesis prepared under the supervision of Professor Paul van Rensburg and submitted in full fulfillment of the requirements for the Degree of Doctor of Philosophy in Finance in the School of Management Studies of the Faculty of Commerce at the University of Cape Town

Cape Town, Republic of South Africa

February 2010

Declaration

Apart from the assistance which is acknowledged and the quotations which are specifically referenced in the text and bibliography section of the thesis, this thesis is entirely my own work and not being submitted for degree purposes at any other university.

Heng-Hsing Hsieh

February 2010

University of Cape Town

Dedication

Dedicated unconditionally to my parents, Mr. J.S. Hsieh and Mrs. T.W. Wang

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Most thanks to my supervisor, Prof. Paul van Rensburg, for his unconditional assistance and guidance in my humble learning process to complete this thesis, and his invaluable insights into the exciting investment world. His comments and suggestions are sincerely appreciated.

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All of the mistakes are mine.

Abstract

Based on the noise trading argument of Hsu (2006), the cap-weighted market portfolio is a mean-variance suboptimal portfolio in practice. The success of the Fama and French (1993) 3-factor model in explaining empirical anomalies of the Capital Asset Pricing Model (CAPM) suggests that style investing which places portfolios out-of-sync with the broad market has the potential to generate significant alpha. Since momentum abnormal return is the only anomaly that is not explained by the 3-factor model, it could well be the third style-based factor in addition to the size factor and the value factor to complete the model. With the goal of searching for practical mean-variance efficient allocation mechanisms in the global capital market, this study develops and examines the long-only, long-short leverage and market neutral strategies from the global size, value and momentum proxies along with the Morgan Stanley Capital International World Index (MSCI World Index) over the examination period from 1 January 1991 to 31 December 2008. Keeping in mind the systemic impact of the global financial crisis on the performances of all asset classes, cash protection mechanisms based on the filter rule and exponential moving average (EMA) techniques are tested on the above-mentioned investment strategies.

Candidate global style indices are developed from the monthly largest 300 constituents of the Dow Jones Sector Titans Composite Index over the period from 1 January 1991 to 31 December 2008. Each candidate index is unique in terms of its weighting method, index coverage, the firm-specific attribute upon which the index is constructed and the specific investment style represented by the index. Candidate style indices are evaluated in terms of their risk-adjusted returns, representativeness of the underlying investment style and implicit trading costs through rebalancing. Using the MSCI World Index as the market proxy and the U.S. 3-month Treasury bill to represent the risk-free asset, large cap-weighted indices are found to exhibit significant negative alpha over the examination periods. By contrast, large equally-weighted indices and fundamental indices are price-insensitive and are not subject to the performance drag inherent in the cap-weighted indices. The cross-sectional regression residuals proposed by Yu (2008) are found effective in classifying global value and glamour stocks based on multiple fundamental attributes. In addition, the innovative mean-adjusted past returns represent an unbiased approach to classify prior winner and loser stocks. By removing the most recent month return from the past 12-month return based on the observed 1-month reversal of momentum stocks, momentum indices constructed from the lagged 11-month prior returns earn significant alpha over the examination period.

The global size, momentum and value proxies chosen from the candidate indices are found to outperform the MSCI World benchmark, which in turn outperforms the counterpart global cap-

weighted proxy, the global loser proxy and the global glamour proxy on a risk-adjusted basis. The global value proxy is found to provide consistent performance throughout the examination period and appears to be defensive in terms of its standard deviation, maximum drawdown, 5 percent value-at-risk (VaR) and portfolio turnover. By contrast, the aggressive global momentum proxy achieves the best risk-adjusted performance during the bullish first sub-period but provides ordinary performance in the bearish second sub-period. The return attribution analysis indicates that the return difference between the global momentum and value proxies is mainly due to the differences in their sector allocation policies. All these differences serve as evidence that value investing and momentum investing are two segmented investment style categories in the global capital market. On the other hand, the return of the global size proxy is found to be highly correlated with the returns of the global value proxy and the MSCI World Index. In addition, the global momentum and value proxies together with the MSCI World Index are found to be successful in replicating the investment styles of selected global equity funds without the support from the global size proxy. With limited contribution from the selection return to the actual fund return in the replication procedure, the return of the replicated style portfolio serves as an unbiased estimate of the actual fund return. This result suggests that managers of global equity funds in general do not add value through their stock picking skills.

The rolling out-of-sample performances of the long-only, long-short leverage and market neutral tactical style allocation (TSA) strategies developed from the global style proxies along with the MSCI World Index are in line with their corresponding Sharpe ratio-optimised portfolios developed within the static in-sample period. This result indicates that the optimisation procedure using the weighted least squares (WLS) approach is robust in replicating the hypothetical Sharpe ratio-optimised portfolio. In general, tests conducted in this study reveal that value investing produces consistent long-term performances throughout different phases of the economic cycle. Although momentum stocks exhibit upward lift in their returns above value stocks during market peaks, they suffer from significant drawdown during the subsequent market crash. Thus, the most practical mean-variance efficient allocation method is to pursue value investing as a long-term strategy and tactically allocate investments in momentum stocks during market peaks based on the preferred TSA strategy. The long-short and market neutral TSA strategies have built-in cash protection during turbulent times through their cash component. To protect the value of the long-only TSA strategy in turbulent times, the majority of the scenarios tested on the cash-protected MSCI World Index and the style proxies based on the filter rule and EMA strategies successfully outperform the unprotected counterpart indices over the examination periods. Alternatively, the risk-free proxy can be incorporated in the optimisation procedure of the long-only TSA strategy to signal cash protection for the expected upcoming market downturn.

Table of Contents

Applications of Global Equity Style Indices in Active and Passive Portfolio Management	(i)
Declaration.....	(ii)
Dedication	(iii)
Acknowledgement.....	(iv)
Abstract	(v)
Table of Contents.....	(vii)
List of Figures and Tables	(xi)

1 INTRODUCTION	1-1
1.1 Background	1-1
1.2 Overview.....	1-3
1.3 Contributions.....	1-5
2 THEORETICAL OVERVIEW.....	2-1
2.1 Introduction.....	2-1
2.2 The Efficient Market Hypothesis (EMH)	2-3
2.3 Asset Allocation in an Efficient Capital Market	2-6
2.4 Asset Pricing in an Efficient Capital Market – The Capital Asset Pricing Model (CAPM)	2-13
2.5 Problems with the Market Portfolio and the Development of the Arbitrage Pricing Theory (APT).....	2-16
2.5.1 The Benchmark Error	2-16
2.5.2 Derivation of the APT.....	2-17
2.5.3 Identities of the APT Factors.....	2-20
2.5.4 The Implications of the APT in Asset Allocation.....	2-21
2.6 Behavioural Finance	2-22
2.6.1 Prospect Theory.....	2-23
2.6.2 Sources of Behavioural Biases	2-26
2.7 Conclusion	2-28

3	REVIEW OF PRIOR LITERATURE.....	3-1
3.1	Introduction.....	3-1
3.2	Market Anomalies and Investment Styles	3-4
3.2.1	Abnormal Returns of Momentum and Contrarian Strategies.....	3-4
3.2.2	Value and Size Anomalies	3-8
3.2.3	South African Evidence of Market Anomalies.....	3-14
3.3	Applications of Style Indices in Active and Passive Portfolio Management	3-18
3.3.1	Style-Based Performance Attribution.....	3-19
3.3.2	Tactical Style Timing versus Tactical Stock Picking	3-24
3.4	Risk Management in Turbulent Times	3-30
3.5	Merits and Criticisms of Fundamental Indexation	3-33
3.6	Conclusion	3-38
4	DATA AND METHODOLOGY	4-1
4.1	Introduction.....	4-1
4.2	Problem Statement and Research Objectives.....	4-2
4.3	Research Database.....	4-5
4.4	Sample Selection in the Research Database.....	4-7
4.5	Potential Research Biases	4-12
5	PERFORMANCES OF GLOBAL STYLE INDICES	5-1
5.1	Introduction.....	5-1
5.2	Index Weighting Methodology	5-3
5.3	Descriptive Statistics for the Global Style Indices	5-5
5.3.1	Global Size Style Indices	5-5
5.3.2	Global Momentum Style Indices.....	5-7
5.3.3	Global Value Style Indices.....	5-10
5.4	Performance Evaluation Measures	5-15
5.4.1	Risk-Adjusted Performance Measures.....	5-17
5.4.2	Portfolio Turnover and Implicit Transaction Costs	5-23
5.4.3	Measures of Representativeness.....	5-25
5.4.4	Global Performance Attribution Analysis.....	5-27
5.5	Results: Performances of Global Style Indices.....	5-33
5.5.1	Global Size Indices	5-34
5.5.2	Global Momentum and Loser Indices.....	5-37
5.5.3	Global Value and Glamour (Growth) Indices	5-39
5.6	Results: Characteristics of the Global Style Proxies.....	5-41
5.7	Results: Performance Attributions of the Global Style Proxies.....	5-53
5.8	Conclusion	5-58

6	PASSIVE REPLICATION OF THE INVESTMENT STYLES OF GLOBAL EQUITY FUNDS	6-1
6.1	Introduction.....	6-1
6.2	Methodology and Descriptive Statistics	6-3
6.3	Results: Style Analysis of the Global Equity Funds	6-7
6.3.1	South African-Based Global Equity Funds	6-7
6.3.2	Internationally-Domiciled Global Equity Funds	6-14
6.4	Conclusion	6-19
7	ACTIVE GLOBAL STYLE PORTFOLIO OPTIMISATION.....	7-1
7.1	Introduction.....	7-1
7.2	Methodology and Descriptive Statistics	7-3
7.3	Results: Optimal Global Style-Based Portfolios.....	7-7
7.4	Results: Global Sharpe Ratio-Optimised Portfolios	7-20
7.5	Conclusion	7-24
8	ACTIVE GLOBAL STYLE TIMING STRATEGIES.....	8-1
8.1	Introduction.....	8-1
8.2	Methodology and Descriptive Statistics	8-3
8.2.1	Value-Momentum Rotation Strategy	8-3
8.2.2	Tactical Style Timing (TSA) Strategies	8-6
8.3	Results: Global Style Timing Strategies	8-8
8.4	Conclusion	8-30
9	GLOBAL CASH PROTECTION MECHANISMS	9-1
9.1	Introduction.....	9-1
9.2	Methodology and Descriptive Statistics	9-3
9.2.1	Trend-Following Model Based on Drawdown and Drawup	9-4
9.2.2	Exponential Moving Average Trend-Following Model.....	9-5
9.3	Results: Cash-Protected MSCI World Index	9-7
9.4	Results: Cash-Protected Global Momentum Proxy	9-17
9.5	Results: Cash-Protected Global Value Proxy	9-26
9.6	Conclusion	9-33
10	CONCLUSION.....	10-1
	BIBLIOGRAPHY	Z-1

APPENDICESA to L

APPENDIX A: Performances of the Candidate Size Indices.....A
APPENDIX B: Performances of the Candidate Momentum IndicesB
APPENDIX C: Performances of the Candidate Value IndicesC
APPENDIX D: Performances of the Candidate Loser IndicesD
APPENDIX E: Performances of the Candidate Glamour Indices.....E
APPENDIX F: Performances of the South African-Based Global Equity Funds..... F
APPENDIX G: Performances of the Internationally-Domiciled Global Equity FundsG
APPENDIX H: Cash Protection on the MSCI World Index (1970 to 1990)H
APPENDIX I: Cash Protection on the MSCI World Index (1991 to 2008) I
APPENDIX J: Cash Protection on the MSCI World Index (1970 to 2008)J
APPENDIX K: Cash Protection on the Global Momentum Proxy (1991 to 2008).....K
APPENDIX L: Cash Protection on the Global Value Proxy (1991 to 2008) L

University of Cape Town

List of Figures and Tables

LIST OF FIGURES

Figure 2.1: Risk Aversion and Marginal Utility	2-6
Figure 2.2: Markowitz Efficient Frontier of Risky Assets	2-9
Figure 2.3: The Security Market Line (SML).....	2-15
Figure 2.4: Performance Evaluation Bias	2-17
Figure 2.5: Utility Function of Prospect Theory	2-24
Figure 4.1: Composition of the Research Sample.....	4-9
Figure 4.2: Concentration of the Research Sample by Market Capitalisation.....	4-11
Figure 4.3: Locations of Central Tendency Measures.....	4-15
Figure 5.1: Different Selection Mechanisms of Value Determinants.....	5-13
Figure 5.2: The Derivation of the M-Squared Measure	5-19
Figure 5.3: Log Cumulative Returns of the Global Style Proxies.....	5-46
Figure 5.4: Relative Performances of the Style Proxies Measured by the Empirical Capital Market Line (ECML).....	5-48
Figure 5.5: Relative Performances of the Style Proxies Measured by the Empirical Security Market Line (ESML).....	5-49
Figure 5.6: Cross-Sector Contributions to the Returns of the Global Style Proxies	5-56
Figure 5.7: Cross-Country Contributions to the Returns of the Global Style Proxies.....	5-58
Figure 7.1: Long-Only Mean-Variance Portfolio Optimisation with No Leverage	7-8
Figure 7.2: Long-Only Mean-Tracking Error Portfolio Optimisation with No Leverage	7-10
Figure 7.3: The Mean-Variance Efficient Frontier for the Long-Only Portfolios with No Leverage	7-12
Figure 7.4: Long-Short Mean-Variance Portfolio Optimisation with Leverage Capped at 200%	7-14
Figure 7.5: The Mean-Variance Efficient Frontier for the Long-Short Portfolios with Leverage Capped at 200%.....	7-16
Figure 7.6: Market Neutral Mean-Variance Portfolio Optimisation with Leverage Capped at 200%	7-18
Figure 7.7: The Mean-Variance Efficient Frontier for the Market Neutral Portfolios with Leverage Capped at 200%.....	7-19
Figure 7.8: Relative Performances of the Sharpe Ratio-Optimised Portfolios Measured by the Empirical Security Market Line (ESML).....	7-23

Figure 8.1: Performance of the Global Value-Momentum Spread	8-9
Figure 8.2: The Influences of Economic Forces on the Global Value-Momentum Spread	8-11
Figure 8.3: Time-Series Predictions for the Global Value-Momentum Rotation Strategy	8-15
Figure 8.4: Time-Series Portfolio Composition of the Global Long-Only Tactical Style Allocation (TSA) Strategy with No Leverage.....	8-17
Figure 8.5: Time-Series Portfolio Composition of the Cash-Protected Global Long-Only Tactical Style Allocation (TSA) Strategy with No Leverage.....	8-19
Figure 8.6: Time-Series Portfolio Composition of the Global Long-Short Tactical Style Allocation (TSA) Strategy with 200% Capped Leverage.....	8-21
Figure 8.7: Time-Series Portfolio Composition of the Global Market Neutral Tactical Style Allocation (TSA) Strategy with 200% Capped Leverage.....	8-22
Figure 8.8: Relative Performances of the Global Style Timing Strategies Measured by the Empirical Capital Market Line (ECML)	8-26
Figure 8.9: Relative Performances of the Global Style Timing Strategies Measured by the Empirical Security Market Line (ESML)	8-27
Figure 8.10: Log Cumulative Returns of the Global Style Timing Strategies	8-29
Figure 9.1: Performance of the 100% Cash-Protected MSCI World Index Based on the Filter Rule Strategy (1970 to 2008)	9-13
Figure 9.2: Performance of the 50% Cash-Protected MSCI World Index Based on the Filter Rule Strategy (1970 to 2008)	9-14
Figure 9.3: Performance of the 100% Cash-Protected MSCI World Index Based on the Exponential Moving Average (EMA) Strategy (1970 to 2008)	9-15
Figure 9.4: Performance of the 50% Cash-Protected MSCI World Index Based on the Exponential Moving Average (EMA) Strategy (1970 to 2008)	9-16
Figure 9.5: Performance of the 100% Cash-Protected Global Momentum Proxy Based on the Filter Rule Strategy (1991 to 2008)	9-21
Figure 9.6: Performance of the 50% Cash-Protected Global Momentum Proxy Based on the Filter Rule Strategy (1991 to 2008)	9-22
Figure 9.7: Performance of the 100% Cash-Protected Global Momentum Proxy Based on the Exponential Moving Average (EMA) Strategy (1991 to 2008)	9-24
Figure 9.8: Performance of the 50% Cash-Protected Global Momentum Proxy Based on the Exponential Moving Average (EMA) Strategy (1991 to 2008)	9-25

Figure 9.9: Performance of the 100% Cash-Protected Global Value Proxy Based on the Filter Rule Strategy (1991 to 2008)	9-29
Figure 9.10: Performance of the 50% Cash-Protected Global Value Proxy Based on the Filter Rule Strategy (1991 to 2008)	9-30
Figure 9.11: Performance of the 100% Cash-Protected Global Value Proxy Based on the Exponential Moving Average (EMA) Strategy (1991 to 2008)	9-31
Figure 9.12: Performance of the 50% Cash-Protected Global Value Proxy Based on the Exponential Moving Average (EMA) Strategy (1991 to 2008)	9-32

LIST OF TABLES

Table 5.1: Descriptions of the Size Style Attributes	5-6
Table 5.2: Descriptions of the Momentum Style Attributes	5-8
Table 5.3: Descriptions of the Value and Glamour Attributes	5-14
Table 5.4: Performances of the Global Style Proxies	5-45
Table 5.5: Correlation Matrix of the Global Style Proxies	5-50
Table 5.6: Effects of Rebalancing Frequency on the Performances of the Global Style Proxies	5-52
Table 5.7: Performance Attributions of the Global Style Proxies	5-54
Table 6.1: Return Attributions of South African-Based Global Equity Funds	6-11
Table 6.2: Return Attributions of Internationally-Domiciled Global Equity Funds	6-17
Table 7.1: Summarised Statistics for the Global Sharpe Ratio-Optimised Portfolios ...	7-21
Table 8.1: Regression Statistics for the 2-Factor Global Value-Momentum Spread Forecasting Model	8-13
Table 8.2: Performances of the Global Style Timing Strategies	8-24
Table 9.1: Performance Statistics of the Cash-Protected MSCI World Index (1970 to 2008)	9-11
Table 9.2: Performance Statistics of the Cash-Protected Global Momentum Proxy (1991 to 2008)	9-19
Table 9.3: Performance Statistics of the Cash-Protected Global Value Proxy (1991 to 2008)	9-27

INTRODUCTION

“Style indexes are useful for performance evaluation of individual managers and combined manager mixes. In this sense, they can be used as normal portfolios. If the style indexes accurately measure manager style, we would expect that the mean returns of universes of managers would behave more like the style indexes than broad market measures” (Christopherson and Williams, 1997: 1).

1.1 Background

The market portfolio that contains all risky assets in proportion to their relative market values is the ideal risky portfolio that all investors should hold in the perspective of the modern portfolio theory (MPT) pioneered by Markowitz (1952). The separation theorem of Tobin (1958) suggests that the mean-variance efficient allocation for an investor is to split the investment between the market portfolio and the risk-free asset in accordance with the degree of the investor’s risk aversion. The capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965) and Mossin (1966) is subsequently developed to determine the risk-adjusted return of assets in an efficient capital market using the sensitivity of asset returns to movements in the market return, known as the beta coefficient, as the relevant risk measure. The efficient market hypothesis (EMH) of Fama (1970, 1991) supports the mean-variance efficiency of the market portfolio and postulates that the efficient dissemination of information prevents investors from outperforming the market portfolio in a consistent manner. Roll (1977, 1978) criticises

the testability of the CAPM based on the argument that the true market portfolio is not observable. A multifactor model proposed by the arbitrage pricing theory (APT) of Ross (1976) opens avenues for alternative asset allocations other than indexing the market portfolio. Tests on the joint hypothesis of the EMH and the asset pricing relationship of the CAPM also reveal that the market portfolio represented by broad market indices are not capable of explaining the value effect of Basu (1977) and size effect of Banz (1981).

Prospect theory of Kahneman and Tversky (1979) and the overreaction hypothesis of De Bondt and Thaler (1985, 1987) propose an alternative paradigm to the EMH that investors are irrational in making decisions and are often influenced by behavioural biases, which lead asset prices to overshoot. Tests conducted by Jegadeesh and Titman (1993) reveal that the momentum of temporarily overpriced securities can be a possible source of abnormal returns. In the belief that the CAPM anomalies documented in empirical research represent risk factors rather than evidence of market inefficiencies, Fama and French (1993) develop factor mimicking portfolios to represent the value and size effects in addition to the market risk premium in a 3-factor model. The 3-factor model is found to explain all empirical anomalies with the exception of the momentum effect of Jegadeesh and Titman (1993) across markets and time periods. This finding evokes asset managers to position their portfolios out-of-sync with the broad market by pursuing investments styles based on the CAPM anomalies. The success of fundamental indices of Arnott, Hsu and Moore (2005) in outperforming the alternative cap-weighted index and the noise argument of Hsu (2006) provide further support to the use of price-insensitive style indices rather than indexing the cap-weighted market proxy in asset management.

1.2 Overview

This study undertakes to examine the practicality of applying global style indices in active and passive portfolio management over the examination period from 1 January 1991 to 31 December 2008. The ultimate goal of this research is to search for practical mean-variance efficient style allocation mechanisms in the global capital market with sufficient downside protection during turbulent times. The research database is the constituents of the Dow Jones Sector Titans Composite Index, which is comprised of the 30 most established global equities from each of the 19 sectors in the second tier of the Supersector structure defined by the Industry Classification Benchmark (ICB).

Chapter 2 provides an overview of the theories underlying this research, which includes the theories relating to asset allocation decisions in efficient capital markets and behavioural finance that serves as an alternative theory to the EMH. Chapter 3 reviews significant tests regarding market efficiency and potential market anomalies. The chapter also reviews prior literature on various applications of style indices in active and passive portfolio management. In addition, empirical tests on style timing strategies are also discussed.

Chapter 4 presents an overview of the problem statement, research objectives, composition of the research sample and potential biases with their possible remedies in the research. Chapter 5 initiates the research by developing global style indices from pre-specified firm-specific attributes for the global size, momentum and value investment styles. The risk-return characteristics, portfolio turnover and representativeness of the global style indices are cross-examined, with the proxies for

each investment style chosen for further research. The global style proxies are subject to global performance attribution analysis to determine whether their return differences are attributable to their differential country or sector allocation policies.

Chapter 6 investigates the empirical validity of replicating South African-based and internationally-domiciled global equity funds by constructing style-based benchmarks that synthesise the underlying investment styles of the respective global equity funds. The style analysis of the global equity funds gives an indication as to whether the fund returns are driven mainly by their underlying investment styles or by the fund manager's alternative stock allocations from the style benchmark. As opposed to passively replicating the returns of the global equity funds in Chapter 6, Chapter 7 performs portfolio optimisation on the global style proxies based on the various active portfolio management strategies of different constraints in terms of short and leverage positions.

Chapter 8 investigates the potential benefits of tactical style allocation (style timing) in the global equity market. A style rotation model, based on the global momentum and value proxies, is implemented and subsequently evaluated in this chapter. The global financial crisis of 2008 systemically impacts all asset classes. The benefits of style timing and diversification dissipate during turbulent times. On the recognition of the systemic impact of the global financial crisis, Chapter 9 undertakes to develop a trend-following model that signals the initiation of overlay hedging during global financial market turmoil. The consolidated findings from the results of the tests conducted by this research are presented in Chapter 10. Recommendations on the insights discovered by this research are also provided.

1.3 Contributions

Studies conducted in and the results obtained from this research contribute to the existing literature in the applications of style indices in various ways. First, the increased integration in the global economy due to globalisation implies that sector allocation as opposed to country allocation may be a more effective approach of managing a global equity portfolio. The well-balanced sector representation in the database of this research provides ample diversification benefits and exposures to different dimensions of risk in the global sectors. Although the importance of sector allocation is recognised by researchers, no study has taken into account the sector representation of the database when conducting empirical research. This research further conducts studies on the relative importance of country and sector allocations in explaining the return differences between the global style proxies. Empirical studies of this nature generally focus on the relative diversification benefits of the two allocation approaches, and their relative abilities in explaining global fund returns instead of explaining the differences between fund returns. The results of the cross-country, cross-sector analysis contribute to the existing literature in determining whether the performance differences between global investment styles are mainly due to the differences in their country or sector allocation policies.

Significant empirical literature on the application of style indices in South Africa is limited to Yu (2008), who investigates the effectiveness of style and sector indices in active and passive management on the JSE Securities Exchange (JSE) over the period from 1 January 2001 to 31 December 2006. This research extends the tests of style indices to a global scale with an extended 18-year period from 1 January 1991 to 31 December 2008. This is the longest period for tests conducted on style indexation to

date at the time of writing. Important economic shocks documented in this time period include the Asian financial crisis in 1998, the crash of the information technology (I.T.) bubble in 2000, and the subprime crisis in 2007 which led to the market crash in 2008. The results of the relative performances of global style indices provide insights into the specific timing of the global style indices.

Major contributions also come from innovative index construction methodologies. Yu (2008) selects value stocks based on their negative cross-sectional residuals. This method has an advantage of ranking stocks based on multiple fundamental attributes relative to their market prices. This approach has not yet been applied to global value stocks. In the belief that the cross-sectional regression estimated from multiple attributes provides an unbiased estimate of the intrinsic value of a stock, global glamour indices are constructed based on their positive cross-sectional residuals. The results of this test serve to determine whether the glamour indices ranked and classified by the cross-sectional regression approach represent relatively overpriced stocks in the research sample. This research also attempts to classify momentum (winner) stocks and the counterpart loser stocks based on their respective mean-adjusted returns. This innovative approach does not filter out stocks with negative returns in the classification process. The mean-adjusted return approach also makes it possible for allocating weights to shares with negative returns for the construction of style-weighted momentum indices and loser indices. An additional advantage of the mean-adjusted return approach is that it avoids temporary drastic rebalancing of the momentum indices during economic shocks when the majority of the stocks exhibit negative returns.

Although exhaustive research has been conducted on the replication of fund returns based on the return decomposition approach of Sharpe (1992) using a large number of asset classes and style indices, no prior study has attempted to test the replication of fund returns using major global style indices. This research presents the first research conducted on the power of major global style indices in replicating the underlying investment styles of South-African based and internationally-domiciled global equity funds. In addition, this research develops tactical style allocation (TSA) strategies of various portfolio constraints in short and leverage positions by replicating the hypothetical Sharpe ratio-optimised portfolios in the most recent prior period. Developing TSA strategies based on the optimisation procedure is limited to Amenc, Goltz and Le Sourd (2006), who develop market neutral strategy from the Standard and Poor's style indices over the period from 2000 to 2002 based on the optimisation procedure using multifactor models.

To the author's knowledge at the time of writing, no extensive research has been conducted regarding the construction and application of style indices in the global context. Various global style-based hedge fund strategies developed in this study open avenues for investment opportunities and further research in the growing Chinese economy that recently approved margin trading and launched single stock futures on stocks traded on the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE).

Finally, this paper conducts extensive research on various cash protection mechanisms on the MSCI World Index since its inception in 1970 to 2008. The cash protection mechanisms are also applied to the global style proxies. Significant prior research of this nature is limited to Faber (2009), who devises a trading strategy that signals long

and short positions in the underlying index based on moving average crossover. Exhaustive permutations for the filter rule and exponential moving average cash protection strategies are tested over the examination period and sub-periods in order to determine whether the strategies are robust over time. The results of the performances of the protected indices relative to the unprotected indices assist managers of different investment styles in protecting fund values from expected significant drawdown.

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THEORETICAL OVERVIEW

2.1 Introduction

This chapter reviews the theoretical framework of the research, which includes the various forms of the efficient market hypothesis (EMH), the development of modern portfolio theory (MPT) and the role of the market portfolio in MPT. The implications of MPT in asset allocation decisions, criticisms regarding the market portfolio and the development of the arbitrage pricing theory (APT) are also reviewed. Prospect theory and the role of behavioural finance that describe investment decisions in imperfect capital markets are presented.

The EMH is regarded as the fundamental theory underpinning all areas of finance. Modern Portfolio Theory (MPT), pioneered by Markowitz (1952) and the separation theorem of Tobin (1958) provide solutions for risk-averse investors to allocate assets in an efficient capital market. Under the assumptions of MPT, risk-averse investors have homogeneous expectations regarding the mean, variance, and covariance of asset returns, and aim at maximising their expected utility when making investment decisions. The concept of risk aversion stems from the expected utility theory, which describes the decision making of investors under the presence of risk based on investor rationality.

As an extension to the existing framework of MPT, the capital asset pricing model (CAPM) is developed to price assets in an efficient capital market. At the core of MPT,

there is a completely diversified optimal risky portfolio called the market portfolio that all investors would hold, and the only source of risk in an investment is its sensitivity to movements in the market portfolio since the firm-specific risk can be diversified away by holding the market portfolio. The concept of the market portfolio is criticised and a multifactor asset pricing model developed under the arbitrage pricing theory (APT) is viewed as an alternative to the CAPM.

While traditional finance make suggestions regarding the manner in which assets should be priced in efficient capital markets, behavioural finance, on the other hand, argues that the cognitive behaviour of irrational investors have pervasive impacts on the pricing of assets in capital markets. Kahneman and Tversky (1979) question the basic tenets of the expected utility theory, and introduce prospect theory that describes how investors make decisions under the influences of cognitive psychologies.

2.2 The Efficient Market Hypothesis (EMH)

An efficient market is the term used to describe a market where investors cannot outperform their rivals by generating abnormal risk-adjusted returns in a consistent manner. With the intention to maximise their wealth, investors utilise information that are accessible to them as tools in trading available assets in the market. The historical price patterns and volume data of assets are regarded as the most basic tool available to investors in the market. Other types of information include public announcements of company performance results and inside information that are either not fully understood or accessible to average investors in markets that are not perfectly efficient. Investors who utilise historical price patterns and volume data of assets to time the market and allocate their assets are called technical analysts or technicians. For technicians to outperform the market, the movements of asset prices cannot be predictable. In other words, the asset prices cannot follow a “random walk”, which is defined by Fama (1970) as successive price changes being independent over time.

In an attempt to test whether historical price patterns of assets are repetitive and thus predictable to technicians, Kendall (1953) statistically analyses the time-series behaviour of 22 economic series over the period from 1883 to 1934 using the actuaries’ indices of industrial share prices as the dataset. The test results reveal that asset prices are unpredictable in that the serial correlations within the selected series are weak, and there are no statistically meaningful lag correlations between the series. Samuelson (1965) offers mathematical proof to support the findings of Kendall (1953) based on stochastic modeling of asset prices. In addition, Samuelson (1965: 41) suggests that *“in competitive markets there is a buyer for every seller. If one could be sure that a price will rise, it would have already risen”*. Based on the analogy of

Samuelson (1965), the random walk behavior of asset prices documented in Kendall (1953) is attributable to the instantaneous incorporation of new information in asset prices via the competition of market participants. For competition in the market to be regarded as a fair game, accurate information must be accessible to all interested parties instantaneously and there has to be no barriers to trade. Ideally, a perfectly efficient capital market is *“a market in which firms can make production-investment decisions and investors can choose among the securities that represent ownership of firms’ activities under the assumption that security prices at any time fully reflect all available information”* (Fama, 1970: 383).

Fama (1965, 1970 and 1991) reviews the empirical work on the random walk of asset prices and introduces different forms of market efficiency under the efficient market hypothesis (EMH) based on the manner in which different types of information are reflected in asset prices. According to Fama (1965), the levels of market efficiency can be divided into three forms: the weak form, semi-strong form and the strong form. Each of the forms of the EMH has the ability to rule out the possibilities of consistent outperformance by a certain group of investors who use certain type of information as the tool in their trading activities. As the market become more efficient, the particular “tool” that investors used to beat the market become less effective since most of the investors would have learnt the use of it and practice their trading activities accordingly.

While asset prices fully reflect historical price patterns in the weak-form of the EMH, asset prices in the semi-strong form of the EMH reflect all publicly available information such as corporate earnings and share splits, etc. This implies that technical analysts who employ price charts and volume data in making their

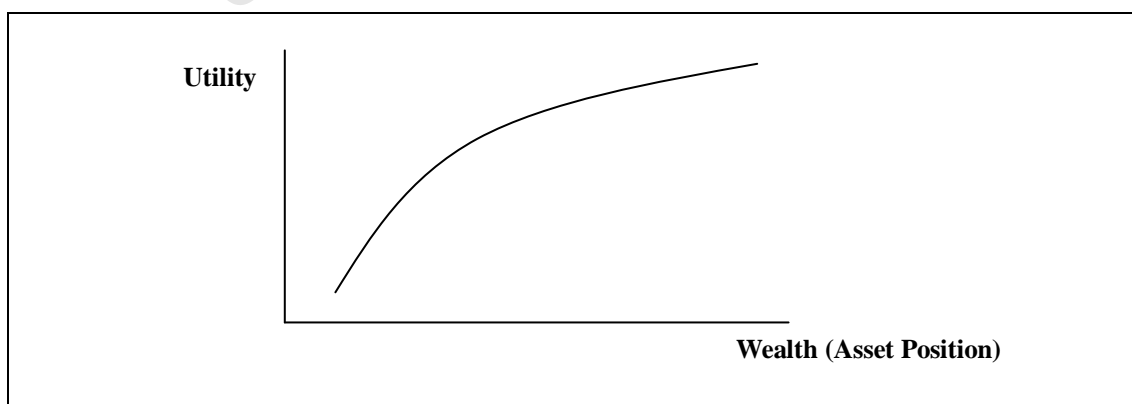
investment decisions cannot earn positive abnormal returns in a consistent manner in a market that is weak-form efficient. On the other hand, fundamental analysts who study macroeconomic forces and company performances cannot beat a market that is semi-strong form efficient. When a market is categorised as being strong-form efficient, company insiders do not have monopolistic access to information relevant for price formation, and hence inside information does not exist in such a market.

2.3 Asset Allocation in an Efficient Capital Market

“The primary role of the capital market is allocation of ownership of the economy’s capital stock” (Fama, 1970: 383). Based on the assumption of market efficiency and the principle of diversification, Markowitz (1952) developed the first theory that incorporates the concept of risk in the portfolio management process. The attitude of investors towards risk in the portfolio theory of Markowitz (1952) is based on the concept of risk aversion described by the expected utility theory, which is expressed by the conventional utility curve illustrated in Figure 2.1. Using the asset position as an indication of wealth, the positive slope of the utility function indicates that the higher the asset position, the higher the utility of an investor. However, the utility function is concave, indicating that the marginal utility derived from the growth in the asset position is diminishing. This implies that investors will reject a risky venture without adequate compensation for its risk (Bodie, Kane and Marcus, 2008).

Figure 2.1 Risk Aversion and Marginal Utility

Figure 2.1 is adapted from Bodie *et al* (2008: 400). It illustrates the diminishing marginal utility of risk-averse investors from additional growth of the asset position.



Under the expected utility theory, investors make decisions between the alternative investments based on the expected utility that can be achieved from the respective investments as shown in Equation 2.1 (Kahneman and Tversky, 1979: 263):

$$E(U) = p_1u(x_1) + p_2u(x_2) + \dots + p_nu(x_n) \quad \dots\dots\dots (2.1)$$

Where:

- $x_1, x_2 \dots x_n$ are the possible asset positions of the investment; and
- $p_1, p_2 \dots p_n$ are the probabilities assigned to the possible asset positions of the investments.

The decision making process based on the utility function depicted by Equation 2.1 is rational and not subject to psychological biases since the decision relies purely on the probabilities of the various possible asset positions of an investment. Applying the concept of risk aversion to the portfolio construction process, rational investors will prefer to include assets that offer higher expected return for a given level of risk, or lower risk for a given level of expected return in their portfolios. Equation 2.2 and Equation 2.3 mathematically demonstrate the expected return and the variance of a portfolio that consists of 2 assets i and j . The weights carried by the constituents i and j are proportional to their relative market values:

$$E(R_p) = (w_i \times E(R_i)) + (w_j \times E(R_j)) \quad \dots\dots\dots (2.2)$$

$$\sigma_p^2 = (w_i^2 \sigma_i^2) + (w_j^2 \sigma_j^2) + (2w_i w_j \sigma_i \sigma_j \rho_{ij}) \quad \dots\dots\dots (2.3)$$

Where:

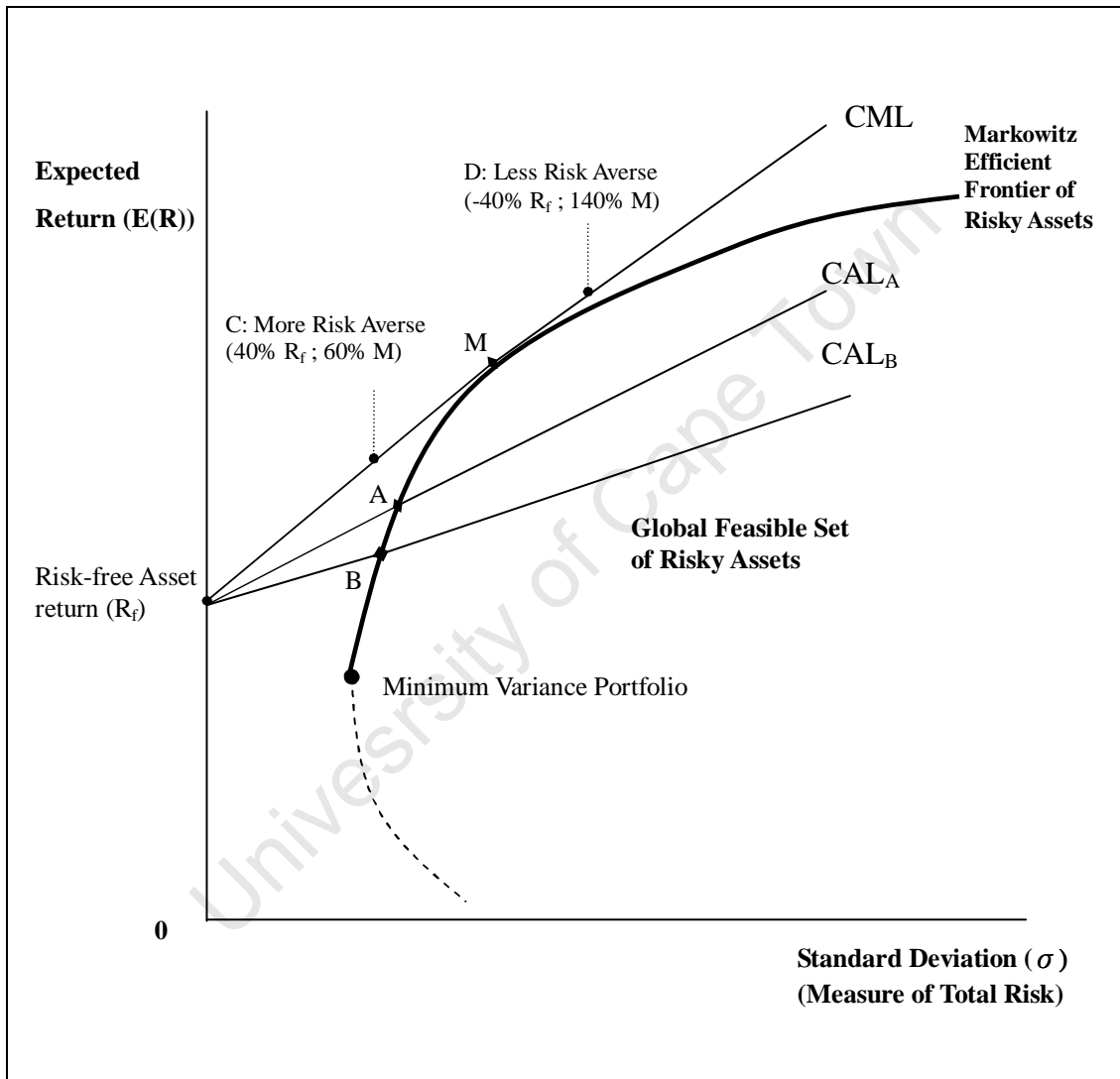
- w_i and w_j are the weights of constituent i and j in portfolio P ;
- σ_i and σ_j are the standard deviations of constituents i and j in portfolio P ; and
- ρ_{ij} is the correlation coefficient between the historical returns of the constituents i and j in portfolio P .

While the expected return of a portfolio is computed as the weighted average of the expected returns of its constituents, the portfolio risk measured by the standard deviation (square root of variance) of historical returns is less than the weighted average of the standard deviations of its constituents. This is because the returns of the constituents in a portfolio are likely to be less than perfectly correlated, and hence the firm-specific risk of a large portfolio is effectively diversified away. As shown in Equation 2.3, the lower the correlation coefficient between the returns of the constituents in the portfolio, the lower is the variance and hence the standard deviation of the portfolio. As a result, the total risk of the portfolio does not increase in the same proportion as the increase in the portfolio expected return when a new asset with higher expected return is added in the portfolio.

Incorporating the concept of diversification discussed above, the Markowitz efficient frontier of risky assets is derived from efficient mean-variance optimisation with the objective of maximising the expected return of the portfolio at each level of portfolio standard deviation from the feasible set of risky assets. Figure 2.2 illustrates the umbrella-shaped Markowitz efficient frontier of risky assets. The assets plotted on the efficient frontier represent the mean-variance efficient risky assets attainable from the feasible set of risky assets. The risky assets plotted on the efficient frontier are preferred by risk-averse investors to other assets in the feasible set as they offer the highest attainable returns for the given levels of risk.

Figure 2.2 Markowitz Efficient Frontier of Risky Assets

Figure 2.2 is modified from Bodie *et al* (2008: 228). The Markowitz efficient frontier of risky assets represents the mean-variance efficient assets in the global market that have the highest expected returns for the given levels of risk, and the lowest levels of risk for the given expected returns. The capital asset allocation lines (CAL) represent the risk-return characteristics for a portfolio comprised of the risk-free assets and an efficient asset on the Markowitz efficient frontier. The capital market line (CML) is the highest attainable CAL, and the tangent portfolio M is termed the market portfolio of risky assets.



The Markowitz efficient frontier is comprised of only risky assets. To manage the risk of the portfolio effectively, investors can invest a fraction of their capital in an asset that provides returns of certainty. The proxy for the risk-free asset is usually a highly liquid Treasury security with low probability of default. Consider the mean-variance efficient portfolios A and B in Figure 2.2. Any combination of portfolio A and the risk-free asset in an investor's portfolio can be represented by a linear capital allocation line (CAL_A) drawn from the risk-free rate (R_f) through A.¹ Similarly, CAL_B represents any combination of portfolio B and the risk-free asset in an investor's portfolio. CAL_A dominates CAL_B because combinations of portfolio A and the risk-free asset provide a higher expected return for any level of risk than combinations of portfolio B and the risk-free asset. Therefore, all investors would prefer to form their portfolios using the risk-free asset with portfolio A rather than with portfolio B. In this manner, one can continue to ratchet the CAL upward until it reaches the ultimate point of tangency with the efficient frontier of risky assets at M.

The ultimate CAL tangent to the optimal risky portfolio is termed the capital market line (CML), which offers the highest possible expected return for any given level of risk, and the lowest possible risk for any given level of expected return. Equation 2.4 depicts the mathematical representation of the CML, which states that the expected return on an efficient portfolio is equal to the return on the risk-free asset (R_f) plus a market risk premium ($E(R_M) - R_f$) proportional to the total risk of the portfolio (σ_p^2) relative to the total risk of the market portfolio (σ_M^2):

¹ A capital allocation line (CAL) is a plot of risk-return combinations available by varying portfolio allocation between a risk-free asset and a risky portfolio. The line is linear (as opposed to the curved efficient frontier) because there is no diversification benefit by including the risk-free asset in the portfolio. This is so because the variance of the risk-free asset is zero by definition, and hence there exists a zero correlation between the return on any risky asset and the risk-free rate.

$$E(R_P) = R_f + \sigma_P^2 \times \left(\frac{E(R_M) - R_f}{\sigma_M^2} \right) \quad \dots\dots\dots (2.4)$$

Where:

$E(R_P)$ is the expected return of portfolio P ;

$E(R_M)$ is the expected return of the market portfolio M ;

R_f is the return on the risk-free asset;

σ_P^2 is the variance of portfolio P ; and

σ_M^2 is the variance of the market portfolio M ;

The tangency portfolio M is termed the market portfolio, which is regarded as the optimal risky portfolio on the Markowitz efficient frontier of risky assets. The market portfolio is also a completely diversified portfolio, which contains not only domestic stocks and bonds, but also real estate, options, art, stamps, coins, human capital, foreign stocks and bonds, etc. In addition, supply and demand ensure that all assets included in the market portfolio are in proportion to their respective market values in equilibrium (Reilly and Brown, 2003). According to the separation theorem of Tobin (1958), the identification of the market portfolio is the first step in the asset allocation process. Investors with homogeneous expectations would arrive at the same optimal risky portfolio.

The second task of the asset allocation process involves the determination of the split between the risk-free asset and the market portfolio (i.e. choosing the best point on the CML). This task, however, depends on a particular investor's risk preference. If an investor is relatively risk-averse, he might lend some part of his portfolio at the risk-free rate (e.g. 40%) by buying some risk-free assets and investing the remainder (e.g. 60%) in the market portfolio (see point C in Figure 2.2). On the contrary, if an

investor prefers more risk, he might borrow funds at the risk-free rate (e.g. -40%) and invest everything (all of his capital plus what he borrowed: 140%) in the market portfolio (see point D in Figure 2.2). The separation theorem serves as the guideline for rational investors with different degrees of risk aversion to allocate assets in an efficient capital market.

University of Cape Town

2.4 Asset Pricing in an Efficient Capital Market – The Capital Asset Pricing Model (CAPM)

Fuller (1981) argues that Markowitz portfolio theory and the separation theorem make no statement about how assets or portfolios should be priced in an efficient market. The capital asset pricing model (CAPM) on the other hand is a single factor linear equilibrium pricing model that assists investors in determining the equilibrium rates of returns of assets in an efficient capital market. The CAPM is an extension of Markowitz portfolio theory. Sharpe (1964), Lintner (1965) and Mossin (1966) independently contribute to the development of the CAPM. The CAPM is built on the insight that the unsystematic risk can be diversified away, and hence investors only require to be compensated for bearing systematic risk. The CAPM further states that the relevant risk (i.e. systematic risk) measure for any risky asset i is its covariance with the market portfolio ($\sigma_{i,M}$). By substituting $\sigma_{i,M}$ for σ_p^2 in Equation 2.4, the expected return-systematic risk relationship can be expressed as follows:

$$E(R_i) = R_f + \sigma_{i,M} \times \frac{(E(R_M) - R_f)}{\sigma_M^2} \quad \dots\dots\dots (2.5)$$

By defining $\frac{\sigma_{i,M}}{\sigma_M^2}$ as the beta of asset i (β_i), Equation 2.5 can be restated as:

$$E(R_i) = R_f + \beta_i (E(R_M) - R_f) \quad \dots\dots\dots (2.6)$$

Equation 2.6, known as the security market line (SML), assists investors in determining the “*conditions for equilibrium of exchange of the assets*” (Mossin, 1966: 769). As stated in Mossin (1966: 769), “*each individual brings to the market his*

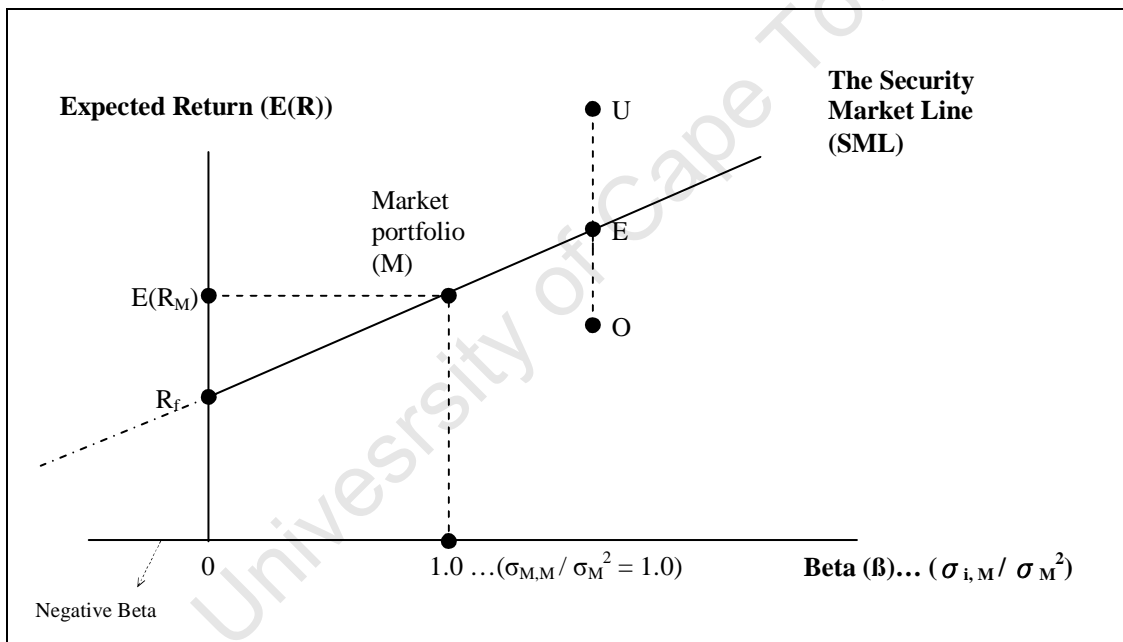
present holdings of the various assets, and an exchange takes place. We want to know what the prices must be in order to satisfy demand schedules and also fulfill the condition that supply and demand be equal for all assets. To answer this question we must first derive relations describing individual demand. Second, we must incorporate these relations in a system describing general equilibrium. Finally, we want to discuss properties of this equilibrium”. According to the pricing system of the SML described by Equation 2.6, the expected return on any asset or portfolio i ($E(R_i)$) is equal to the risk-free rate (R_f) plus the market risk premium ($E(R_m)-R_f$) proportional to its systematic risk (β_i) when the capital market is in equilibrium. In other words, assets with higher values of beta must offer higher returns to compensate investors for bearing higher systematic risk.

Figure 2.3 graphically depicts the systematic risk-expected return relationship described by the SML. When the capital market is in equilibrium, all assets must be plotted on the SML and offer returns that are justified for their respective levels of systematic risk. An asset plotted above the SML is undervalued since it offers higher returns than what is expected based on its systematic risk exposure. On the other hand, an asset is overvalued if it is plotted below the SML since it offers lower returns than what is expected for its systematic risk exposure. Consider two assets U and O that offer differential returns with the same value of beta in Figure 2.3. Homogeneous investors will buy asset U and sell asset O since asset U offers higher returns than asset O with the same level of risk. The trading activities of the investors will bid up the price of asset U and reduce the price of asset O. As a result, the return of asset U decreases while the return of asset O increases. This process brings both assets U and O to the equilibrium price indicated by the SML at point E in Figure 2.3. Due to the fact that the beta coefficient of the SML relates the covariance of any asset i with the

market portfolio ($\sigma_{i,M}$) to the variance of the market portfolio (σ_M^2), the market portfolio has a beta of 1.0 as shown in Figure 2.3.² The standardisation of systematic risk using the movements in the market return as the benchmark implies that the market risk is the single relevant measure of risk in an efficient capital market.

Figure 2.3 The Security Market Line (SML)

Figure 2.3 is modified from Reilly and Brown (2003: 251). The security market Line (SML) describes the expected return-systematic risk relationship for an asset or portfolio. The systematic risk of the market portfolio is standardised to 1.0. Thus, an asset or portfolio with higher (lower) than average systematic risk will have a beta value of greater (less) than 1.0.



² The covariance of any asset with itself is its variance. Hence, the covariance of the market portfolio with itself is the variance of the market return (i.e. $\sigma_{M,M} = \sigma_M^2$). Therefore, $\sigma_{M,M} / \sigma_M^2 = 1.0$.

2.5 Problems with the Market Portfolio and the Development of the Arbitrage Pricing Theory (APT)

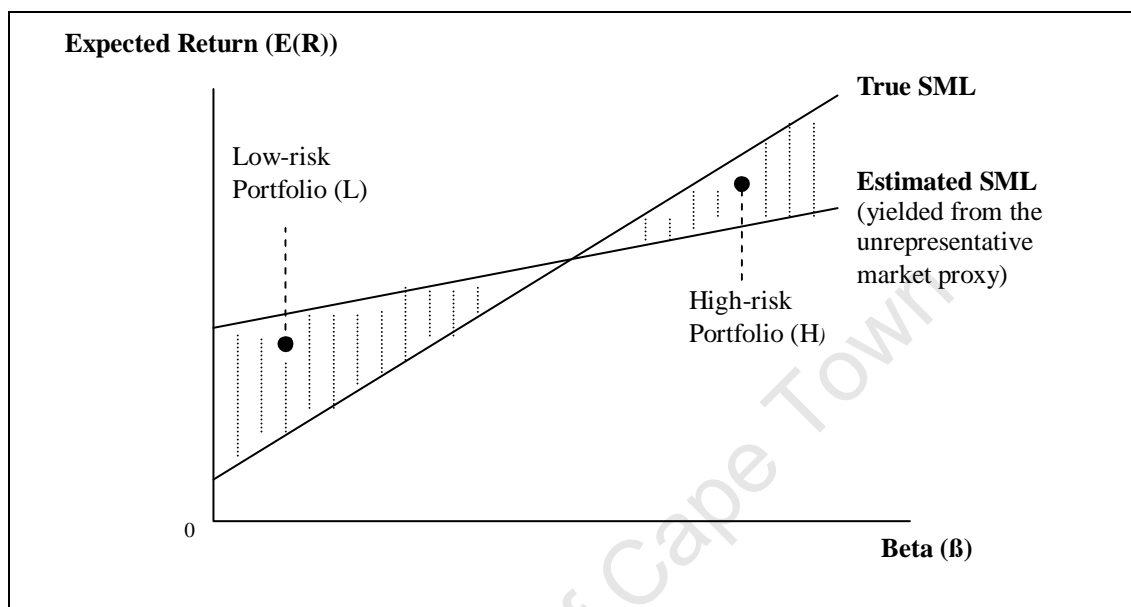
Although the derivation of the CAPM under MPT is intuitive in nature, Roll (1977: 129) argues that “*no correct and unambiguous test of the CAPM theory has appeared in the literature, and there is practically no possibility that such a test can be accomplished in the future*”. This argument is based on the unobservable nature of the market portfolio since it must contain all assets in the universe in proportion to their respective market values. Thus, empirical tests of the CAPM that involve the use of general stock market indices such as the Morgan Stanley Capital International World Index (MSCI) or the Standard and Poor’s 500 Index (S&P500) as the proxy for the market portfolio are ambiguous.

2.5.1 The Benchmark Error

Roll (1978) points out that the use of a misspecified market proxy also suffers from the benchmark problem in pricing assets since the beta estimated and the SML derived from the inappropriate market proxy are biased. This problem is demonstrated in Figure 2.4 where the estimated SML yielded from the unrepresentative market proxy overvalues the high-risk portfolio H against the low-risk portfolio L. However, portfolio L is indeed undervalued while portfolio H is overvalued based on the evaluation of the true SML. As a result, assets plotted in the shaded areas in Figure 2.4 obtain conflicting evaluations based on the estimated SML and the true SML.

Figure 2.4 Performance Evaluation Bias

Figure 2.4 is modified from Reilly and Brown (2003: 268). The estimated SML is assumed to be biased due to the use of an unrepresentative market proxy based on the argument of Roll (1977) that the true market portfolio is unobservable. The shaded areas in the diagram represent the conflicting evaluations made by the true SML and the estimated SML.



2.5.2 Derivation of the APT

An alternative asset pricing model called the arbitrage pricing theory (APT) developed by Ross (1976) partially addresses the benchmark problem of the CAPM since the APT does not require the identification of the market portfolio in its assumptions. Roll and Ross (1980) indicate that the APT recognises that the return on the market portfolio is not the only systematic risk factor that affects the long-term average returns on individual assets or portfolios. By decomposing the market risk, the APT seeks to identify major component systematic risk factors of the market risk that determine the variations of asset returns in the efficient capital market. The

identification of these factors helps companies and investors to gain an intuitive understanding of the factors' relative strengths in determining asset returns.

The expected return-systematic risk relationship of the APT is depicted in Equation 2.7 where asset i 's expected return is a linear combination of its exposures to the major systematic risks in the multifactor model:

$$E(R_i) = R_f + b_{i1} \langle E(RF_1) - R_f \rangle + \dots + b_{ik} \langle E(RF_k) - R_f \rangle \quad \dots \quad (2.7)$$

Where:

- F_k is the k th systematic risk factor that is common to all assets;
- $E(RF_k)$ is the expected return on an asset with an average sensitivity to movements in F_k ;
- $E(RF_k) - R_f$ is the expected risk premium on F_k ; and
- $b_{i,k}$ is the sensitivity of asset i 's expected return to movements in the risk premium on risk factor k .

As a multifactor model, the APT permits companies and investors to identify various attributions of asset returns and their relative significance in determining asset returns (Modigliani and Pogue, 1988). The underlying philosophy of the APT is the law of one price. That is, two assets that bear the same level of risk cannot sell at different prices. When the law of one price is violated, there will be arbitrage opportunities allowing investors to make riskless profits with zero investment. When this occurs, an arbitrageur will sell short the asset in the high-priced market and purchase a similar asset in the low-priced market. Reconsider the undervalued asset U and the overvalued asset O in Figure 2.4 (refer to Section 2.4). An arbitrageur who identifies this opportunity will sell short asset O and use the proceeds to finance the purchase of

asset U. Such activity brings the mispriced assets to their equilibriums with no upfront investment required (Fuller, 1981). While the CAPM assumes that each investor in the investment public will take limited positions in the opportunity to bring about the capital market equilibrium, the APT proposes that any investor will take an infinite position in it.

Another major development of APT is the recognition that the unanticipated part of the return that results from surprises is the only relevant risk of an investment. “*After all, if we had already got what we had expected, there would be no risk and uncertainty*” (Ross, Westerfield and Jaffe, 1990: 297). Based on this argument, the APT can be rewritten in an *ex post* form as shown in Equation 2.8 where the realised return of asset i is divided into the expected portion of the return (described by Equation 2.7) and the unexpected portion of the return that is determined by the unanticipated movements in k number of risk factors:

$$R_i = E(R_i) + b_{i1} \langle RF_1 - E(RF_1) \rangle + \dots + b_{ik} \langle RF_k - E(RF_k) \rangle + \epsilon_i \dots \dots \dots (2.8)$$

Where:

$RF_k - E(RF_k)$ is the risk premium on F_k that is not anticipated by the market participants; and

ϵ_i is a normally distributed random error. The correlation of ϵ_i and ϵ_j is equal to zero.

2.5.3 Identities of the APT Factors

Although the APT avoids the benchmark problem by focusing on few major systematic risk factors rather than the overall market risk, it suffers from similar criticisms since it does not indicate what the factors are. However, the possible identities of the major factors suggested by empirical research conducted internationally are generally in line with the major factors identified by Chen, Roll and Ross (1986). Chen *et al* (1986) conducted research on stocks listed on the New York Stock Exchange (NYSE) over the period from 1953 to 1983. The test results indicate that the unanticipated movements in the industrial production, inflation, yield spread between low-grade bond and government bond and the slope of the term structure of interest rates are significant risk factors that determine stock market returns. Chen *et al* (1986) further suggest that other potential factors may exist, however, they only influence asset returns through their impacts on the above-mentioned factors. Harrington (1987) indicates that these factors are also supported by the economic rationale that they exert their influences on the key determinants of the discounted cash flow (DCF) model: industrial production is the indication for future cash flows (D_1) and inflation enters to adjust the nominal growth rates (g). The interest rates and the spread between low-grade and high-grade bonds are determinants of the discount rate for future cash flows (k).³

³ Given $V_0 = D_1 / (k - g)$; where V_0 is the intrinsic value of the asset.

2.5.4 The Implications of the APT in Asset Allocation

Modigliani and Pogue (1988) suggest that the distinctive advantage of the APT is that it permits investors to specifically tailor their portfolios to their tastes and circumstances by adjusting the exposure to individual risk factors. This is opposite to the CAPM because the CAPM suggests that the market portfolio is the optimal risky portfolio, and that all investors will hold part or all of their investments in the market portfolio. Roll and Ross (1984: 24) also states that *“to argue that there is one best strategy for everyone – such as “buying the market” – is simply wrong”*. This argument implies that different investors could have portfolios with the same CAPM beta but have quite different exposures across the various risk factors. For example, blue-collar workers may be exposed to greater inflation risk than white-collar workers. Hence, Roll and Ross (1984) indicate that the major task of strategic portfolio management is to decide on the most desirable exposures to various systematic risks for the clients. The APT enhances this task by allowing portfolio managers to segment portfolio risk, and manage portfolios actively through predicting movements in critical risk factors. For example, asset A has an inflation beta of 2 and asset B has an inflation beta of 1. Then, a desired inflation beta of 1.4 for a particular client's portfolio can be achieved by allocating 40 percent of the capital in A and 60 percent of the capital in B [given $(0.4*2) + (0.6*1) = 1.4$]. Although the APT is appealing and innovative in its own merit, the capital market theory remains the mainstream of the traditional finance regarding portfolio management.

2.6 Behavioral Finance

“People are rational in standard finance; they are normal in behavioural finance. Rational people care about utilitarian characteristics but not value-expressive ones, are never confused by cognitive errors, have perfect self-control, are always averse to risk, and are never averse to regret. Normal people do not obediently follow that pattern” (Statman, 1999: 26).

Behavioral finance is an area of study that analyses the impacts of systematic psychological biases on the decision making process of investors. The proponents of behavioral finance believe that investors are influenced by their emotions in addition to the mean, variance and covariance of asset returns in making investment choices. This implies that investors will not arrive at the same optimal risky portfolio as suggested by the separation theorem of Tobin (1958). Based on this analogy, it can be argued that the proposed asset allocation decision of MPT is essentially a suggestion for the “what if the market is efficient” scenario, and the studies of behavioral finance serve to provide alternative scenarios for investors in an irrational market. If the market is not as efficient as suggested by the EMH, the risk-return pricing relationship depicted by the SML of the CAPM would be biased and the portfolios constructed based on this relationship will cease to be mean-variance efficient. The major development of behavioral finance stems from prospect theory of Kahneman and Tversky (1979), which presents a critique of the expected utility theory.

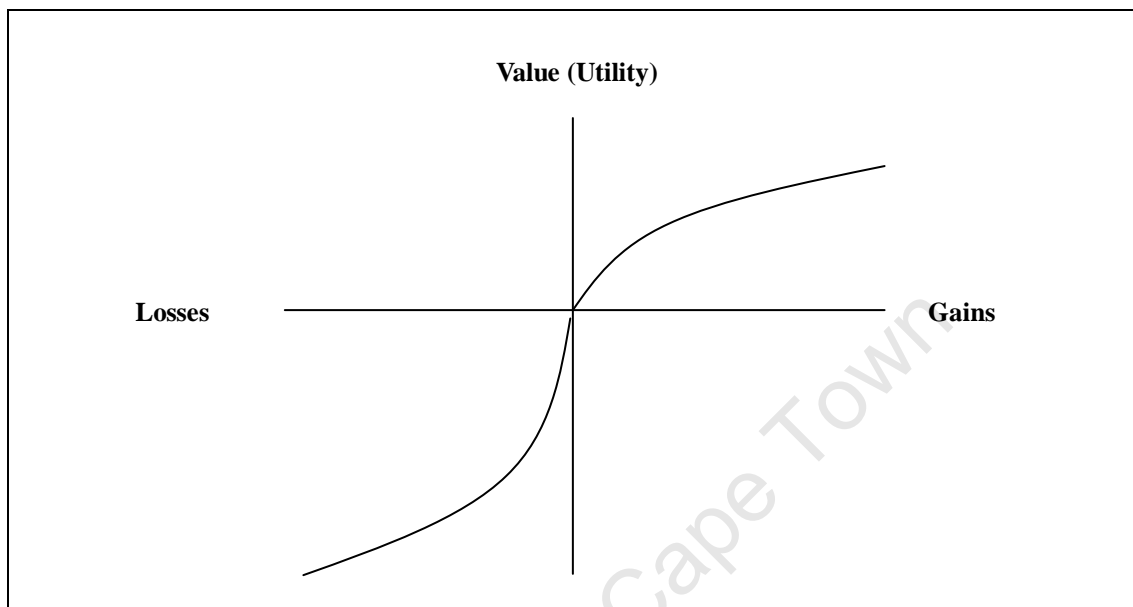
2.6.1 Prospect Theory

Prospect theory asserts that choices of investors under risk exhibit several pervasive effects that are inconsistent with the basic tenets of the expected utility theory. As a critique of the expected utility theory, prospect theory studies the decisions of investors under the presence of uncertainty based on cognitive psychology rather than investor rationality.

As discussed in Section 2.1, the expected utility theory suggests that investors are risk averse when making investment decisions. In addition to the recognition of risk aversion, prospect theory introduces the concept of loss aversion, which states that investors prefer to avoid loss to acquiring gains. To demonstrate the concept of loss aversion, prospect theory suggests that investors judge the gains and losses of an investment relative to a specific reference point such as the purchase price of an asset. The utility derived from an investment can be expressed in an S-shaped value function displayed in Figure 2.5 (in comparison to Figure 2.1), where positive utility is derived from gains and negative utility is derived from losses. This value function is in line with the expected utility theory (or the marginal utility function) in that the function is concave for gains, meaning that the marginal utility derived from additional gains is increased at a decreasing rate. However, prospect theory also implies diminishing marginal disutility for losses since the function becomes convex when the asset position is below the reference point. In addition, the function is steeper for losses than for gains, which implies that the extent of the disutility derived from making losses is larger than the level of utility derived from an equal amount of gains.

Figure 2.5 Utility Function of Prospect Theory

Figure 2.5 is adapted from Kahneman and Tversky (1979: 279). It illustrates that the utility of an investor from an investment is a function of estimated gains and losses relative to the specific reference point such as the purchase price of an asset.



Shefrin and Statman (1985) indicate that loss aversion is the consequence of seeking pride and avoiding regret by investors, which often leads them to hold losers for too long and sell winners too soon. This tendency is referred to as the disposition effect. The disposition effect is particularly strong when investors use the purchase price of their assets as the reference point to determine their gains and losses associated with their assets.

In addition to the recognition of loss aversion, Kahneman and Tversky (1979) found that investors tend to underweight positive outcomes that are merely probable compared to positive outcomes that can be obtained with certainty. For example, people prefer to take an option that offers guaranteed \$3,000 to an alternative that

offers 80% chance of winning \$4,000 or 20% of winning nothing, while the expected value of the preferred choice is indeed \$200 ($\$3,000 - 80\% * \$4,000$) lower than the alternative choice. This observation is termed the certainty effect, which violates the expected utility theory that weights the utilities of outcomes purely by their respective probabilities.

However, when the signs of the outcomes from the above experiments are reversed so that the potential gains in the positive domain are replaced by losses in the negative domain, Kahneman and Tversky (1979) find a reflection effect in that the preference order for the given options is reversed. More specifically, people prefer to take an option that involves 80% chance of losing \$4,000 to an option that guarantees a sure loss of \$3,000. Similar to the consequence of the choice in the positive domain, the expected loss for the preferred choice is \$200 more than the alternative choice. This observation indicates that the decisions of investors are affected by their psychological biases for ranking choices amongst positive prospects as well as negative prospects. While the certainty effect suggests that investors are over-conservative when making decisions in the positive domain, the risk seeking of investors is exhibited in the negative domain due to the reflection effect.

Although the reflection effect suggests that investors are risk seeking in the negative domain with high probability of loss, Kahneman and Tversky (1979) find investors to be risk-averse for small probabilities of losses. For example, people pay insurance premium that far exceeds the expected actuarial cost. The conflicting attitudes toward risk in the negative domain might contribute to the attractiveness of both insurance and gambling to investors (Kahneman and Tversky, 1979).

Another cognitive error of investors pointed out by prospect theory is that investors often segregate individual investments in their portfolios with the objective to track their individual gains and losses. This practice is referred to as mental accounting by Thaler (1985). Mental accounting neglects the importance of diversification in the portfolio concept and prevents portfolios from being mean-variance efficient.

2.6.2 Sources of Behavioural Biases

Hirshleifer (2001) divides the sources of behavioural biases into three major categories: heuristic simplification, self-deception and emotions. According to Hirshleifer (2001), emotions play an important role in all kinds of behavioural biases. For example, risk aversion, fear of regret and loss aversions are essentially calculated avoidance of unpleasant feelings. The importance of emotion in the decision making of people is also reflected in the great amount of marketing effort by companies in advertising and promoting their products.

While economists maintain that cognitive errors are unique to individuals and are offset in equilibrium, Hirshleifer (2001) argues that people often share similar heuristics. Heuristic simplification arises because cognitive constraints such as limited attention and memory force people to simplify complicated decision making process. Hirshleifer (2001) further suggests that *“an information signal is salient if it has characteristics (e.g. differing from the background or from a past state) that are good at hooking our attention or at creating associations that facilitate recall”*. The psychological bias pointed out in prospective theory that involves highlighting different reference points for comparing outcomes of separate mental accounts is an

act of heuristic simplification. Investors may also suffer from representativeness bias if they simplify their investment choices by allocating capital to companies with good historical results without analysing their future prospects. Investors who use past winning stocks to represent future winning stocks fail to take into account the sustainability of the past achievements. Another mental shortcut pointed out by Nofsinger (2005) is that people often invest in companies they are familiar with, such as the companies they work for or companies in their home town. Investment choices based on familiarity lead to over-concentration of a portfolio and lack of diversification.

Self-deception, on the other hand, leads investors to feel overconfident in their decisions due to the illusion of their knowledge. Daniel, Hirshleifer and Subrahmanyam (1998) propose a theory describing investor underreaction and overreaction in capital markets due to overconfidence and biased self-attribution of investors. The theory states that investors overreact to private information signals and underreact to public information signals due to their overconfidence about the precision of private information. On the other hand, the biased self-attribution of investors cause asymmetric shifts in the confidence of investors as a function of their investment outcomes. Possible consequences of biased self-attribution include stock market short-term momentum, short-term earnings drift and long-term reversals from the drift.

2.7 Conclusion

The efficient market hypothesis (EMH) is based on the notion that the market is informationally efficient, meaning that asset prices reflect all relevant information as a consequence of investors competing to act on new information to maximise the values of their investment portfolios. While Markowitz (1952) introduces the efficient frontier of risky assets in an efficient capital market, the separation theorem of Tobin (1958) proposes the method in which investors with different degrees of risk appetite should form their portfolios by altering the proportions of their investments between the risk-free asset and the market portfolio. Sharpe (1964), Lintner (1965) and Mossin (1966) extend the existing framework of Markowitz (1952) and Tobin (1958) to develop the capital asset pricing model (CAPM) for pricing assets in an efficient capital market. The CAPM postulates that the only relevant risk for an asset is market risk since firm-specific risk is eliminated once the asset is included in a well diversified portfolio. Due to the critique of Roll (1977; 1978) that the identity of the true market portfolio is unobservable, a multi-factor asset pricing model developed under the arbitrage pricing theory (APT) of Ross (1976) offers an alternative approach in pricing assets to the CAPM.

Theories and asset pricing models such as the MPT, CAPM and APT are based on the assumption of market efficiency, which provide solutions for asset allocation in markets where investors are rational in making investment decisions. The expectation theory states that investors are rational if they make their decisions purely based on the probability concept of outcomes. Behavioural finance, on the other hand, suggests that investors are irrational and often influenced by psychological biases in making decisions. The major development of behavioural finance stems from prospect theory

of Kahneman and Tversky (1979), which presents several arguments against the basic tenets of the expectation theory. While the expectation theory utilises the function of diminishing marginal utility to emphasise the risk aversion of investors, the prospect theory specifically indicates that investors are risk averse for gains but exhibit diminishing marginal disutility when it comes to losses. In addition, the prospect theory introduces the concept of loss aversion, which suggests that the extent of disutility derived from losses is larger than the utility derived from an equal amount of gains. Behavioural biases lead investors to violate the assumptions of traditional finance. Instead of making investment decisions based on the mean, variance and covariance of asset returns, behavioural finance suggests investors base their decisions on heuristics. The argument of Hirshleifer (2001) that heuristics are shared by investors suggests that assets prices may not reflect their long-term intrinsic values indicated by efficient capital market theories.

REVIEW OF PRIOR LITERATURE

3.1 Introduction

In a market where investors violate the assumptions of modern portfolio theory (MPT) and behave irrationally, they are prone to make systematic errors in their trading activities. Consequently, the movements in the market portfolio will not be the single source of risk for assets in such market since it does not capture the risk of systematic errors of irrational investors. Thus, the results of the empirical work on the various forms of the efficient market hypothesis (EMH) have significant implications on the manner in which investors should allocate their assets. De Bondt and Thaler (1985) suggest that irrational investors overreact to the arrivals of new information in making their investment decisions. This behaviour leads to systematic overshooting of asset prices, and the reversals of the asset prices to their equilibrium levels should be predictable. This proposition is known as the overreaction hypothesis, and tests of the overreaction hypothesis, tests of the random walk of asset prices and other tests of technical trading rules based on past price and volume data all form parts of the tests of the weak-form EMH.

With regard to tests of the semi-strong form EMH, if investors are able to outperform the market using publicly available information other than historical prices and volume data in a consistent manner, the market is less efficient than the semi-strong form EMH. According to Reilly and Brown (2003), tests of the semi-strong form EMH can be divided into return predicting studies and event studies. Return

predicting studies aim at examining the forecasting ability of financial models that incorporate public information as model inputs. Firm-specific attributes such as accounting ratios are generally employed as factors in addition to macroeconomic variables to enhance return forecasting in financial modeling. However, significant contributions of firm-specific attributes to asset pricing are in contradiction to the EMH since firm-specific risks are diversifiable within the framework of the CAPM and hence are irrelevant in explaining asset returns. On the other hand, event studies attempt to determine the speed at which asset prices adjust to specific economic events or company announcements.

While tests of the weak form and semi-strong form EMH aim at determining the profitability of various strategies employed by average investors, tests of the strong form EMH involve analysing the performance of corporate insiders. If the market is efficient of a strong form, strict regulations and sound corporate governance are in place to prevent corporate insiders from acting on unreleased information that are relevant for price formation. For the purpose of this thesis, the review of prior research discussed in this chapter focuses on empirical studies of the weak form and the semi-strong form EMH that are applicable to average investors.

The various forms of empirical tests mentioned above attempt to reject the EMH (i.e. the null hypothesis) by finding evidence that the markets being examined are less efficient than suggested by the EMH. Empirical findings in support of the alternative hypothesis are termed market anomalies, which can be used to develop profitable investment strategies of different styles. *“As active managers attempt to differentiate expected returns based on explicit or implicit criteria, they position their portfolios to be out of sync with the broad market”* (Kao and Shumaker, 2001: 37). One way of

doing so is to construct indices that represent major investment styles. The most pronounced market anomalies that are frequently employed to construct style indices include the long-term price reversals, short-term return momentum, small firm effect and value effect. The investment styles formed based on these anomalies have a broad following among fund managers who believe that tilting their portfolios towards the desired investment styles can positively differentiate their performances from the broad market.

In a competitive fund industry, fund managers have a further desire to distinguish their performance from their rivals who follow similar investment styles. In order to fight for their survivals in the industry, fund managers allocate capital to the stocks within each style category differently from the style benchmarks. Sharpe (1992) proposes the return decomposition approach that can be used to conduct performance attribution on the actively-managed funds. This approach determines the exact style tilts followed by the manager, and subsequently evaluates the effectiveness of the manager's stock allocation policy compared to the style benchmark. While stock-picking ability adds value by allocating stocks differently from the style benchmark, tactical style timing serves as an alternative method of adding value by re-allocating funds between alternative investment styles at different phases of the business cycle in the belief that the profitability of alternative investment styles might be cyclical.

The global financial crisis of 2008 demonstrates that there are periods of uncertainty during which most asset classes experience inescapable drawdown. Thus, the desired style exposures during these periods would be zero. A basic trend-following model introduced by Faber (2009) that predicts the timing of portfolio rebalancing using derivative overlay during turbulent times is also discussed in this chapter.

3.2 Market Anomalies and Investment Styles

An investment style is defined by Kao and Shumaker (2001) as a system of classification by market segments that have distinguishing characteristics. Asset managers who allocate assets based on investment styles believe that the market portfolio is not mean-variance efficient and abnormal returns can be gained by exploring the apparent market anomalies. A market anomaly generally divides the cross-section of assets into two distinguishable asset classes or investment styles: momentum versus contrarian based on investor overreaction; value versus glamour based on the value anomaly and large versus small caps based on the size anomaly.

3.2.1 Abnormal Returns of Momentum and Contrarian Strategies

De Bondt and Thaler (1985) attribute the phenomenon of investor overreaction to the persistent overweighting of recent information and underweighting of long-term fundamental information by irrational investors. Given that the fundamentals stay the same, the overstated or understated share prices would be expected to correct to their long-term fundamental values. If investor overreaction is present in the equity market, momentum strategies that focus on acquiring past winners can be devised to profit from the temporary overshooting of asset prices before the market corrections take place. On the other hand, contrarian strategies that bet on past losers can be used to take advantage of the reversal of asset prices when the market is ready to correct.

De Bondt and Thaler (1985) test the overreaction hypothesis on the New York Stock Exchange (NYSE) by examining the average cumulative abnormal returns (ACAR) of

the prior winner and loser portfolios over the period from 1 January 1933 to 31 December 1982. The prior 36-month loser portfolios outperform their winner counterparts by 24.6% 36 months after formation, on average, over the examination period. The loser portfolios are found to accumulate positive abnormal returns while the winner portfolios accumulate negative abnormal returns since formation. The abnormal returns of the loser portfolios are less significant for the portfolios formed using shorter formation periods. In addition, the mean reversals of the loser portfolios are three times stronger than the mean reversals of the winner portfolios on average in terms of their 36-month ACARs. However, due to the fact that the majority of the positive abnormal returns of the loser portfolios are earned in January, the study results might be attributable to the tax-loss selling for the losers in addition to the investor overreaction due to behavioural biases.

In the follow-up paper, De Bondt and Thaler (1987) re-evaluate the overreaction hypothesis by including factors such as firm size, seasonality and market risk in their study. The January excess returns are found to be negatively related to prior December excess returns for the past winners, which serves as an evidence of capital gains tax lock-in effect for the past winners. On the other hand, the proposed tax-loss selling for the losers is not found in the study. In general, the re-evaluation supports the overreaction hypothesis in that the mean reversals of past winners and losers cannot be explained by size effect and market risk. However, Chan (1988) argues that the beta of losers increases while the beta of winners decreases over time. When the risk changes are controlled for, the abnormal returns between prior losers and winners appear to be insignificant in the study conducted by Chan (1988) over the period from 1 January 1933 to 31 December 1985.

In order to clarify the issue as to whether the findings of De Bondt and Thaler (1985, 1987) are biased by the changes in beta or size of the portfolios under examination, Chopra, Lakonishok and Ritter (1992) perform regression analysis on the abnormal returns of prior winners and losers on the NYSE over the period from 1 January 1931 to 31 December 1986. The results reveal that significant differences in the abnormal returns of prior losers and winners are realised even when the time-varying betas are taken into account. Chopra *et al* (1992) further argue that since size, prior returns and betas are interrelated in general, any study that attempts to relate security performance to just one or two of these factors would suffer from an omitted variable bias. When these three factors are incorporated in a multiple regression analysis, the study results indicate that prior losers outperform prior winners by 4.8% on average 5 years post formation after controlling for size and beta. The degree of mean reversal is nevertheless stronger for smaller firms. They attribute this result to the fact that large firms are held predominantly by institutional investors and hence are less subject to investor overreaction as opposed to smaller firms that are held by individual investors.

Jegadeesh and Titman (1993), on the other hand, examine the returns to buying prior winners and selling prior losers as a form of relative strength strategy on the NYSE and the American Stock Exchange (AMEX) over the period from 1 January 1965 to 31 December 1989 based on 3- to 12-month prior returns. They find that abnormal returns are available for short- to medium-term relative strength strategies in the first year after formation and subsequently dissipates in the following 2 years. This finding, in conjunction with the positive correlation between the length of the formation period and the degree of mean reversal documented by De Bondt and Thaler (1985), imply that the return momentum of short- to medium-term momentum portfolios are non-exhaustive and are indications of their near-term performance after formation.

When tests of the overreaction hypothesis are conducted on the Frankfurt Stock Exchange (FSE), Schiereck, De Bondt and Weber (1999) find that the momentum strategies formed based on prior 6-month and 12-month excess returns outperform passive investing in the DAX stock index by the largest margin amongst other strategies over the period from 1 January 1961 to 31 December 1991. On the other hand, the contrarian strategies formed based on prior 36-, 48- and 60-month excess returns outperform the DAX stock index over the examination period. When similar tests are conducted on the Spanish Stock Exchange, Forner and Marhuenda (2003) find that the 12-month momentum strategy and the 60-month contrarian strategy yield significant positive abnormal returns over the period from 1 January 1963 to 31 December 1997.

Chan, Hameed and Tong (2000) extend the studies of investor overreaction to international capital markets with an aim to explore the profitability of momentum investing in broad equity market indices over the period from 1 January 1980 to 30 June 1995. The 23 equity market indices that are available for constructing the relative strength strategies include 9 countries from the Asia-Pacific region, 11 countries from Europe and 2 countries from North America and South Africa. The relative strength strategy is implemented by buying the winner country indices and simultaneously selling the loser country indices based on 1-, 2-, 4-, 12- and 26-week prior return momentums of the respective indices. The results indicate that momentum profits are statistically significant for short holding periods of less than 4 weeks.

3.2.2 Value and Size Anomalies

The EMH asserts that the future prospects of a company are accurately reflected in its share price. This implies that good investments are those with high expected future growth. Thus, glamour firms that have high market values relative to their current earnings are expected to outperform value firms with low price-earnings multiples. This proposition is regarded as a risky investment approach by Graham and Dodd (1934) who suggest that the share price of a glamour firm reflects the future earnings estimated from its historical trend and is often exaggerated and later collapses. This is especially true in a market where share prices systematically overshoot as a result of investor overreaction.

Basu (1977) examines the relationship between the price-to-earnings (P/E) ratio of common stocks and their future performances on the NYSE over the period from 1957 to 1971. The results show that the bottom two P/E quintiles earn 16.3% and 13.5% while the top two P/E quintiles earn 9.3% and 9.5% per annum respectively over the examination period. The results of the regression analysis based on the market model indicate that the low P/E quintiles also outperform the high P/E quintiles on a risk-adjusted basis in terms of their Jensen's alpha (the intercept of the regression as an indication of abnormal returns). The regression analysis also reveals that the bottom two P/E quintiles have lower beta coefficients in comparison to the top two P/E quintiles. This implies that investing in low P/E firms can achieve outstanding performance at a relatively lower risk than investing in high P/E firms. This implication suggests that investors are not risk averse when making investment decisions since the riskier glamour stocks are priced higher than the safer value stocks, which indeed, offer higher returns. Based on this analogy, Basu (1977) attributes the

observed P/E effect to exaggerated investor expectations for the glamour stocks, which is in line with the opinion of Graham and Dodd (1934).

In addition to the earnings multiple, value proxies can also be constructed from other accounting ratios that enhance the comparison between the company's market value relative to its fundamental values such as sales, cash flow, dividends and book value. Lakonishok, Shleifer and Vishny (1994) examine the value phenomenon on the NYSE and the AMEX over the period from 1963 to 1990. The value proxies used in this study include book-to-market ratio (B/M), cash flow-to-price ratio (C/P) and earnings yield (EY). In addition, the average historical 5-year growth rate of sales is used as a proxy for growth firms. The results reveal that all of the value proxies exert their influences in differentiating the cross-sectional equity returns to different extents. On the other hand, portfolios that consist of firms with high historical growth rate for their sales underperform portfolios with lower historical sales growth.

Irrespective of their growth or value characteristics, small firms generally earn higher returns than large firms (Haugen, 1995). Firms with smaller market capitalisation (small caps) are less established and less actively traded, and are generally regarded as riskier investments. According to the risk-return relationship demonstrated by the CAPM, small caps are riskier and should yield higher returns compared to large firms as long as their returns are justified for their risk. However, empirical research has found that small firms tend to earn higher returns than what is predicted by the CAPM.

Banz (1981) examines the relationship between the return and the market capitalisation of the companies listed on the NYSE over the period from 1936 to 1975. The results of the regression analysis based on the market model indicate that firms in

the smallest size quintile earned significantly higher risk-adjusted returns than firms in the larger size quintiles over the examination period. However, the size effect is concentrated in the smallest size quintile and is not obvious across the other four size quintiles. This non-linear distribution of abnormal returns across the five size quintiles remains evident even though the market capitalisations of the sample shares are logged. In addition, the magnitudes of the size payoffs in the regression appear to be substantially different over the sub-periods. Banz (1981) attributes the size effect to the misspecification of the CAPM and calls for further tests to investigate the relationship between firm size and other anomalies. However, Banz (1981) argues that it is unlikely that the size effect is subsumed by the earnings yield anomaly. This argument is based on the results of a study conducted by Reinganum (1981), who finds that the earnings yield effect disappears when the size of the sample is controlled for in his study over the examination period from 1967 to 1975. On the contrary, the size effect persists when the sample is controlled for size. Based on this observation, Reinganum (1981) suggests that the size and earnings yield effects tend to relate to the same set of missing factors in the CAPM. However, the factors seem to be more closely associated with firm size than earnings yield.

Roll (1981) suggests that the size effect documented by the above studies could be due to the fact that small firms are less liquid and thus have a downward bias in their beta estimates in research based on the market model. Reinganum (1983), on the other hand, speculates on the January tax-loss selling effect as one of the possible explanations for the size effect. This suggestion is based on the rationale that a portfolio consisting of small firms would exhibit relatively high volatility throughout the year. In addition, such portfolio is more likely to be negatively affected by drastic loss of few constituents within the portfolio. In order to detect whether the size effect

is seasonal, Reinganum (1983) conducts further research on the NYSE and the AMEX stocks over the period from 1963 through 1980. The results indicate that the abnormal returns earned by small firms are concentrated at the very beginning of January over the examination period. This is consistent with the tax-loss selling proposition. The seasonality of abnormal returns to small firms remains significant even when the sample consists of only prior year winners, which are least likely to be sold for tax purposes.

Brown, Kleidon and Marsh (1983) conduct further studies on the size effect using the same sample studied by Reinganum (1981) with extended period from 1967 to 1979 using the market model. The relationship between excess returns and firm size is found to be inversely linear between the excess returns of the sample shares and the logarithm of market capitalisation. The excess returns earned by the size deciles in their study appear to be unstable over the period from 1969 to 1973, but are statistically stationary thereafter.

Fama and French (1992) consolidate the empirical findings on the value and size anomalies and test both anomalies jointly on the NYSE, the AMEX and the NASDAQ over the period from 1963 to 1990. They find that B/M and market capitalisation are able to describe the cross-sectional equity returns over the examination period. Similar to the findings of Basu (1977), Fama and French (1992) find that value firms have lower beta compared to glamour firms. The fact that glamour stocks have high risk and low returns provides solid evidence against the case of the CAPM being correctly specified. Based on the empirical findings of their work in 1992, Fama and French (1993) recognise that the value and size anomalies represent potential risks in the portfolio, and investors anticipate compensations for holding value stocks and

small caps. They propose a 3-factor asset pricing model that incorporates the size risk premium and the value risk premium in addition to the market risk premium of the CAPM as shown in Equation 3.1:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i \left(R_{M,t} - R_{f,t} \right) + s_i SMB_t + h_i HML_t + \varepsilon_{i,t} \quad \dots\dots\dots (3.1)$$

Where:

$R_{i,t}$ is the return on asset i in month t ;

$R_{f,t}$ is the return on the risk-free asset in month t ;

α_i is the regression intercept;

β_i is the beta coefficient of asset i ;

$R_{M,t} - R_{f,t}$ is the market risk premium in month t ;

s_i is the sensitivity of asset i 's return to movements in the size risk premium SMB ;

h_i is the sensitivity of asset i 's return to movements in the value risk premium HML ; and

$\varepsilon_{i,t}$ is the residual (random error) of the regression for asset i in month t .

The size risk factor, SMB , is estimated by the spread between the returns of the small- and large-firm portfolios. On the other hand, the value risk factor, HML , is computed from the spread between the returns of the high- and low-B/M portfolios.

Fama and French (1996) apply the 3-factor model to explain the returns of the portfolios formed based on the documented stock market anomalies such as the short-term return momentum of Jegadeesh and Titman (1993), the long-term price reversal of De Bondt and Thaler (1985) and C/P, EY and historical sales growth as additional

value/glamour proxies recommended by Lakonishok *et al* (1994). Except for the momentum factor of Jegadeesh and Titman (1993), the 3-factor model adequately explains the returns of the portfolios formed based on the attributes mentioned above. Fama and French (1996) argue that since these variables are all scaled versions of a firm's value, it is reasonable to expect that the effects of some variables to be subsumed by the more important variables. They conclude that except for the short-term return momentum, the alternative variables do not uncover dimensions of risk beyond those required to explain the returns of portfolios formed on size and B/M.

The value and size anomalies are not just a U.S phenomenon, but also an international phenomenon. Fama and French (1998) conduct studies on the value anomaly at a global scale. The study sample covers EAFE (Europe, Australia and the Far East), the NYSE, the AMEX and the NASDAQ stocks over the period from 1975 to 1995. The value proxies used in their study include B/M, C/P, EY and DY. Portfolios formed on these value proxies demonstrate strong value premiums that correlate positively with their respective fundamental values. The B/M proxy is the most consistent value proxy over the examination period in that the high B/M portfolios outperform the low B/M portfolios across all the countries with the exception of Italy. The results of the regression analysis also indicate that a standard international CAPM has failed to explain the international value anomaly over the examination period. Based on the same value attributes studies by Fama and French (1998), Bauman, Conover and Miller (1998) investigate the value and size anomalies on EAFE as well as Canadian stocks over the period from 1986 to 1996. They find that value portfolios do not outperform glamour portfolios each year. However, when value portfolios earn higher returns, they tend to outperform glamour portfolios by a wide margin. They also find the size effect to be evident across all the countries in most years of the study period.

Chan and Lakonishok (2004) provide further evidence on the value anomaly in the international equity markets. They construct a composite value proxy that incorporate B/M, C/P, EY and sales-to-price ratio of the sample firms based on the expected value payoffs from a cross-sectional regression model. They believe that the composite value proxy is able to diversify across signals generated from various value attributes. The sample used in Chan and Lakonishok (2004) include large-caps in the MSCI Morgan Stanley Capital International (MSCI) EAFE Index. The results show that the highest ranked portfolio by composite value proxy generates a geometric return of 12.3% compared to a return of 4.5% per annum earned by the MSCI EAFE Composite Index over the period from 1989 to 2001.

3.2.3 South African Evidence of Market Anomalies

Page and Way (1992/1993) test the overreaction hypothesis on the Johannesburg Stock Exchange (now the JSE Securities Exchange) over the period from 1974 to 1989. The loser portfolios of 50 shares formed based on 36-month prior cumulative excess returns earned cumulative abnormal returns of 10%, while their winner counterparts accumulate 4.5% negative abnormal returns, on average, over the examination period. Overall, the loser portfolios outperform the winner counterparts by 14.5%, on average, 36 months after formation. Consistent with international studies, the past winners and losers mainly accumulate their abnormal returns from 12 months after formation. In addition, the asymmetrical mean reversals of winners and losers observed by De Bondt and Thaler (1985) are also observed. The results provide evidence of investor overreaction on the JSE and indicate that the JSE is less than weak-form efficient over the examination period.

Muller (1999) further investigates the investor overreaction on the largest 200 shares by market capitalisation on the JSE over the period from 1985 to 1998. The middle-third of the examination period is divided into 30 equally-spaced sub-periods to provide 30 randomly-chosen portfolio formation dates within the respective sub-periods. This selection method avoids the seasonality bias in the studies conducted by De Bondt and Thaler (1985) and Page and Way (1992/1993). However, the seasonality adjustment is deemed unnecessary in the research conducted by Page and Way (1992/1993) based on the argument that the January effect documented in the U.S. studies are unlikely to impact on the tests conducted on the JSE since the majority of shares in South Africa are held by institutional investors, and companies are free to choose the calendar month to end their financial years. The size of the winner and loser portfolios are kept to either 30 or 60 shares and the formation and holding periods are varied from 60 days to 4 years based on computer simulations. The results indicate that both winner and loser portfolios yield positive abnormal returns initially. However, while the holding period of the loser portfolios is optimised at 340 days, the winner portfolios lose their initial momentum after approximately 600 days. This observation suggests that the asymmetrical reversals of the winners and losers might be due to their unique timings in market correction.

Fraser and Page (2000) evaluate the interaction of value and momentum strategies on the JSE over the period from 1978 to 1997 based on the results of the cross-sectional regression analysis. Their results indicate that value investing and momentum investing independently explain the cross-sectional returns on the JSE. Van Rensburg (2001) tests the effect of style anomalies on the JSE by estimating the exposures of JSE equity returns to movements in the style-mimicking portfolios on the JSE over the period from 1983 to 1999. A variety of style attributes that fit into the value, future

earnings growth and irrationality/neglect style categories are examined in this study. The regression results indicate that EY, past 12-month returns, market capitalisation, DY, past 6-month returns, leverage, cash flow-to-debt ratio, turnover and past 3-month returns cannot be explained by the 2-factor APT of Van Rensburg and Slaney (1997), which segments the market risk into the resource risk factor and the industrial factor. The results of the cluster analysis on these candidate factors reveal that EY, market capitalisation and past 12-month returns represent major style risks on the JSE.

Van Rensburg and Robertson (2003a) re-investigate the risk factors tested by Van Rensburg (2001) on the JSE over the period from 1990 to 2000 based on the characteristic-based approach. The time-series factor payoffs to the individual style attributes are estimated in the univariate test. Those style attributes that are rewarded with significant payoffs are subsequently employed in a stepwise permutation procedure in multivariate analysis. The multifactor model continues to add attributes that improves its explanatory power and simultaneously eliminate attributes that drag the performance of the model until the explanatory power of the model can no longer be improved. P/B, DY, EY, cash flow-to-price ratio, price-to-profit ratio and market capitalisation are extracted after the initial univariate test. The results of the multivariate analysis indicate that EY and market capitalisation subsume all other factors and thus represent the two significant sources of style risk on the JSE over the examination period. Although the momentum factors based on past short-term returns dominate the study conducted by Van Rensburg (2001), they do not receive significant factor payoffs even in the initial univariate test in this study. Van Rensburg and Robertson (2003b) extend the research by adopting the methodology of Fama and French (1992) to cross-examine the two sources of style risk (EY and market capitalisation) documented by Van Rensburg and Robertson (2003a) on the JSE.

Consistent with the results of international studies, they find value firms proxied by high EY earn higher returns and have lower beta. However, they find that small caps earn higher returns and have lower beta, which is inconsistent with international research that generally find small caps to be riskier investments. In addition, the results of the two-way sorted portfolios by both the size and EY confirm the results of Fraser and Page (2000) and Van Rensburg and Robertson (2003a) in that the size and the value effects tend to operate independently of each other on the JSE.

Rousseau and Van Rensburg (2004) investigate the length of holding period and potential payoffs to value portfolios on the JSE over the period from 1982 to 1998. They find that the returns to the value portfolios improve significantly for holding periods beyond 12 months. This implies that value investing is best employed as a long-term strategy. However, the results show that the returns to the value stocks are strongly right skewed, indicating that the rewards to value stocks are not evenly distributed. Rousseau and Van Rensburg (2004) suggest that a diversified value portfolio is more likely to achieve outstanding performance since the abnormal return earned by the value portfolio is dominated by few members of the portfolio.

3.3 Applications of Style Indices in Active and Passive Portfolio Management

Empirical studies of market efficiency generally find that the market is not as efficient as stated by the EMH, suggesting that market anomalies should be taken into account when making asset allocation decisions rather than indexing the market portfolio. Actively-managed funds generally possess unique asset allocation approaches that tilt their performances toward certain investment styles, which differentiate their performances from the broad equity market indices. Therefore, the appropriate benchmarks for actively-managed funds are the indices that reflect the underlying styles of the funds rather than the broad market indices.

In order to outperform the return of the designated style benchmark, a fund manager needs to overweight potentially outperforming stocks and underweight potentially underperforming stocks relative to the weights allocated by the benchmark. This task reflects the manager's ability in identifying the future winners and losers within the assets held by the benchmark, while maintaining their exposures to the benchmark without significant deviations from the benchmark. According to the fundamental law of active management presented by Grinold (1999), the success of this task depends on two crucial factors, namely the accuracy of the manager in forecasting stock returns and the breadth of the strategy measuring the number of distinctive investment bets. Whether a manager performs this task in a satisfactory manner can be evaluated by conducting performance attribution on the fund returns.

3.3.1 Style-Based Performance Attribution

Performance attribution refers to the procedure that determines the relative importance of the various sources from which a fund generates its returns. Sharpe (1992) proposes the return-based style decomposition approach to analyse the performance attribution of actively-managed funds based on a multifactor model that incorporates different asset classes and investment styles as its factors. The implementation of this approach requires the construction of style indices and factor-mimicking portfolios that symbolise the major investment styles and asset classes. Equation 3.2 demonstrates the style-based factor model employed by Sharpe (1992):

$$R_{i,t} = \sum_{k=1}^N b_{i,k} \times R_{k,t} + \varepsilon_{i,t} \quad \dots\dots\dots (3.2)$$

Where:

$R_{i,t}$ is the return of fund i in month t ;

$R_{k,t}$ is the return on the k th asset class/style index in month t ;

$b_{i,k}$ is the exposure of fund i 's return to movements in $R_{k,t}$; and

$\sum_{k=1}^N b_{i,k} \times R_{k,t}$ is the part of the return that tracks the returns of major asset classes/styles (i.e. the style return); and

$\varepsilon_{i,t}$ is the part of the return that cannot be explained by the major asset classes/styles (i.e. the selection return).

Equation 3.2 distinguishes a fund's style return from its selection return that is unrelated to the fund's underlying investment styles or asset classes. The style return of the equation effectively decomposes a fund's return to the component returns generated from various asset classes/investment styles. When the sum of the coefficients is constrained to be 100%, the coefficient attached to an asset class/style

index represents the weight or proportion of the fund's investment allocated to that asset class/style index. Assume that the fund's exposures to the asset classes/styles are consistent over time, the style return of Equation 3.2 represents a composite benchmark that accurately replicates the inherent investment styles of the fund. The selection return of the fund, on the other hand, arises from the fund manager's stock-picking skill when allocating stocks differently from the designated asset class/style, which further contributes to the deviations of their performance to the performance of the broad market indices. A fund manager's stock picking skill is proven to add value if the selection return estimated is positive and statistically significant.

Sharpe (1992) analyses the performance of mutual funds in the U.S. over the period from 1985 through 1989. The 12 asset classes and style indices employed by Sharpe (1992) include the 90-day U.S. Treasury bill, the intermediate-term government bond index, the long-term government bond index, the corporate bond index, the mortgage-back security index, the large-cap value stock index, the large-cap growth stock index, the medium-cap stock index, the small-cap stock index, the non-U.S. government bond index, the European stock index and the Japanese stock index. The wide variety of the mutual funds (395 funds) covered by this research include growth funds, growth and income funds, utility funds and balanced funds. The results indicate that the return-based style decomposition method effectively explains the performances of U.S. mutual funds with out-of-sample *R*-squared of above 80% based on monthly-updates of the style exposures estimated over the prior 60 months. In addition, the selection returns of the funds under analysis are negative, on average, and statistically insignificant over the out-of-sample period. Sharpe (1992) concludes that the returns of the U.S. mutual funds are mainly driven by the performance of their underlying asset classes and investment styles rather than the manager's stock picking skills.

Fung and Hsieh (1998) conduct further analysis on the investment styles inherent in 2,525 mutual funds and 409 hedge funds in the U.S. over the period from 1991 to 1995. They argue that the factors employed by Sharpe (1992) are not sufficient to describe the return attributions of hedge funds that engage in short sales, leverage and derivatives in their trading activities. Hedge funds are also different from traditional mutual funds in that the mandates of hedge funds require the manager to achieve an absolute return target regardless of the economic environment rather than earning a return relative to the benchmark returns. To address this issue, Fung and Hsieh (1998) extend the factor model of Sharpe (1992) by updating the identities of the factors in the model to incorporate the dynamics of the hedge fund industry. The location factors adapted by Fung and Hsieh (1998) include the MSCI U.S. Equity Index, the MSCI Non-U.S. Equity Index and the International Finance Corporation (IFC) Emerging Market Equity Index. Factors representing bond returns in this research include the JP Morgan Non-U.S. Government Bond Index and the Merrill Lynch High Yield Corporate Bond Index. The 1-month Eurodollar deposit rate is adapted as the cash return and the gold price is used to model commodity returns. The Federal Reserve's Trade-Weighted Dollar Index is used to model currency movements. The style indices are obtained from the results of factor analysis rather than the existing style indices. Fung and Hsieh (1998) argue that factor analysis has an ability to extract style rotation or hedge fund styles that are not available from common style indices.

The results of Fung and Hsieh (1998) indicate that the original model of Sharpe (1992) is unable to accommodate changing asset class mixes. On the other hand, the explanatory power of the regressions improves drastically using the extended model with limited contributions from the selection return. Further analysis points out that the hedge fund returns have low correlations to the returns of mutual funds and

standard asset classes. Fung and Hsieh (1998) conclude that the additional factors extracted from factor analysis adequately capture the effects of dynamic hedge fund strategies and provide insight into the strategic difference between relative return styles for mutual funds and absolute return requirements for hedge funds. Baghai-Wadji and Klocker (2007) also recognise the inability of the traditional asset classes in mapping the dynamics of hedge fund returns. They analyse the performances of U.S. hedge funds from 1992 to 2004 using factors extracted from the cluster analysis based on self-organising map (SOM) algorithm in a neural network that groups hedge funds into homogenous style-consistent categories. Their approach is based on the linear regression of Sharpe (1992) to replicate hedge fund performances while exploring the non-linearities in the regressors. The results confirm the failure of hedge fund managers to add value beyond the performances of their respective style benchmarks.

Ibbotson and Kaplan (2000) study the performance attribution of U.S. balanced funds over the period from 1988 to 1998. They regress the returns of the selected funds on the returns of the selected asset classes including U.S. large caps, U.S. small caps, non-U.S. stocks, U.S. bonds, cash and total equity. The results reveal that around 90% of the variations in fund returns are explained by these factors over time. The selection returns for the study appears to be insignificantly negative over the examination period. Vardharaj and Fabozzi (2007) conduct performance attribution studies on the U.S. equity funds and global equity funds over the period from 1995 to 2004. They find that over 90% of the variations in the U.S. and global equity fund returns are explained by the economic sector indices, size and value indices, and regional indices. Similar to the findings of Ibbotson and Kaplan (2000), Vardharaj and Fabozzi (2007) find that the performances of the selected funds are dominated by their asset allocation decisions with their selection returns being slightly negative over time.

The return decomposition methodology of Sharpe (1992) is also followed by Yu (2008), who analyses the return attribution of South African unit trusts over the period from 2001 to 2006. The factors adapted by Yu (2008) include three local sector indices, namely, the JSE Resource Index (RESI), the JSE Industrial Index (INDI), the JSE Financial Index (FINI), and three constructed style proxies, namely, the lag 11-month momentum proxy, the undervalued residual proxy and the equally-weighted top 100 size proxy. The out-of-sample regressions yield significant R -squared and the selection returns for the funds examined in this study are statistically insignificant. These findings support the argument of Sharpe (1992) that the performances of actively-managed funds are mainly attributed to their inherent investment styles, rather than fund managers' stock picking ability.

After analysing the performance attribution of the South African unit trusts, Yu (2008) performs portfolio optimisation based on the same set of local sector and style indices. The mean-variance optimal portfolios are constructed by searching for the optimal allocations of sector and style indices that minimise portfolio variance at each level of portfolio return. Yu (2008) first constructs mean-variance optimal portfolios with constraint on short sales and leverage. The short and leverage constraints are subsequently removed by permitting short positions in the FTSE/JSE All Share Top 40 Index and leveraging the portfolio up to 200% of its combined long and short exposures. Thus, the sum of the absolute weights of all indices are capped at 200%, and cash serves as a balancing item when the long positions in the style and sector indices combined are more or less than 100% of the capital. The optimisation procedure is also conducted on the market neutral strategy and mean-tracking error portfolios.

The results of Yu (2008) indicate that the long-short leverage equity strategy has the ability to generate higher returns at the same level of portfolio volatility compared to the long-only strategy. The Sharpe ratio of the long-short leverage strategy and the market neutral strategy continue to improve steadily until the 200% capped leverage is reached. The Sharpe ratio deteriorates thereafter due to the drastic increase in the portfolio standard deviation. The size proxy is found to be redundant in the optimisation procedure for all of the strategies tested in this study. The optimisation procedure also reveals that portfolio returns can be improved by reallocating more capital into the momentum proxy from the value proxy at the expense of higher portfolio standard deviation. The different approaches of style-based portfolio optimisation demonstrated by Yu (2008) provide great insights into the applications of style indices in active portfolio management.

3.3.2 Tactical Style Timing versus Tactical Stock Picking

Empirical studies on performance attribution of the actively-managed funds do not find that stock picking strategies add value in excess of the style return underlying the funds, and the ability of fund managers to outperform their designated benchmarks remains questionable. Based on the Barron's report documented by Bary (1997) cited in Sorensen, Miller and Samak (1998), only 11% of the U.S. mutual funds beat the performance of the S&P 500 Index over the period from 1977 to 1997. The most recent report published by Standard & Poor's Indices Versus Active (SPIVA) scorecard service indicates that the S&P Composite 1500 Index outperforms 59.5% of all U.S. domestic equity funds over the period from 2004 to 2009. During the same period, the S&P Small Cap 600 Growth Index outperforms 76.88% of the U.S.

domestic small cap growth funds while the S&P 500 Growth Index outperforms 71.22% of the U.S. domestic large cap growth funds. Only 2 out of 16 fund categories in the report beat the performances of their respective S&P benchmarks: 51.39% of the real estate funds outperform the S&P U.S. REIT Index and 52.36% of the U.S. domestic large cap value funds outperform the S&P 500 Value Index.

The limited contribution of the selection return to the fund performance, coupled with the evidence of underperformance of the mutual fund industry, suggest that money managers should focus on tilting their investments towards the potential outperforming investment styles as a value-added approach instead of picking their favourite stocks. While stock picking strategies focus on exploiting potential predictability in individual stock-specific risk, tactical style timing (TSA) aims at exploiting the predictability in investment styles (Amenc, Malaise, Martellini and Sfeir, 2003). TSA strategies periodically switch between the major investment styles in order to tilt their performances towards the best performing styles in different phases of the business cycle. TSA strategies can also be implemented as market neutral strategies that focus on delivering absolute returns throughout the business cycle.

Kao and Shumaker (1999) explore the potential benefits of tactical style timing in the U.S. equity market over the period from 1979 to 1997. They test the effect of perfect monthly switches between alternative investment styles namely, value versus growth, large caps versus small caps and equity versus bonds. They find that switching between equity and bonds delivers the highest risk-adjusted returns over other timing strategies. Kao and Shumaker (1999) conduct further tests to investigate the potential benefits of style timing for the market neutral strategy with perfect foresight in

swapping the long and short positions in alternative styles. The results indicate that there are significant return potential for all 3 strategies. However, the return spread available for switching between equity and bonds deteriorated drastically since the late 1980s. Kao and Shumaker (1999) suggest that the decline in the potential for the strategy could be due to the declining volatility in the equity and bond markets, increasing popularity of derivatives and increasing correlation between equity and bond returns over time. The authors also find that when value stocks outperform growth stocks, they tend to have larger spreads than when growth stocks outperform value stocks. The asymmetrical size of the value and growth spread is also documented by Bauman, Conover and Miller (1998) for the non-U.S. stock markets (see Section 3.2.2). In addition, a strong seasonality of the value-growth spread is found in this study in that the significant value premium is observed in the first quarter of the calendar year while the value premium turns significantly negative in the last quarter of the calendar year, on average, over the examination period.

After the potential benefits of style timing are confirmed by the results of their empirical tests, Kao and Shumaker (1999) conduct further tests to determine the predictability of the timing to switch between the value and growth investment styles. They explain that the return differences between these two styles are more likely to be driven by economic fundamentals throughout the business cycle. This is because *“business cycles and trends in earnings underpin the differences in returns between the value and growth segments of the stock market and that these fundamental relationships persist; therefore, abnormal return opportunities exist for short-term switching strategies”* (Kao and Shumaker, 1999: 39). Kao and Shumaker (1999) identify 7 macroeconomic variables as potential determinants of successful value-growth switch. These variables include the yield-curve spread, the real bond yield, the

corporate credit spread, the high-yield spread, the forecasted GDP growth, the earnings-yield gap and the historical CPI. These factors represent key indicators of the stage of the business cycle. The results of this analysis reveal that the yield-curve spread, the real bond yield and the forecasted GDP growth are positively correlated with the 12-month forward value premium. The earnings-yield gap is the only variable that has negative correlation with the 12-month forward value premium.

Amenc *et al* (2003) conduct further research on the predictability of style timing strategies on the S&P style indices over the period from 2000 to 2002. Their objective is to develop systematic timing strategies for market neutral funds that aim at delivering absolute returns over the full business cycle. They adopt a robust dynamic multifactor modelling approach that systematically forecasts the optimal style allocations of the market neutral strategy. This approach is forward-looking with dynamic updates of style allocations over time in contrast to the ex post static optimisation procedure of Yu (2008). The explanatory variables considered by the model include the term structure of interest rates, the slope of the term structure of interest rates, the quantity of risk proxied by the historical volatility and the implied volatility, the price of risk proxied by the credit spread and the value proxies such as B/M, EY and DY. The variables are updated over time. The optimisation procedure for the market neutral strategy is conducted on the S&P 500 Index (large cap), the S&P Large Cap Growth Index, the S&P Large Cap Value Index and the Russell 2000 Index (small cap).

The results of the optimisation procedure indicate that the S&P Value Index receives positive weights in almost all of the months over the 3-year out-of-sample period. On the other hand, the S&P Growth Index is held short in most of the months under

review. The weights allocated to the S&P500 Index (large cap) and the Russell 2000 Index (small cap) are mixed. This evidence supports the view of Kao and Shumaker (1999) that the most dominant and predictable style timing strategy is to switch between the value and the growth investment styles. The style timing strategy achieves a 10.9% annualised return with an annualised standard deviation as low as 4.71%. During the same period, the S&P 500 Index has an annualised return of -18.03% and an annualised standard deviation of 18.72%. The strategy also provides good downside protection in that it has downside standard deviation of 2.26% compared to 11.49% of the S&P 500 Index, and the maximum monthly drawdown of -1.56% compared to -11% of the S&P 500 Index. However, it can be argued that such performance might be period-specific since the global economy experienced turbulence over the examination period.

With regard to the evidence of style timing strategies in the South African equity market, Mutooni and Muller (2007) examine the profitability of style timing strategies on the JSE over the period from 1986 to 2006. To control for the size effect, sample shares are divided into large caps and small caps, and the stocks in each size group are subdivided into an equal number of value stocks and growth stocks based on their respective P/B ratios. The results show that value stocks outperform growth stocks across the size spectrum. Mutooni and Muller (2007) further investigate the predictive power of the value-growth style timing strategy using time-series analysis over the out-of-sample period from 1994 to 2006. The variables employed in their research include the yield curve spread, the corporate credit spread, the earnings-yield gap, the equity risk premium, the inflation rate, the index of coincident economic indicators, the rate of change of M3 money supply, the All Share Index (ALSI) returns and the index of leading economic indicators. A time-series forecasting model is used to

determine the timing to switch between the value and the growth indices. The strategy invests fully in the value index at the beginning of 1994 but switches to growth index if the model indicates that the value-growth spread will narrow over the next two consecutive months. The results indicate that the timing strategy successfully outperforms the ALSI, the value index and the growth index over the examination period. The cumulative return over the 13-year period is as high as 745%, compared to 675%, 307% and 432% being achieved by the value index, the growth index and the ALSI respectively. This performance is, however, much lower compared to 4,162% achieved by the perfect timing strategy over the out-of-sample period.

3.4 Risk Management in Turbulent Times

While tactical style timing strategies described above benefit from style shifts throughout the normal business cycle, most asset classes experience large declines during the abnormal state of the economy such as the recent global financial crisis in 2008, which is led by the sub-prime crisis of 2007. During the abnormal state of the economy, the benefits of diversification dissipate as many insignificantly-correlated asset classes experience significant drawdowns simultaneously (Faber, 2009). Hedge fund strategies that claim to generate absolute returns throughout the business cycle suffer from the impacts of the global financial crisis.

Ballio, Getmansky and Pelizzon (2006) analyse the time-varying exposures of hedge fund indices to risk factors using switching regime beta modeling over the period from 1994 to 2005. They find that hedge fund exposures to systematic risk factors are very low during the normal state of the market. However, the exposures increase drastically when the market is characterised by negative S&P 500 returns and high volatility. Calson and Steinman (2008) examine the relationship between financial market conditions and the likelihood of U.S. hedge fund failures over the period from 1994 to 2006. They find that hedge funds are more likely to fail during the periods when a four standard deviation drop in the S&P 500 Index as well as a four standard deviation fall in the value of the U.S. dollar.

Billio, Getmansky and Pelizzon (2009) investigate the effects of financial crises on hedge fund exposures from 1994 to 2008. They find that although the hedge fund exposures to the S&P 500 returns decline or turn negative during crisis, the average volatility and correlation of hedge fund returns increase during global financial crises.

Further analysis indicates that the increased volatility and correlation between hedge fund returns are due to the increase in their common exposures to latent risk factors that are potentially related to margin spirals, massive redemptions, credit freezes, and interconnectedness between financial institutions during financial crisis. These findings raise the question as to whether the hedge fund strategies are indeed better hedged than traditional mutual funds and asset classes during global financial crises.

Faber (2009) examines the maximum drawdown of the major 5 asset classes, namely the U.S. stocks, the EAFE stocks, commodities and the real estate investment trusts (REIT) over the period from 1973 to 2008. The results reveal that all asset classes had drawdown around 40% to 60% with the exception of the U.S. government bonds, which declined almost 20% over the examination period. The buy-and-hold investors would find themselves unable to recover from the severe drawdown due to their limited life span and personal liquidity constraints. Faber (2009: 3) regards any reason to hold any asset during a global financial crisis a “*decidedly unwise course of action*”.

Faber (2009) tests the ability of a moving average timing model to implement overlay hedging that converts fund exposures to a synthetic cash position during crises. The timing strategy is applied to the 5 common asset class indices, namely the S&P 500 Index, the MSCI EAFE Index, the Goldman Sachs Commodity Index (GSCI), the National Association of Real Estate Investment Trusts (NAREIT) Index and the 10-year U.S. Treasury Bond Index over the period from 1900 to 2008. The trading system signals a long position in the index when the monthly index level is higher than its 200-day moving average, vice versa. The results reveal that the timing strategies have few occurrences of both large gains and large losses, with correspondingly higher

occurrences of small gains and losses over the examination period. The average returns of the timing strategies are in line with their respective indices. However, the timing strategies have considerably lower volatilities and drawdown compared to the long-only indices. Faber (2009) concludes that the moving average trading system is an effective mechanism to avoid the impact of financial market disasters in that it achieves equity-like returns with bond-like volatility and drawdown.

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3.5 Merits and Criticisms of Fundamental Indexation

One of the most important issues in the applications of style indices is to find an appropriate proxy that represents the performance of the most established firms in the market, which drives the broad market returns. Market capitalisation is traditionally regarded as the primary indicator of firm size by academia and practitioners. Broad equity market indices such as the S&P 500 Index and the FTSE/ALSI All Share Index are also market capitalisation-weighted (cap-weighted) based indices. The cap-weighted indices provide a convenient method to participate in the broad equity market, which is also a cost-effective way of achieving portfolio diversification. In addition, tracking the performance of a cap-weighted index incurs low rebalancing cost as the weights of the constituents in the index are self-adjusted through the fluctuation of their respective market prices (Arnott, Hsu and Moore, 2005).

Despite the potential benefits offered by the cap-weighted indices, evidence of investor overreaction documented by empirical literature has serious implications on the performances of the cap-weighted market proxies due to the cost incurred through noise trading. Noise trading refers to the trading activity based on information that is already reflected in the share price. Noise trading results in the systematic overshooting of the share prices, and introduces unnecessary volatility without contributing to the fair valuation of the stock. Due to the fact that a constituent of a cap-weighted index receives greater (less) weight in the index when it appreciates (depreciates), the index tends to overweight overvalued shares and underweight undervalue shares over time in a market where share prices systematically overshoot through noise trading. Consequently, the cap-weighted market proxies are likely to underperform over time, preventing them from being mean-variance efficient (Arnott,

2005). Hsu and Campollo (2006) point out that the more the prices fluctuate independently of the changes in the fundamentals, the greater is the drag in the cap-weighted index. *“As long as these pricing errors are not persistent, market prices will collapse toward fair value over time and a cap-weighted portfolio would tend to experience greater price decline than other non-price-weighted portfolios due to its heavier exposure to stocks with positive pricing error”* (Hsu, 2006: 2). The influence of noise trading suggests that there are better ways of constructing a broad market index to represent the general performance of blue chip companies in the market than using the market capitalisation as a measure of firm size in the index construction process. Based on this argument, Arnott *et al* (2005) propose the use of price-insensitive measures of firm-size that excludes the systematic overshooting of asset prices. Possible candidates suggested by Arnott *et al* (2005) include book value, cash flow, revenue, employment, sales and gross dividends of a firm. These attributes represent fundamental values of an enterprise and are used as the definition of firm size in events such as mergers or initial public offerings (IPO).

Arnott *et al* (2005) employ the fundamental attributes mentioned above to construct fundamentally-weighted indices of 1,000 companies in the U.S. equity market over a 43-year period from 1962 through 2004. They find that the returns produced by the fundamental indices outperform the S&P 500 Index and the cap-weighted benchmark constructed from the same sample statistically significantly. The sales-weighted index achieves the highest annual geometric return of 12.91% over the examination period, which is 2.38% higher than the S&P 500 Index (10.53%), and 2.56% higher than the cap-weighted benchmark (10.35%).

Arnott *et al* (2005) further construct a fundamentally-weighted composite index that includes book value, cash flow, sales and dividends jointly to provide a more accurate assessment of the size of the sample shares. The average values of the four attributes are used as the score to determine the relative weights of the constituents in the composite. The results indicate that the fundamental composite index outperforms the S&P 500 Index and the cap-weighted benchmark by 1.94% and 2.12% per annum respectively. When the performance of the respective indices are evaluated on a risk-adjusted basis, it is found that the fundamental indices and the fundamental composite index offer better returns with more or less similar levels of volatility as the cap-weighted benchmark. With the exception of the dividend-weighted index, the fundamental indices and the fundamental composite index achieve more than 50% for their information ratios over the examination period. The fundamental indices and the fundamental composite index are more liquid compared to the cap-weighted benchmark in that their portfolio concentration ratios are lower and portfolio turnover rates are higher than the cap-weighted alternative. When the relative performances of the indices are evaluated over the sub-periods, it is found that the underperformance of the cap-weighted benchmark relative to that of the fundamental indices are robust across different phases of the business cycle and different interest rate regimes.

Fundamental indexation also protects the impact of speculative bubbles. Speculative bubbles such as the tulip bubble in the 17th century or the technology bubble in the late 1990s are created by irrational investors who continuously bid up prices in the hope that the fundamentals would eventually justify their prices. In contrast to the EMH that regards all price increases to be justified, the weight of a constituent in a fundamental index does not increase with its price until it is proven to be fundamentally viable (Siegel, 2003).

Estrada (2006) extends the research of fundamental indexation to international capital markets with an additional objective of determining whether there exist additional benefits of international diversification for fundamentally-weighted global equity indices over the period from December 1973 to December 2005. The 16 countries that comprise the research sample include Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Ireland, Italy, Japan, Netherlands, Singapore, South Africa, the United Kingdom and the United States. A dividend yield-weighted fundamental index is constructed from the equity market indices of the 16 countries in the sample. The benchmarks used to evaluate the performance of the dividend yield-weighted index include the DataStream World Market Index and the cap-weighted composite of the 16 equity market indices. The results indicate that the dividend yield-weighted index outperforms the benchmarks in terms of the cumulative returns over the examination period, with slightly higher monthly volatility, but slightly lower beta than the cap-weighted benchmark. The dividend yield-weighted index also outperforms the benchmarks on a risk-adjusted basis in that it achieves a higher return-to-volatility ratio, a lower worst month return and a higher best month return compared to the benchmarks. Although the dividend yield-weighted index appears to weight the component country indices more evenly than the cap-weighted index, no significant improvement in portfolio volatility is found in the study. Estrada (2006) concludes that while fundamentally-weighted indices are proven to be more mean-variance efficient than an alternative cap-weighted index, no further international diversification benefits can be explored through fundamental indexation of global indices.

Although the success of fundamental indexation is pronounced in the empirical research, Kaplan (2008) argues that fundamental indexation also introduces weighting errors by ignoring the future prospects of the firm contained in the market price. By allocating less weight to shares that are highly priced, fundamental indices might be just an alternative way to incorporate the value bias into the portfolio. In the opinion of Arnott (2005), fundamental indexation is not just another way of constructing value indices since it enjoys the benefits offered by investing in small caps and value stocks and simultaneously avoid the capitalisation bias inherent in large caps and growth stocks whose prices are overinflated as a result of noise trading. Hsu and Campollo (2006) also argue that fundamental indexation has the ability to underweight stocks that are not growing their fundamentals, which is far from simple value investing. In addition, value indices are generally not well diversified and do not provide broad market participation. Hsu and Campollo (2006) examine the performances of the U.S. fundamental indices over the period from 1979 to 2004. They find that the fundamental indices outperform their respective Russell value indices. In addition, the fundamental indices outperform the cap-weighted S&P 500 Index during bull markets and expansionary economic environments, which are not achieved by the Russell value indices.

3.6 Conclusion

Systematic overshooting of stock prices due to investor overreaction results in momentum stocks continuing to outperform until the market is ready to correct. In such market, the glamour stocks and large caps are likely to be overpriced, and value stocks and small caps are likely to be underpriced temporarily relative to their long-term fundamental values. In the belief that the CAPM anomalies represent risk factors rather than evidence of investor irrationality, Fama and French (1993) develop factor mimicking portfolios to represent the value and the size effects in addition to the market risk premium in a 3-factor model. The Fama and French (1993) 3-factor model is found to capture all empirical anomalies with the exception of the momentum effect. This suggests that short-term return momentum could be included as the fourth factor in the model. Thus, the two existing style factors (size and value) in the 3-factor model accompanied by the momentum factor represent major investment styles that fund managers can follow to positively distinguish their performances from the broad capital market.

When style indices are included in the optimisation procedure, the value index is overweighted consistently across various studies. While increasing investments in the momentum index provides higher returns, it also increases portfolio risk accordingly. The use of the size index in the application of style indexation appears to be controversial. A downward performance bias due to noise trading is introduced when the size index is proxied by the cap-weighted index. However, using the price-insensitive weighting method such as the equally-weighted method or the fundamentally-weighted method to construct a large cap index may cannibalise the power of the existing value index in the factor model.

For those managers who wish to add value to the existing strategy, empirical evidence has proven that tactical stock picking is an ineffective way of generating active returns beyond what can be achieved by the style benchmarks. Tactical style allocation that requires managers to reallocate investments among alternative investment styles at different phases of the business cycle seems to be a better alternative to add value. However, tactical style allocation can only add value during normal states of the economy. Empirical evidence has shown that even the hedge funds that target at absolute returns, irrespective of the market movements, fail to hedge their positions against the impacts of global financial crises. Diversification benefits dissipate during turbulent times as long positions in any asset class would experience massive drawdown that is unrecoverable for an average investor with limited lifespan and liquidity constraints. A reasonable action would be to protect the value of the portfolio by temporarily rebalancing the fund exposure to an equivalent cash position using overlay hedging. A moving average trend following model recommended by Faber (2009) can assist fund managers in detecting the timing of rebalancing before the fund value suffers from major impacts of the crisis. This approach enables the fund to retain the return potential from its underlying investment styles while maintaining bond-like risk by avoiding the impact of major drawdown.

DATA AND METHODOLOGY

4.1 Introduction

This research is motivated by the empirical evidence that the market portfolio ceases to be mean-variance efficient once real world constraints and pricing inefficiencies are taken into account. The inefficiencies of the market portfolio stems from the critique of Roll (1977, 1978), the misspecification argument of Fama and French (1992, 1993, 1996) and the capitalisation error pointed out by Arnott, Hsu and Moore (2005). In order to perform asset allocation without being subject to a misspecified market proxy that contains capitalisation errors, this research undertakes to search for alternative methods of allocating assets in the global equity market through style-based portfolio optimisation. The three major investment styles identified and examined for this research include the size, the value and the momentum investment styles. The size and the value risk premia represent the compensations for style risks in the 3-factor model of Fama and French (1993). Since the momentum effect is the only anomaly that is not captured by the 3-factor model of Fama and French (1993), it could well be the third style-based factor that is required to complete the model. These three major investment styles are also recognised by Cavaglia and Morez (2002) and Yu (2008) in their empirical studies. This chapter highlights the research problem and discusses the goals and objectives to be achieved in order to solve the research problem. The rationale behind the database and sample selection, challenges and biases in the research procedure and the steps taken to mitigate the impacts of the research biases are presented.

4.2 Problem Statement and Research Objectives

This paper aims at exploring different applications of global style indices for allocating assets in the global equity market over an 18-year period from 1 January 1991 to 31 December 2008. The question to be answered includes whether the three broad investment styles (size, value and momentum) effectively capture the dimensions of risk inherent in the global equity funds. If so, whether the performances of actively-managed global equity funds can be accurately replicated, and subsequently improved through portfolio optimisation and tactical style allocation using global style indices, in normal economic states, and in turbulent times. The ultimate goal of this research is to construct optimal global style portfolios that achieve the highest attainable returns while maintaining the stipulated constraints regarding portfolio variance, tracking error, short position, leverage and drawdown in the global equity market. This goal is achieved through the accomplishment of the following objectives:

1. Construct candidate style indices for each of the three major investment styles namely, size, value and momentum in the global equity market.
2. Evaluate the performances of the candidate style indices and subsequently identify the most appropriate proxies to represent each of the three investment styles in the global equity market.
3. Analyse the characteristics of the global style proxies selected for this research in terms of their relative risk-adjusted performances, rebalancing requirements, correlations of their historical returns, cross-sector allocations and cross-country allocations of assets.

4. Evaluate the power of the global style proxies in replicating the performances of the selected global equity funds using the return-based style decomposition approach of Sharpe (1992).
5. Perform portfolio optimisation on the global style proxies and subsequently analyse the risk-return characteristics of the optimised style-based portfolios.
6. Explore the potential benefits available to style-based portfolio optimisation in active portfolio management.
7. Develop and subsequently evaluate the out-of-sample tactical style allocation (TSA) models that replicate the hypothetical Sharpe ratio-optimised portfolios for investment strategies of various constraints over the examination period.
8. Develop a style timing model to perform global style rotation between the global value and momentum proxies based on the movements in the pre-specified macroeconomic variables.
9. Develop trend following models based on information such as moving average and drawdown to provide signals for overlay hedging that create equivalent cash exposure for the portfolio during turbulent times.
10. Develop and subsequently evaluate the performances of the cash-protected indices relative to the unprotected indices based on the cash protection strategies.

The major empirical studies adopted by this research include the research of Yu (2008) for the research design in which the style-based portfolios are developed and optimised for various investment strategies; Sharpe (1992) for the return-based style decomposition approach used to analyse the performances of actively-managed funds; Kao and Shumaker (2001) and Mutooni and Muller for the methods of developing tactical style-timing models; and Faber (2009) for the method of developing trend following models to protect portfolio values during economic turmoil. The outcomes of the tests conducted in this research provide insights into asset allocation decisions in the global equity market throughout different phases of the business cycle, and in turbulent times.

4.3 Research Database

In order to exploit the advantages of style indexation in the global equity market, the database for this research should provide sufficient exposures to different dimensions of risk inherent in the global equity market. Cavaglia and Morez (2002) indicate that the traditional international asset allocation approach that overlays securities within countries is only effective when the integrations amongst countries remain weak. The increased integration in the global economy, as a result of globalisation, implies that allocating assets into different industries rather than different countries may be a more effective method of exploring different dimensions of risk in the global equity market. Vardharaj and Fabozzi (2007) also point out that sector and style allocations are intercorrelated as sectors tend to tilt towards certain investment styles at times. For example, during the information technology (I.T.) bubble, the price multiples of I.T. stocks outpaced the price multiples of stocks in all other sectors. The I.T. sector represents the glamour segment in the equity market. Ignoring the importance of sector representation leads to misrepresentation of an important style in the sample.

Cavaglia and Moroz (2002) propose the use of the cross-industry, cross-country allocation (CICCA) approach for allocating assets in the global equity market. Strategies derived from the CICCA approach outperform their respective global benchmarks over the period from 1990 to 2001. Cavaglia and Moroz (2002) further analyse the risk-adjusted performance of global portfolios sorted by country, global industry or on a bottom-up basis by regressing portfolio returns on the world, value, size and momentum factor-mimicking portfolio returns. The global industry portfolios are found to dominate all other portfolios on a risk-adjusted basis. With regard to the relative diversification benefits between country and sector allocations, LaBarge

(2008) finds that sector diversification achieves greater risk reduction than country diversification in both the developed and developing markets over the period from 2004 to 2008. The growing importance of industry factors relative to country factors is also documented by Cavaglia, Brightman and Aked (2000), Beca, Garbe and Weiss (2000), Diemeier and Solnik (2001) and Hopkins and Miller (2001). These findings suggest that a global equity database, with sufficient sector representation, is required for this research to provide ample diversification benefits and exposures to different dimensions of risk in various sectors. Global equity indices such as the Morgan Stanley Capital International (MSCI) World Index and the Standard and Poor's Global Index (S&P Global 1200), that select component equities based on geographical regions, without paying attention to sector representation, are not suitable for this research. On the other hand, the Dow Jones (DJ) Sector Titans Composite Index, that consists of the largest 30 international firms by market capitalisation from each of the 19 sectors, is a good proxy for the research database.

The 19 sectors of the DJ Sector Titans Composite Index represent the second tier of the Supersector structure defined by the Industry Classification Benchmark (ICB). These sectors include automobiles and parts, banks, basic resources, chemicals, construction and materials, financial services, food and beverages, health care, industrial goods and services, insurance, media, oil and gas, personal and household goods, real estate, retail, technology, telecommunication, travel and leisure and utilities. The DJ Sector Titans Composite Index provides broad coverage of the equities from the component sectors. Unlike the MSCI World Index, the DJ Sector Titans Composite Index does not place restrictions on security selections from only developed countries. These advantages support the use of DJ Sector Titans Composite Index as the database for the construction of candidate style indices in this research.

4.4 Sample Selection in the Research Database

Siegel (2003) indicates that the construction of equity indices face a direct trade-off between breadth and investability. The breadth of the index refers to the number of shares held in the index. On the other hand, the investability of the index refers to the extent to which the index constituents can be traded with the minimum price pressure and transaction costs.

As mentioned earlier, the DJ Sector Titans Composite Index consists of the largest 30 companies from each of the 19 sectors. This implies that some of the index constituents may be large enough to represent their respective sectors, yet are substantially smaller than the rest of the composite constituents. The inclusion of these shares may potentially compromise the liquidity of the style indices since large shares are usually more liquid. Siegel (2003) suggests that the liquidity (rather than the breadth) of the index should be prioritised when constructing international indices. This is because there are more constraints placed on the investability of international securities, especially for small caps and closely-held companies in emerging markets. On the other hand, the breadth of the index is less of a concern since the feasible set of the international indices expands significantly, compared to that of the local indices. In order to ensure that sufficient liquidity is available for trading the candidate style indices, only the largest 300 constituents of the DJ Sector Titans Composite Index in each month are employed as the investable pool for the construction of candidate style indices. The information for the larger stocks in the database also appears to be more complete compared to the smaller stocks.

As of 1 February 2009, the monthly firm-specific data of the 570 companies (30 members from each of the 19 sectors) comprising the DJ Sector Titans Composite Index, spanning the period from 1 January 1991 to 31 December 2008, are downloaded from the database of DataStream International. The constituents of the DJ Sector Titans Composite Index are ranked monthly based on their respective U.S. dollar-denominated market capitalisation, and the largest 300 shares are extracted as the initial sample for the construction of candidate style indices.

Chart (a) of Figure 4.1 illustrates the average monthly weights carried by each of the sectors in terms of the market capitalisation (in U.S. dollars) over the examination period. Although the sectors have equal representation in terms of the number of members in the original database, their weights in the research sample in terms of the market capitalisation are quite different. However, the overall sector representation is not unduly imbalanced, since the maximum number of members from any sector is restricted to 30 in the original database. The weights of the sectors range from 1.41% carried by the travel and leisure sector to 10.39% carried by the health care sector.

The average monthly country composition is illustrated by Chart (b) of Figure 4.1. The representation of the emerging economies in the sample is substantially lower than that of the developed economies. The 7 industrialised countries (known as G7) namely, the United States, Japan, the United Kingdom, France, Germany, Italy and Canada, receive considerable weights in terms of their market capitalisation in the research sample. The most dominant countries in the research sample are the United States (43.10%), Japan (20.76%), the United Kingdom (11.17%) and France (3.70%).

Figure 4.1 Composition of the Research Sample

The constituents of the Dow Jones Sector Titans Composite Index are ranked monthly over the examination period from 1 January 1991 to 31 December 2008 based on their respective U.S. dollar-denominated market capitalisation. The top 300 U.S. dollar-denominated market caps are extracted as the sample set for the construction of the candidate style indices. Chart (a) illustrates the sector composition of the sample shares. The weight of each of the 19 sectors for the research sample is calculated monthly, and the average monthly sector weights are displayed in the pie chart. Similarly, the average monthly country weights for the research sample are computed and demonstrated in Chart (b). Countries that carry weights of less than 1% are grouped into the “Others” category.

Chart (a) Sector Composition

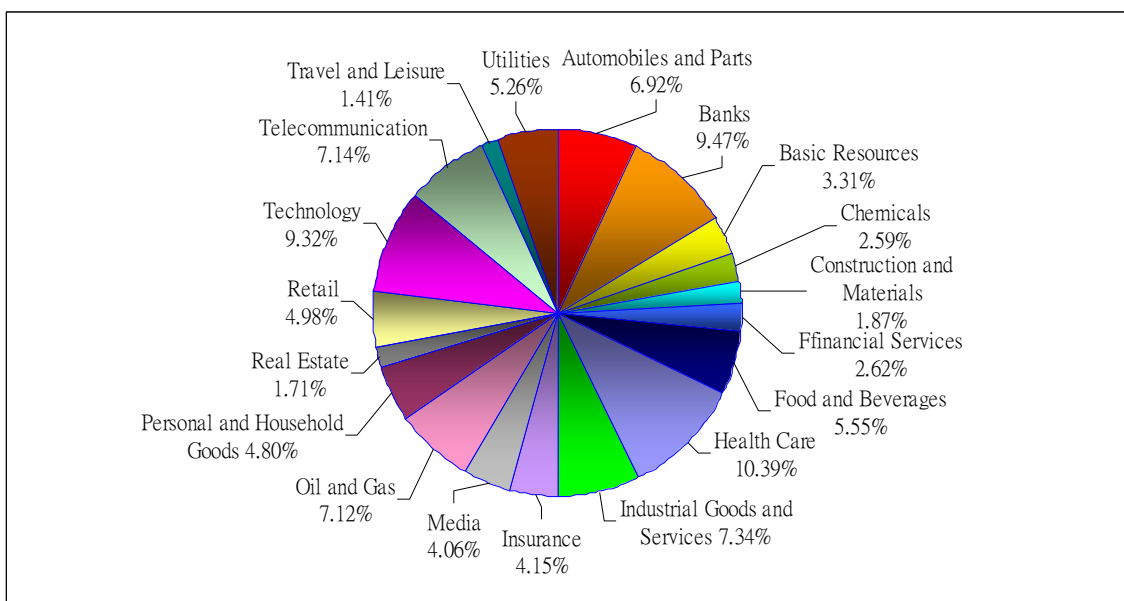
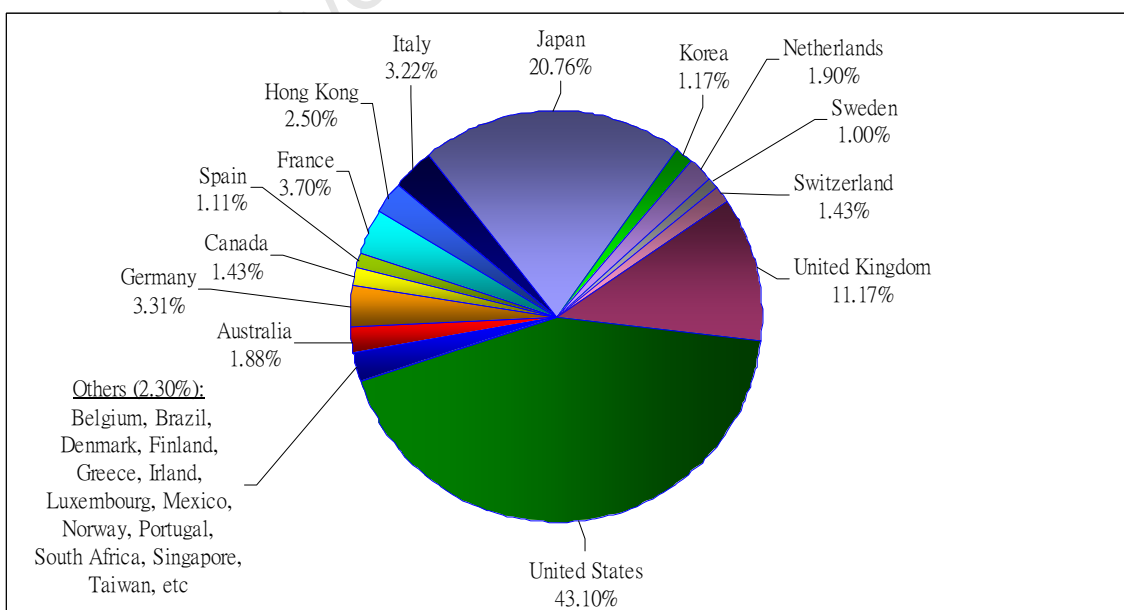


Chart (b) Country Composition



The fastest growing economy, China, is not neglected in the sample as large Chinese companies such as China Mobile and Hutchison Whampoa are listed on the Hong Kong Stock Exchange, which accounts for 2.50% of the total market capitalisation in the research sample.

Figure 4.2 demonstrates the concentration of the research sample in terms of the U.S. dollar-denominated market capitalisation. Chart (a) of Figure 4.2 displays the weight carried by each size quintile. The shares are ranked and grouped into size quintiles based on their market capitalisation as at 31 December 2008. The sample is heavily loaded by the largest size quintile, which counts for more than 50% of the total market capitalisation in the research sample. Examining the quintile concentration demonstrated by Chart (a) also reveals that the top 300 shares are roughly covered by the top 2.5 size quintiles, which effectively count for above 70% of the total market capitalisation of the index. This finding implies that the constituents of the index outside the largest 300 range are considerably smaller than the top 300 shares, and their inclusions in the construction of style indices may have serious liquidity implications.

Chart (b) of Figure 4.2 depicts the relative weights and market capitalisation of the 20 largest shares in the research sample as at 31 December 2008. Exxon Mobil is by far the largest share in the sample. It has a market capitalisation of U.S.\$377.99 billion, which constitutes 3.29% to the total market capitalisation in the research sample. The second largest firm, Walmart Stores has a market capitalisation of U.S.\$208.54 billion, which constitutes 1.82% to the total market capitalisation in the research sample. The U.S. firms appear to dominate the large cap segment in that 11 out of the top 20 market caps in the sample are U.S. firms.

Figure 4.2 Concentration of the Research Sample by Market Capitalisation

The U.S. dollar-denominated market capitalisation of the sample shares are computed and ranked in descending order as at 31 December 2008. The sum of the market capitalisation for shares in each quintile of 60 shares is computed to demonstrate the quintile concentration of the research sample in Chart (a). On the other hand, the top 20 shares with the largest U.S. dollar-denominated market capitalisation in the research sample are extracted to demonstrate their respective weights by market capitalisation in the research sample as shown in Chart (b).

Chart (a) Quintile Concentration (Proportion of Market Cap in U.S. Dollars)

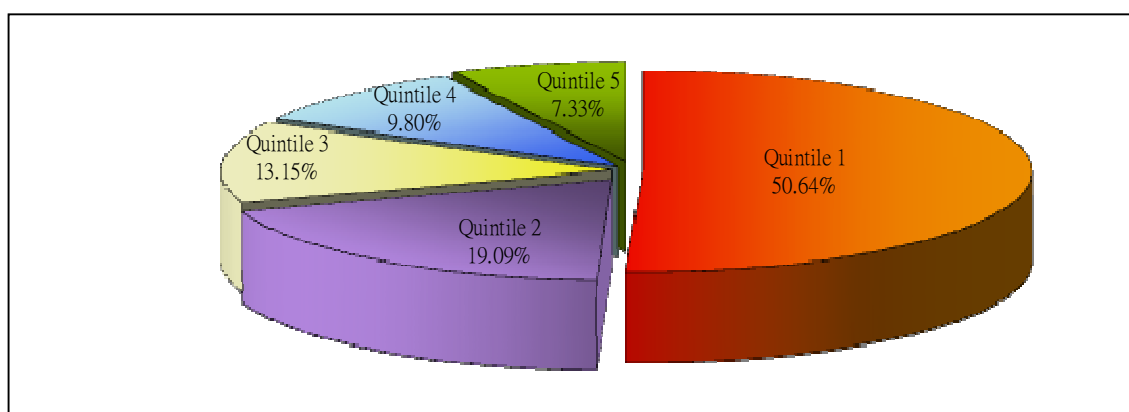
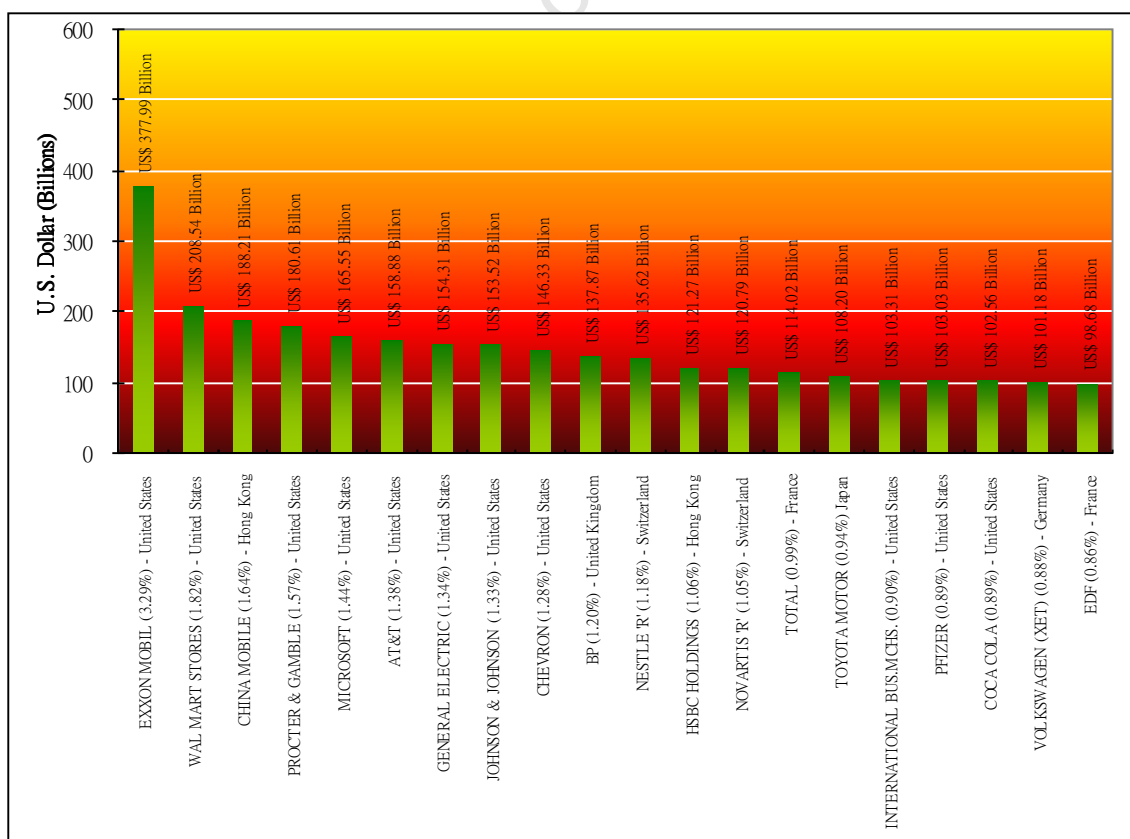


Chart (b) Top 20-Cap Concentration



4.5 Potential Research Biases

The potential biases that might unduly influence the research outcomes include data-snooping bias, look-ahead bias, survivorship bias and outliers. DeFusco, McLeavey, Pinto and Runkle (2004) define data-snooping bias as the bias in the inference as a result of prying into the empirical studies to guide the directions of the research outcome. Data-snooping bias generally arises when the tests are conducted based on the related historical database from prior empirical studies. This research is unlikely to encounter data-snooping bias due to its unique time period and database. To the author's knowledge, global style analysis has not been conducted on a database with balanced sector representation like the DJ Sector Titans Composite index. The possible look-ahead bias of the sample is also avoided by employing financial year-end accounting data at least 3 months prior to the construction of style portfolios and indices. In addition, the performances of the candidate style indices are examined over the two sub-periods and the entire examination period to avoid research results being time-period specific.

A survivorship bias is inevitably introduced into the research since the database of the research only includes the index constituents at the time of data collection. The impact of the survivorship bias on the research results is nevertheless reduced by the fact that the target group of the research consists of only the largest shares in their respective sectors. As suggested by Muller (1999), companies with large market capitalisation are less likely to be non-survivors in the markets. Hence, the robustness of the research results should not be negatively affected by the apparent survivorship bias for other samples confined by the definition of the target group in this research. This argument is challenged by the recent financial market crisis as even the most

dominant market players such as General Motors, AIG, Bear Stearns and Lehman Brothers were facing bankruptcy threats. However, the impact of the global financial crisis is viewed as an abnormality out of the ordinary course of the global economic cycle. The search for a robust method that signals the timing for overlaying hedge during crises is one of the most important missions in this research.

Although the outliers of the firm-specific attributes do not affect the ranking of the sample shares, removing outliers ensures that unbiased weights are assigned to the constituents of the style-weighted indices that allocate weights according to the relative magnitudes of the attributes for the constituents. This is because the shares with extremely large values for their firm-specific attributes are assigned with unreasonably dominant weights in the index. The resulting high index concentration adversely affects the representation of other shares in the index. Similarly, when shares with extremely small values for their firm-specific attributes are included in the index, the weights assigned to these shares in the index might be under-representative. This study adopts the approach employed by Fama and French (1992) and Van Rensburg and Robertson (2003a) that sets the maximum and the minimum values of the firm-specific attributes in the monthly cross-sectional distribution to the 99.5th and the 0.5th percentiles respectively. Since the extreme values of the distribution are restricted to the pre-specified percentile values, the attributes are winsorised around the median of the distribution.

An alternative approach proposed by Haugen and Baker (1996) is to place limits on the values that are greater than a specific number of standard deviations from the monthly cross-sectional arithmetic mean. This approach suffers from the potential drawback of using the arithmetic mean as a measure of central tendency stated in

DeFusco *et al* (2004) in that the mean is located much closer to the outliers than the median. Figure 4.3 demonstrates the locations of the two central tendency measures, mean and median, for asymmetrical distributions. The distribution in Chart (a) skews to the right, while the distribution in Chart (b) skews to the left. For both distributions in Chart (a) and Chart (b), the location of the mean is closer to the direction to which the distribution is skewed compared to the location of the median. Thus, establishing boundaries around the cross-sectional arithmetic mean essentially cut-offs significant amounts of observations within the normal part of the distribution without placing limits on the outliers. On the other hand, winsorising the distribution around the median presents an effective way of removing outliers, which ensures that the attribute values are controlled within the part of the distribution where the majority of the observations lie.

Figure 4.3 Locations of Central Tendency Measures

These diagrams are adapted from Frank and Althoen (1994: 63). Chart (a) displays a positively skewed distribution (i.e. skewed to the right), while Chart (b) displays a negatively skewed distribution (i.e. skewed to the left). The majority of the observations lie to the left of the mean, with the exception of few extreme observations (i.e. outliers), which lie to the right of the mean in Chart (a). On the contrary, the outliers in Chart (b) lie to the left of the mean. For both cases, the location of the median is closer to the majority of the observations than the mean, and hence winsorising the distribution around the median is a preferred method to remove outliers.

Chart (a) Positively Skewed Distribution (Skewed to the Right)

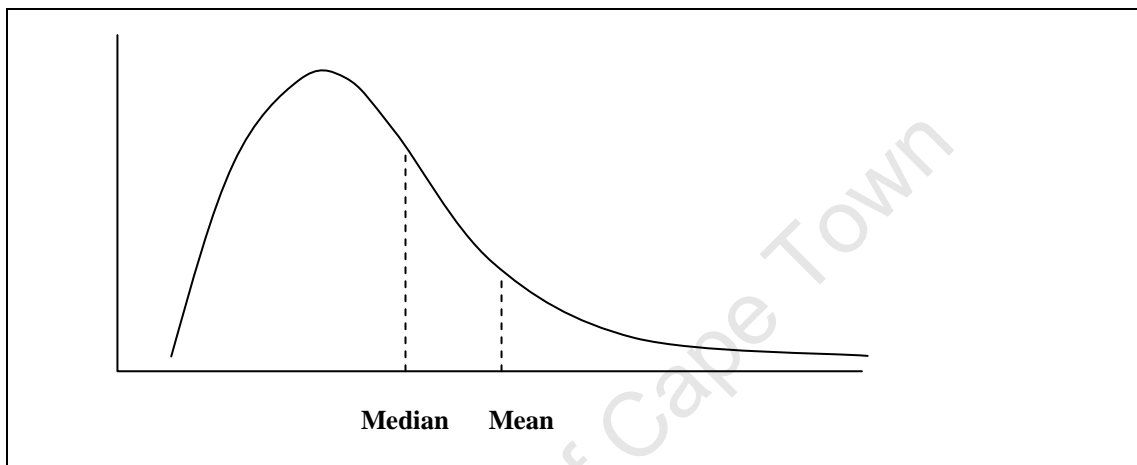
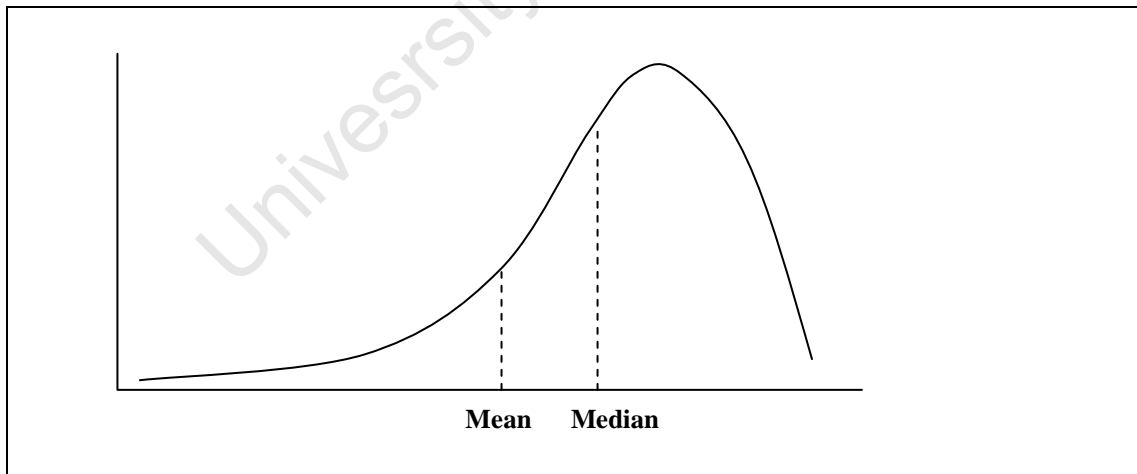


Chart (b) Negatively Skewed Distribution (Skewed to the Left)



PERFORMANCES OF GLOBAL STYLE INDICES

5.1 Introduction

The research begins with the construction of global style indices for each of the size, value and momentum investment styles from the monthly sample of 300 shares extracted from the constituents of the Dow Jones (DJ) Sector Titans Composite Index over the period from 1 January 1991 to 31 December 2008.

A series of firm-specific attributes are assigned to each style category for developing global style indices. The pre-specified firm-specific attributes are presumed to describe the characteristics of the shares belonging to each designated style category. Sample shares, are ranked monthly, based on each of the pre-specified firm-specific attributes, and the top 30, 50, 100, 200 and 300 shares for each attribute are selected as the constituents of the various candidate style indices for the respective attributes. A series of equally-weighted (EW) and style-weighted (SW) global style indices are constructed and rebalanced monthly throughout the examination period. Developing global style indices in this manner ensures that each index is unique in terms of its weighting method (EW or SW), the coverage of the index (30, 50, 100, 200 or 300), the firm-specific attribute upon which the index is constructed and the specific investment style represented by the index (size, value or momentum). The performances of the global style indices are evaluated based on their respective risk-adjusted returns, the representativeness of their investment styles and the transaction costs incurred due to their specific rebalancing requirements.

The objective of the evaluation is to identify the global style indices that are most representative of their designated investment styles as global style proxies. In addition to the global size, momentum and value proxies, the counterpart indices that exhibit the opposite investment styles are also identified to enhance the comparison of their performances. The characteristics of the global style proxies are cross-examined to identify the uniqueness of the respective global investment styles. This analysis is facilitated by comparing the log cumulative returns of the global style indices over the examination period. Performances of the global style proxies are examined over two sub-periods of equal length to determine whether there exists specific style timing throughout the examination period. Correlation analysis will be conducted on the time-series of the global style proxy returns to determine the degree to which their performances move in tandem with each other, and hence the potential benefits of incorporating them in the global style-based portfolio can be evaluated.

In addition, the global style proxies are subject to global performance attribution to determine the sources of the differences between their returns and the benchmark index. The return-based decomposition approach of Solnik and McLeavey (2003) is adapted for this purpose. The return differences between the global style proxies and the benchmark are decomposed under the cross-sector approach and under the cross-country approach separately. This procedure enhances the evaluation of the impacts of the cross-sector allocation versus the cross-country allocation on the abilities of the style proxies in distinguishing their performances from each other.

5.2 Index Weighting Methodology

The index weighting method determines the uniqueness of the underlying investment style reflected in the index. There exists a trade-off between the breadth and the performance of the style indices. For example, an equally-weighted style index that provides balanced and broad coverage of the investable pool fails to capture the uniqueness of the designated investment style, and hence has limited ability in producing distinguishable performance from that of the investable pool. To the contrary, superior performance might be achieved by a style-weighted index that invests heavily in the most style-oriented constituents at the expense of the breadth of the index.

With an investable pool of 300 shares, 30 shares covered by an index (10% of the sample) should be the lowest acceptable breadth to provide satisfactory representation of the designated investment style in the global equity market. The style indices comprised of 30, 50, 100, 200 and the full 300 shares in the sample are examined in this research, and the indices based on the same style attribute are either equally-weighted or style-weighted. The weight of the i th constituent in the index using the equally-weighted (EW) and the style-weighted (SW) approaches are computed using Equation 5.1 and Equation 5.2 respectively. The style-orientation of an equally-weighted style index is reflected by its breadth. For example, an equally-weighted index comprised of 30 constituents will be more unique in reflecting the underlying investment style compared to an equally-weighted index built by the same style attribute with 300 constituents.

$$w_{X(EW)i,t} = \frac{1}{n_{X,t}} \dots\dots\dots (5.1)$$

Where:

$w_{X(EW)i,t}$ represents the weight of the i th constituent in the equally-weighted style index X in month t ; and

$n_{X,t}$ is the number of constituents in style index X in month t .

$$w_{X(SW)i,t} = \frac{A_{i,t}}{\sum_{j=1}^{n_{X,t}} A_{j,t}} \dots\dots\dots (5.2)$$

Where:

$w_{X(SW)i,t}$ is the weight of the i th constituent in the style-weighted index X in month t ; and

$A_{i,t}$ is the value of the firm-specific attribute of the i th constituent in the style-weighted index X developed from attribute A at the beginning of month t .

For equally-weighted indices, the largest constituent weight is 3.33% for indices comprised of 30 shares, and the smallest constituent weight is 0.33% for indices comprised of 300 shares. On the other hand, the maximum constituent weight for style-weighted indices is capped at 10% to ensure that the indices are not overly concentrated. No specific constraint is placed on the minimum constituent weight for style-weighted indices. Overall, the indices that exhibit the strongest style-orientation are the style-weighted indices comprised of only 30 shares.

5.3 Descriptive Statistics for the Global Style Indices

Global style indices are developed from a series of firm-specific attributes that reflect their underlying investment styles: the size attributes are presumed to represent the most established firms in the sample; the value attributes are presumed to identify shares that are worthy of their prices; and the momentum attributes are capable of extracting shares with the strongest short-term return momentum in the monthly cross-section.

5.3.1 Global Size Style Indices

The global size indices are ranked and constructed from two price-sensitive attributes and five fundamental attributes. The summarised descriptions of the size attributes are displayed in Table 5.1. The two price-sensitive attributes examined by this research include the market capitalisation and the market share price. The market capitalisation is a generally accepted indicator of firm size. The market capitalisation of a firm is computed as the product of the current share price and the number of outstanding shares in the company. The style-weighted size indices developed from the market share price are essentially price-weighted indices. The oldest and best-known price-weighted index is the Dow Jones Industrial Average (DJIA) that reflects the performances of the 30 well-established industrial companies in the U.S. economy.

The equally-weighted market cap indices and the equally-weighted price indices are similar in that an appreciation/depreciation of a sample share will increase/decrease the probability of its inclusion in the index. On the other hand, the style-weighted

market cap indices and the style-weighted price indices are similar in that the weights of the index constituents are adjusted in the same direction as their respective price movements.

Table 5.1 Descriptions of the Size Style Attributes

Market capitalisation and the share price are price-sensitive measures of firm size. The fundamental attributes employed by this research include book value, net earnings after tax, gross dividends, gross sales and net cash flow. RAFI (Research Affiliates Fundamental Indices) is a composite fundamental index constructed based on the weighting methodology adopted by the Research Affiliates, LLC.

No.	Size Attributes	Descriptions
1.	Market Capitalisation	= monthly beginning share price * No. of outstanding ordinary shares
2.	Market Share Price	Market share price at the beginning of the month.
3.	Book Value	The latest reported balance sheet net asset value. = total assets – total liabilities
4.	Earnings	Trailing 5-year average net earnings after interests and tax.
5.	Dividends	Trailing 5-year average gross dividends.
6.	Sales	Trailing 5-year average gross sales.
7.	Cash Flow	Trailing 5-year average net cash flow from operating, investments and financial activities.
8.	RAFI	Composite fundamental index calculated as the average of items 3, 4, 5, 6 and 7. For non-dividend-paying firms, it is calculated as the average of items 3, 4, 6 and 7.

The five fundamental attributes employed by this research include current book value, the trailing 5-year average net earnings after tax, the trailing 5-year average gross dividends, the trailing 5-year average gross sales and the trailing 5-year average net cash flow. The purpose for the use of trailing average values is to avoid the substantial volatility of the attributes to impact on year-to-year data, which effectively reduces monthly portfolio turnover and the rebalancing costs (Arnott, Hsu and Moore, 2005). In addition to the individual fundamental attributes, composite fundamental indices that synthesise the Research Affiliate Fundamental Indices (RAFI) are developed based on the composite fundamental attributes calculated as the average of the 5

fundamental attributes.¹ For non-dividend paying firms, the RAFI attributes are computed as the average values of the 4 remaining attributes. According to Arnott *et al* (2005), non-payment of dividends may not be a sign of weak fundamentals since some firms may choose not to pay dividends for tax purposes.

5.3.2 Global Momentum Style Indices

The momentum attributes tested in this research include the prior 1-month return (Mom1), the prior 6-month return (Mom6), the prior 12-month return (Mom12), the 1-month lagged prior 11-month return (Mom12-1), the prior 24-month return (Mom24), the prior 36-month return (Mom36), the prior 48-month return (Mom48) and the prior 60-month return (Mom60). Empirical research discussed in Chapter 2 reveals that short-term prior return is usually an indication of near-term performance.

Based on the reversal effect of MOM1 documented by Exley, Smith and Wright (2004), Yu (2008) develops Mom12-1 indices that exclude the most recent month return from the calculation of prior 12-month return momentum. The author finds that MOM12-1 indices outperform MOM12 indices and other short-term momentum indices on a risk-adjusted basis. Jegadeesh and Titman (1993) also construct short-term momentum indices in a similar manner by excluding the immediate prior 1 week return from the estimation of prior returns. The summarised descriptions of the momentum attributes are displayed in Table 5.2.

¹ Robert D. Arnott is the chairman of Research Affiliates, LLC; Jason Hsu is the director of research at Research Affiliates, LLC; and Philip Moore is the vice president of sales and marketing at Research Affiliates, LLC in 2005.

Table 5.2 Descriptions of the Momentum Style Attributes

The momentum attributes indicate the historical growth rate of the total return index (*TRI*) of the sample shares. The total return index provided by DataStream International database incorporates both capital gains and dividend yield.

No.	Symbol	Momentum Attributes	Formula
1.	Mom1	Prior 1-month return	= $TRI_{t-1} / TRI_{t-2} - 1$
2.	Mom6	Prior 6-month return	= $TRI_{t-1} / TRI_{t-7} - 1$
3.	Mom12	Prior 12-month return	= $TRI_{t-1} / TRI_{t-13} - 1$
4.	Mom12-1	1-month lagged prior 11-month return	= $TRI_{t-2} / TRI_{t-13} - 1$
5.	Mom24	Prior 24-month return	= $TRI_{t-1} / TRI_{t-25} - 1$
6.	Mom36	Prior 36-month return	= $TRI_{t-1} / TRI_{t-37} - 1$
7.	Mom48	Prior 48-month return	= $TRI_{t-1} / TRI_{t-49} - 1$
8.	Mom60	Prior 60-month return	= $TRI_{t-1} / TRI_{t-61} - 1$

Based on the momentum attributes specified above, the return in excess of the cross-sectional mean return (mean-adjusted return) of the sample shares are computed monthly using Equation 5.3:

$$XMom(Z)_{i,t} = \left(\frac{TRI_{i,t-1}}{TRI_{i,t-1-Z}} - 1 \right) - \frac{\sum_{j=1}^{N(Z)_t} \left(\frac{TRI_{j,t-1}}{TRI_{j,t-1-Z}} \right)}{N(Z)_t} \dots\dots\dots (5.3)$$

Where:

- $TRI_{i,t-1}$ the value of the total return index for share *i* in month *t-1*;
- $TRI_{i,t-1-Z}$ the value of the total return index for share *i* in month *t-1-Z*; and
- $N(Z)_t$ is the number of sample shares that exist for *Z* months or longer.

Shares with positive mean-adjusted returns are grouped into the momentum (winner) category. On the other hand, shares with negative mean-adjusted returns are grouped into the loser category. As a result, sample shares are divided into winners and losers by each momentum attribute, depending on whether they earn higher or lower than

the average cross-sectional return for the period concerned. Classifying winners and losers based on the mean-adjusted return is a new concept in contrast to the traditional method that classifies winners and losers as the top and the bottom achievers, based on the respective rankings of their past returns. The mean-adjusted return approach evaluates the performances of the sample shares using the cross-sectional mean return as the benchmark, which is a more appropriate measure compared to the cross-sectional median adopted by the traditional approach. This is because the top 50% of the sample shares in terms of the past returns do not necessarily beat the average return of the entire sample. Based on the mean-adjusted return approach, a share placed in the bottom 50% of the sample is not regarded as a loser if it manages to beat the average performance of the cross-section.

After sample shares are classified into the momentum category or loser category, they are ranked by the absolute values of their mean-adjusted returns in the respective winner or loser category. The absolute values of the mean-adjusted returns are used to determine the weights of the shares in the style-weighted momentum and loser indices. This innovative approach makes it possible for allocating weights to shares with negative returns for the construction of style-weighted momentum or loser indices. This method also avoids drastic rebalancing or changes of index membership during temporary economic shocks when a large proportion of sample shares earn considerable negative returns. However, the style-weighted indices constructed using this approach are more concentrated due to the common subtraction of the cross-sectional mean, and are hence more prone to the adverse effects of outliers in the cross-sectional return. The median-based winsorisation method introduced in Section 4.5 provides the solution to this potential problem.

5.3.3 Global Value Style Indices

The attractiveness of a company's share is based on whether the share can be purchased at a bargain relative to its true worth. The true worth of a company's share is known as its intrinsic value, which is driven by fundamental values of the company such as the company's ability to pay dividends or its available assets to generate profits. Hence, the relative attractiveness of company's share can be estimated by comparing its fundamental values to the current market share price of the company.

The five fundamental values specified for this research (refer to Section 5.3.1) are expressed into per share values without being smoothed through trailing averages. These per share attributes include book value per share (BVPS), earnings per share (EPS), dividends per share (DPS), cash flow per share (CFPS) and sales per share (SALESPS). The book value of the company is the net asset value for the company computed as the remainder of the asset value after subtracting the total liabilities from the total assets of the company. It serves as the liquidation value to the company's shareholders. On the other hand, EPS, CFPS and SALESPS serve as the indicators of the company's operating profitability. The last pre-specified fundamental value per share, DPS, is a measure of the company's ability to distribute earnings in the form of dividends to its ordinary shareholders.

Based on these attributes, five fundamental value-to-price ratios (financial ratios), namely the book-to-price ratio (BVTP), earnings yield (EY), dividend yield (DY), cash flow-to-price ratio (CFTP) and sales-to-price ratio (SALESTP) are computed to indicate the relative attractiveness of the sample shares.

The disadvantage of using financial ratios as value indicators is that only one fundamental attribute is compared to the share price under each financial ratio. Conducting univariate tests in this manner fails to incorporate the complementary properties of various attributes. In order to address this issue, a multiple regression technique proposed by Yu (2008), that allows different fundamental values to be employed jointly to estimate the expected intrinsic value of the sample shares, is adopted to derive a series of value indicators in addition to the five financial ratios. Under this approach, different combinations of the fundamental values per share are used as regressors in the monthly cross-sectional regressions to estimate the monthly payoffs to the respective fundamental attributes as shown in Equation 5.4:

$$\ln P_{i,t} = \sum_{k=1}^m b_{k,t} \times \ln A_{k,i,t} + \varepsilon_{i,t} \quad \dots\dots\dots (5.4)$$

Where:

- $P_{i,t}$ is the market price of share i in month t ;
- $b_{k,t}$ is the factor payoff to the k th fundamental attribute in month t ;
- $A_{k,i,t}$ is the k th fundamental value per share for share i in month t ;
- m is the number of fundamental attributes employed as the independent variables in the regression; and
- $\varepsilon_{i,t}$ is the residual estimate of the monthly cross-sectional regression for share i in month t .

Based on Equation 5.4, whether a company's share is undervalued or overvalued depends on the sign of its regression residual. A positive residual indicates that the share price is higher than the underlying intrinsic value of the share estimated by the fundamental attributes. On the other hand, a negative residual indicates that the share is undervalued by the market. The extent to which the value shares are undervalued

and the extent to which the glamour shares are overvalued are determined by the absolute values of their regression residuals. All of the available combinations of the five fundamental attributes are used to compute the undervalued (negative) residuals (Ures) for value stocks and the overvalued (positive) residuals (Ores) for glamour stocks based on Equation 5.4. The Ures and Ores of the sample shares computed by the cross-sectional regression in month $t-1$ are used to rank and allocate weights to stocks in the value and glamour indices at the beginning of month t .

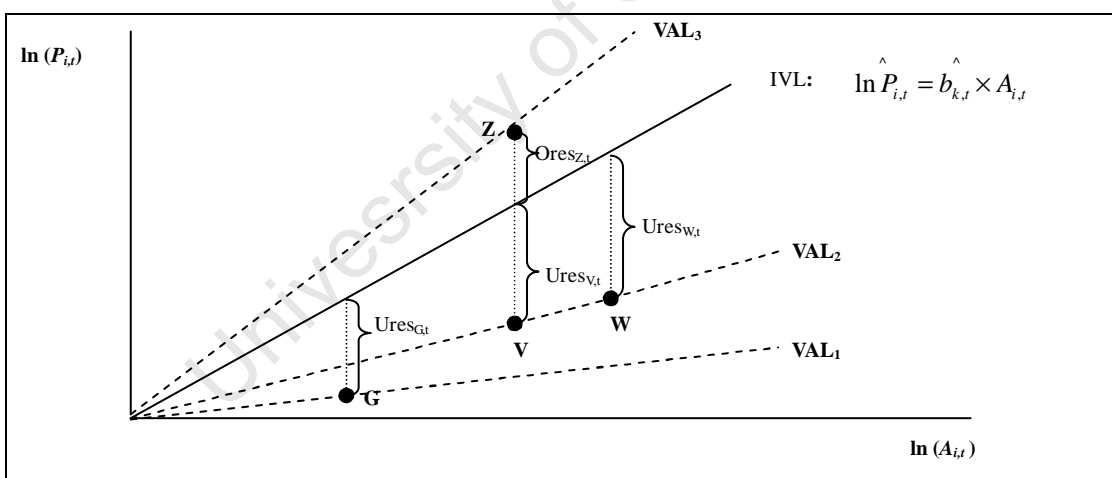
In order to determine whether overvalued stocks are successfully filtered out from the Ures value indices, univariate tests are devised to compare the performances of the Ures value indices derived from the individual fundamental attributes and the performances of the value indices developed from the financial ratios based on the corresponding fundamental attributes. Figure 5.1 demonstrates the differences in the constituent selection mechanisms between the financial ratio approach and the cross-sectional regression approach of Yu (2008). The value allocation lines (VALs) in Figure 5.1 represent the relative financial ratios of the sample shares. On the other hand, the intrinsic value lines (IVL) represent the intrinsic values per share estimated by the cross-sectional regression of Yu (2008) at each level of fundamental value per share for share i in month t . The error of the regression, represented by the vertical distance between the VAL and IVL, indicates the extent to which the share is undervalued (if the VAL is below the IVL) or overvalued (if the VAL is above the IVL) relative to the IVL estimates.

The univariate analysis of the shares plotted in Figure 5.1 reveals that there are circumstances where conflicting constituent selections and rankings may arise between the financial ratio approach and Yu (2008)'s approach. For example, although

share V and share W plotted on VAL₂ obtain identical ranking in terms of their respective attractiveness using the financial ratio approach, share W is considered more undervalued since it has higher Ures (i.e. Ures_{W,t} > Ures_{V,t}). On the other hand, since VAL₁ lies below VAL₂, share G is considered a cheaper investment compared to share V and share W based on their respective financial ratios. However, share G is considered to reserve less value than share V and share W based on Yu (2008)'s approach due to its lower Ures relative to the Ures of share V and share W.

Figure 5.1 Different Selection Mechanisms of Value Determinants

Figure 5.1 demonstrates circumstances where conflicting constituent selections may arise based on value attributes formed by financial ratios and by regression residuals using the same fundamental attribute. The natural logarithm of the fundamental value per share for share *i* in month *t* is represented by $A_{i,t}$, which is plotted on the horizontal axis. On the other hand, the natural logarithm of the market price for share *i* in month *t* is plotted on the vertical axis. The value allocation lines (VALs) represent the price-to-fundamental value ratios of the sample shares. Shares plotted on the same VAL have identical price-to-fundamental value ratios. The intrinsic value line, IVL, is the cross-sectional intrinsic value estimated by the univariate regression based on Equation 5.4. The estimated error (i.e. the distance between the VAL and IVL) indicates the relative attractiveness of the share determined by the cross-sectional regression.



An additional test that contributes to the existing findings of Yu (2008) is the comparison of the performances of Ores glamour indices relative to that of the otherwise identical Ures value indices. The test results together with the results from the univariate tests provide an indication as to whether the sign of the residual is an efficient measure for separating undervalued shares from overvalued shares. Table 5.3

provides the summarised descriptions of the value and glamour attributes employed in this research. The descriptive statistics of the value attributes based on financial ratios are displayed in Panel (a) of Table 5.3. Panel (b) of Table 5.3 displays the complete list of Ures and Ores attributes used to develop the respective value and glamour indices for this research.

Table 5.3 Descriptions of the Value and Glamour Attributes

Panel (a) displays the value indicators derived from financial ratios in this study. The five pre-specified fundamental values per share used to compute financial ratios include book value per share (BVPS), net earnings after tax per share (EPS), gross dividends per share (DPS), gross sales per share (SALESPS) and cash flow per share (CFPS). Panel (b) presents the undervalued residuals (Ures) and overvalued residuals (Ores) used to develop the respective value indices and glamour indices. The symbols of the fundamental attributes are simplified as B, E, D, S and C respectively in the brackets assigned to Ures or Ores as indications of the combinations of the fundamental attributes used to estimate the regression residuals using Equation 5.4.

Panel (a) Value Attributes based on Financial Ratios

No.	Symbol	Value Attributes	Formula
1.	BVTP	Book Value-to-Price	= BVPS / beginning monthly share price
2.	EY	Earnings Yield	= EPS / beginning monthly share price
3.	DY	Dividend Yield	= DPS / beginning monthly share price
4.	SALESTP	Sales-to-Price	= SALEPS / beginning monthly share price
5.	CFTP	Cash Flow-to-Price	= CFPS / beginning monthly share price

Panel (b) Value and Glamour Attributes based on Residuals

	Value Attribute	Glamour Attributes
Univariate:		
1-factor residuals:	Ures(B); Ures(E); URES(D); Ures(S); and URES(C)	Ores(B); Ores(E); Ores(D); Ores(S); and Ores (C)
Multivariate:		
2-factor residuals:	Ures(BE); Ures(BD); Ures(BS); Ures(BC); Ures(ED); Ures(ES); Ures(EC); Ures(DS); Ures(DC); and Ures(SC)	Ores(BE); Ores(BD); Ores(BS); Ores(BC); Ores(ED); Ores(ES); Ores(EC); Ores(DS); Ores(DC); and Ores(SC)
3-factor residuals:	Ures(BED); Ures(BES); Ures(BEC); Ures(BDS); Ures(BDC); Ures(BSC); Ures(EDS); Ures(EDC); Ures(ESC); and Ures(DSC)	Ores(BED); Ores(BES); Ores(BEC); Ores(BDS); Ores(BDC); Ores(BSC); Ores(EDS); Ores(EDC); Ores(ESC); and Ores(DSC)
4-factor residuals:	Ures(BEDS); Ures(BEDC); Ures(BDSC); Ures(EDSC); and Ures(BESC)	Ores(BEDS); Ores(BEDC); Ores(BDSC); Ores(EDSC); and Ores(BESC)
5-factor residuals:	Ures(BEDSC)	Ores(BEDSC)

5.4 Performance Evaluation Measures

Global style indices are evaluated based on their risk-adjusted returns, representativeness of the designated style and implicit transaction costs due to the specific rebalancing requirements. The geometric returns, geometric cumulative returns, arithmetic returns and the time-series standard deviations of the returns of the global style indices are computed to provide indications of their basic risk-return characteristics. The monthly index returns throughout the examination period can be computed using Equation 5.5:

$$r_{X,t} = \sum_{i=1}^n w_{X,i,t} \times r_{i,t} \quad \dots\dots\dots (5.5)$$

Where:

- $r_{X,t}$ is the return of index X in month t ;
- n is the number of constituents in index X ;
- $w_{X,i,t}$ is the weight of the i th constituent in style index X for month t , computed using Equation 5.1 for the equally-weighted indices or Equation 5.2 for the style-weighted indices; and
- $r_{i,t}$ is the return for the i th constituent in style index X in month t .

Once the monthly style index returns for the examination period are computed, the geometric return for style index X over T months is calculated using Equation 5.6:

$$R_X = \left[\prod_{t=1}^T (1 + r_{X,t}) \right]^{1/T} - 1 \quad \dots\dots\dots (5.6)$$

Where:

- T is the number of months in the examination period; and
- $r_{X,t}$ is the return for style index X in month t .

The first term on the right-hand side of Equation 5.6, $\left[\prod_{t=1}^T (1 + r_{X,t}) \right]^{1/T}$, represents the T -month geometric cumulative return for style index X . On the other hand, the arithmetic return for style index X over T months is computed using Equation 5.7:

$$R_{X(Arithmetic)} = \frac{\sum_{t=1}^T r_{X,t}}{T} \dots\dots\dots (5.7)$$

Where:

- $r_{X,t}$ is the return for style index X in month t ; and
- T is the number of months in the holding period.

Both the geometric and arithmetic monthly returns computed using Equation 5.6 and Equation 5.7 can then be annualised using Equation 5.8:

$$R_{X(Arithmetic / Geometric) p.a.} = (1 + R_{X(Arithmetic / Geometric)})^{12} - 1 \dots\dots\dots (5.8)$$

The T -month annualised standard deviation for the monthly returns of style index X is computed using Equation 5.9.

$$\sigma_{X p.a.} = \sqrt{\frac{\sum_{t=1}^T (r_{X,t} - R_X)^2}{T - 1}} \times \sqrt{12} \dots\dots\dots (5.9)$$

Where:

- $r_{X,t}$ is the return for style index X in month t ;
- R_X is the T -month arithmetic average return for style index X ; and
- T is the number of months in the holding period.

5.4.1 Risk-Adjusted Performance Measures

The risk-adjusted performance measures employed in this research include the Sharpe ratio (SR), the Treynor measure (TM), Jensen's alpha (α), the information ratio (IR) and M-squared (M^2). The Sharpe ratio is originally introduced by Sharpe (1966) as the portfolio's excess return per unit of standard deviation to measure the performance of mutual funds. The annualised Sharpe ratio for style index X is calculated using Equation 5.10:

$$SR_{X p.a.} = \frac{R_{X p.a.} - R_{f p.a.}}{\sigma_{X p.a.}} \dots\dots\dots (5.10)$$

Where:

$R_{f p.a.}$ is the annualised geometric return for the risk-free asset;

$R_{X p.a.}$ is the annualised geometric return for style index X ; and

$\sigma_{X p.a.}$ is the annualised standard deviation for style index X .

While the Sharpe ratio measures the excess return as the difference between the return of the global style index and the risk-free rate, the information ratio, on the other hand, measures the performances of the global style indices against the comparable benchmark rather than the risk-free rate. The index return in excess of the return of the benchmark is known as the active return, and the variability of the active return is known as the active risk or tracking error of the index (Bailey, Richards and Tierney, 2007). The active return per unit of active risk is known as the information ratio.

The annualised information ratio for style index X is computed as follows:

$$IR_{X \text{ p.a.}} = \frac{R_{X \text{ p.a.}} - R_{B \text{ p.a.}}}{\sigma_{X-B \text{ p.a.}}} \dots\dots\dots (5.11)$$

Where:

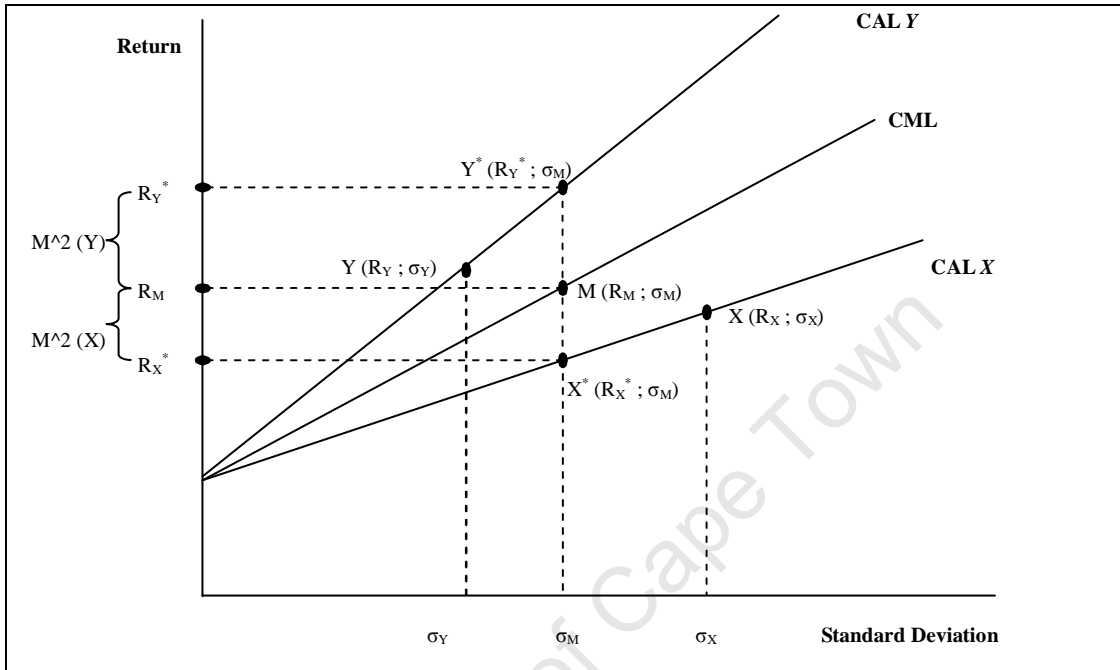
- $R_{B \text{ p.a.}}$ is the annualised geometric return for the benchmark; and
- $\sigma_{X-B \text{ p.a.}}$ is the annualised standard deviation for the active return of style index X in excess of the benchmark return.

Similar to the Sharpe ratio and the information ratio, M-squared (M^2) is a risk-adjusted performance measure that uses standard deviation as the measure of risk embedded in the portfolio. Graham and Harvey (1997) derive M-squared (later popularised by Modigliani and Modigliani (1997)) by levering or unlevering the portfolio being evaluated to achieve the same standard deviation of the market proxy. The return of the levered or unlevered portfolio can thus be compared to the return of the market proxy, on equal footing.

Figure 5.2 (adapted and modified from Bodie, Kane and Marcus, 2008: 855) illustrates M-squared of an underperforming fund X , and an outperforming fund Y . To compute M-squared for the two funds, fund X have to be unlevered and fund Y has to be levered respectively to arrive at the same risk as the market (σ_m). The return of the unlevered fund X (R_X^*) and the levered fund Y (R_Y^*) can then be compared to the return of the market proxy (R_m). Since M-squared for fund X is negative and M-squared for fund Y is positive, fund X is overvalued and fund Y is undervalued based on M-squared measure.

Figure 5.2 The Derivation of the M-Squared Measure

The M-squared measure (M^2) is derived by leveraging or unlevering the fund under evaluation to arrive at the same standard deviation as the market proxy. The return of the new fund after the leverage adjustments (assigned with an asterisk, “*”) can then be compared to the return on the market proxy. The capital allocation line (CAL) that goes through the market proxy, namely, the capital market line (CML), is employed as the benchmark to judge the performance of the funds. Funds located on capital allocation line Y (CAL Y) that lies above CML have positive M-squared and are thus undervalued. On the contrary, funds located on capital allocation line X (CAL X) that lies below CML have negative M-squared and are thus overvalued.



The slope of the capital allocation line (CAL) indicates the reward-to-risk ratio for the assets plotted on the CAL. The slope of CAL X indicates the reward-to-risk ratios for both fund X and fund X* as shown in Equation 5.12.

$$\frac{R_X - R_f}{\sigma_X} = \frac{R_X^* - R_f}{\sigma_M} \dots\dots\dots (5.12)$$

Where:

- R_X is the return for fund X; R_f is the risk-free rate of return;
- R_X^* is the return on the leverage-adjusted fund X, which has the same standard deviation as the market proxy;
- σ_X is the standard deviation of fund X; and
- σ_M is the standard deviation of the market proxy.

Equation 5.12 can be rewritten as $\sigma_X \times (R_X^* - R_f) = \sigma_M \times (R_X - R_f)$.

Dividing both sides by σ_X , the above equation evolves to:

$$(R_X^* - R_f) = \frac{\sigma_M}{\sigma_X} \times (R_X - R_f) ; \text{ and } R_X^* = R_f + \frac{\sigma_M}{\sigma_X} \times (R_X - R_f) .$$

Defining M-squared for fund X as $R_X^* - R_M$, the elements of the above equation are rearranged to arrive at Equation 5.13:

$$M^2(X) = R_X^* - R_M = \left[R_f + \frac{\sigma_M}{\sigma_X} \times (R_X - R_f) \right] - R_M \quad \dots\dots\dots (5.13)$$

According to Bodie *et al* (2008), M-squared and Sharpe ratio are directly related. Extracting σ_M from the right-hand side of Equation 5.13, the link between M-squared and the Sharpe ratio of fund X can be established as follows:

$$M^2(X) = \sigma_M \times \left(\frac{R_f}{\sigma_M} + \frac{R_X - R_f}{\sigma_X} - \frac{R_M}{\sigma_M} \right); \text{ and}$$

$$M^2(X) = \sigma_M \times \left(\left(\frac{R_X - R_f}{\sigma_X} \right) - \left(\frac{R_M - R_f}{\sigma_f} \right) \right) = \sigma_M \times (SR_X - SR_M) \quad \dots\dots\dots (5.14)$$

Where:

SR_X is the Sharpe ratio for fund X; and

SR_M is the Sharpe ratio for the market proxy.

Equation 5.14 states that the M-squared of fund X is equal to the product between the volatility of the market proxy and the Sharpe ratio differential between fund X and the market proxy. Hence, indices with Sharpe ratios higher than the Sharpe ratio of the market proxy are automatically assigned with a positive M-squared. Annualised M-squared for the global style indices are computed from the annualised Sharpe ratios and standard deviations of the respective indices.

The remaining two performance evaluation measures, Jensen's alpha and the Treynor measure, employ the beta coefficient rather than the standard deviation as the measure of fund risk. The Beta coefficient measures the sensitivity of fund returns to movements in the market portfolio return. The beta coefficient of style index X is estimated by regressing the time-series excess return of the style index on the time-series excess return of the market proxy using the following equation:

$$r_{X,t} - r_{f,t} = \alpha_X + \beta_{X,M} \times (r_{M,t} - r_{f,t}) + \varepsilon_{X,t} \quad \dots\dots\dots (5.15)$$

Where:

- $r_{X,t}$ is the return of style index X in month t ;
- $r_{f,t}$ is the return of the risk-free proxy in month t ;
- $r_{X,t} - r_{f,t}$ is the return of style index X in excess of the risk-free rate in month t ;
- $r_{M,t} - r_{f,t}$ is the return of the market proxy M in excess of the risk-free rate in month t ;
- α_X is the intercept of the regression;
- $\beta_{X,M}$ is the beta estimate for style index X against market proxy M ;
- $\varepsilon_{X,t}$ is the residual of the regression for style index X in month t .

Based on the beta estimate obtained from Equation 5.15 together with the annualised fund return, risk-free rate and the return on the market proxy, the annualised Jensen's alpha that measures the abnormal return of style index X is calculated as follows:

$$\alpha_{X\ p.a.} = R_{X\ p.a.} - \left[R_{f\ p.a.} + \beta_{X,M} \times (R_{M\ p.a.} - R_{f\ p.a.}) \right] \quad \dots\dots\dots (5.16)$$

The Treynor measure, on the other hand, is a reward-to-risk ratio that standardises the excess return of the style indices by their respective beta coefficients. Substituting the

beta estimate obtained from Equation 5.15 for the standard deviation of the annualised Sharpe ratio in Equation 5.10, the annualised Treynor measure for style index X is computed in Equation 5.17:

$$TM_{X \text{ p.a.}} = \frac{R_{X \text{ p.a.}} - R_{f \text{ p.a.}}}{\beta_{X,M}} \quad \text{..... (5.17)}$$

While obtaining the standard deviations of the global style indices is a straightforward process, successful estimation of the beta coefficients depends on the representativeness of the market proxy and the risk-free proxy in the research. Although the DJ Sector Titans Composite Index has sufficient coverage of the largest companies across 19 sectors, the number of companies covered by this index does not make it a representative proxy for the market portfolio. On the other hand, the Morgan Stanley Capital International World Index (MSCI World) is a free-float market capitalisation-weighted index comprised of equity indices from 23 developed countries, namely, Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States. The constituent country indices of the MSCI World Index are confined to the market capitalisation-weighting methodology of the market portfolio, and the global equity market coverage of the MSCI World Index is also much broader than the DJ Sector Titans Index (roughly 1,500 constituents for the MSCI World Index compared to 570 constituents for the DJ Sector Titans Index). Based on these arguments, this research employs the MSCI World Index as the market proxy.

With regard to the choice of the risk-free asset, the highly liquid U.S. 3-month Treasury bill with low default risk is employed. The rationale for this choice is that

the majority of the sample shares are U.S.-based (refer to discussions in Section 4.4), and the attributes of the sample shares are expressed in U.S. dollars. This makes the U.S. short-term Treasury bill the best risk-free proxy in this research.

5.4.2 Portfolio Turnover and Implicit Transaction Costs

The rebalancing requirement, or portfolio turnover, for an index is the product of its rebalancing frequency, the number of constituents that are subject to rebalancing and the extent of weight adjustments for the rebalanced constituents. Yu (2008) uses the average monthly percentage of the portfolio value being rebalanced as a measure of portfolio turnover. Adopting this approach, the percentage portfolio turnover for style index X in month t is computed using Equation 5.18:

$$turnover_{X,t} = \sum_{i=1}^{K_t} |\Delta w_{X,i,t}| \quad \dots\dots\dots (5.18)$$

Where:

K_t is the total number of shares in the research sample in month t ;

$$\Delta w_{X,i,t} = w_{X,i,t} - \left(w_{i,t-1} \times \frac{1 + r_{i,t-1}}{1 + r_{X,t-1}} \right);$$

$w_{X,i,t}$ is the weight of share i in index X for month t . If share i is not an index constituent, $w_{X,i,t} = 0$;

$w_{i,t-1}$ is the weight of share i , at the end of month $t-1$, after its price movement in month $t-1$, and just before the rebalancing at the beginning of month t ; and

$r_{i,t-1}$ and $r_{X,t-1}$ are the returns of share i and index X in month $t-1$ respectively.

The portfolio turnover depicted by Equation 5.18 indicates the impacts of both buying and selling activities for an index. When $\Delta w_{i,t}$ is positive, additional acquisition of share i is required. By the same token, a negative $\Delta w_{i,t}$ signals that the reduction in the holding of share i in the index is required. In addition, the updating of the weights for sample shares in an index depends on their performances relative to the performance of the style index. Holding all else constant, an index constituent gains weight in the index if it performs better than the index in the previous month. This self-adjustment effect is taken into account when computing the monthly portfolio turnover using Equation 5.18. Based on this equation, the average monthly percentage index turnover is estimated as follows:

$$\text{Avg. \% Rebalancing}_{x.p.m.} = \frac{\sum_{t=1}^T \text{turnover}_{x,t}}{T} \quad \dots\dots\dots (5.19)$$

In order to gauge the impact of index rebalancing on the performances of style indices, the implicit transaction costs incurred through rebalancing are deducted from the return of style indices monthly to estimate the monthly cost-adjusted return as shown in Equation 5.20. The transaction costs are assumed to be 2% of the rebalanced amount in each month:

$$r_{X,t(\text{cost } t\text{-adjusted})} = r_{X,t} - (2\% \times \text{turnover}_{X,t}) \quad \dots\dots\dots (5.20)$$

The annualised cost-adjusted geometric returns for the style indices can then be computed based on their monthly cost-adjusted returns estimated by Equation 5.20. The assumed 2% trading costs are commonly applied to individual investors. For institutional investors, the trading costs are usually below 1%.

5.4.3 Measures of Representativeness

The extent to which the candidate indices are representative of their designated investment styles are evaluated by their number of index constituents and the portfolio concentration. As discussed in Section 5.2, there exists a trade-off between the breadth and the style-tilt of a style index. Thus, the objective of the research is to identify a proxy for each investment style that is most representative of its underlying investment style, and has the ability to achieve superior risk-adjusted return at the least expense of its breadth. The three measures used to evaluate the representativeness of the global style indices include the average number of index constituents per month, the average effective number of index constituents per month and the maximum constituent holding over the examination period.

The average number of index constituents per month serves as the basic measure of the breadth of an index. The average number of index constituents per month for index X over T months is computed using Equation 5.21:

$$N_X = \frac{\sum_{t=1}^T n_{X,t}}{T} \quad \text{..... (5.21)}$$

Where:

$n_{x,t}$ is the number of constituents for index X in month t .

The effective number of index constituents per month is defined by Van Rensburg and Kruger (2008: 1) as “*the number of equally-weighted shares required to achieve the same share-specific risk as the portfolio*”. In order to derive the average effective number of index constituents per month, the effective number of constituents in each month over the evaluation period has to be computed.

The effective number of constituents for index X in month t is computed as follows:

$$n_{X,t}^* = \frac{1}{\sum_{i=1}^{n_{X,t}} (w_{X,i,t})^2} \quad \dots\dots\dots (5.22)$$

Where:

$n_{x,t}$ is the number of constituents for index X in month t ; and

$w_{x,i,t}$ is the weight of the i th constituent in index X for month t .

The average effective number of constituents for index X over period T can then be calculated using Equation 5.23:

$$N_X^* = \frac{\sum_{t=1}^T n_{X,t}^*}{T} \quad \dots\dots\dots (5.23)$$

For equally-weighted style indices, the average number of index constituents equals the average effective number of index constituents. For style-weighted indices, the average effective number of index constituents is less than the average number of index constituents. The less the effective number of index constituents, the more concentrated and less representative is the style index of its designated investment style.

Lastly, the maximum constituent holding for an index is calculated as the largest weight carried by the largest index constituent over the examination period. As discussed in Section 5.2, the maximum constituent holding in an index is capped at 10% in any given month over the examination period to ensure that the indices are not overly-concentrated.

5.4.4 Global Performance Attribution Analysis

After global style proxies are selected from a variety of candidate indices, country attribution analysis and sector attribution analysis are conducted on the global style proxies to identify possible sources that distinguish the performances of the global style proxies. Although the information regarding the countries from which the sample shares are selected is readily available, the sector information for the sample shares can be ambiguous due to different or overlapping sector classifications from the database. An advantage of using the DJ Sector Titans Composite Index as the research database is that the sample shares are selected from 19 pre-specified sectors based on a standardised classification method (refer to Section 4.3), which enhances the comparison between the country attribution and the sector attribution of the global style proxy returns. While empirical studies related to this subject generally focus on the relative diversification benefits of country and sector allocations and their relative abilities in explaining global fund returns (see Section 4.2), this research focuses on the relative contributions of country and sector allocations in explaining the return differences between the global style proxies.

A more relevant study is conducted by Ku (2000), who uses both the country factor model and the sector factor model to analyse the performance attribution of the CDC Europe equity fund and the MSCI Europe Index over the period from 1996 to 2000. The result reveals that the CDC Europe equity fund outperforms the MSCI Europe Index mainly through alternative allocations in sectors rather than different country allocations from the benchmark. However, this area of research conducted on the global style indices are yet to be explored.

This paper adopts the return-based global performance attribution approach of Solnik and McLeavey (2003) to analyse the return differences of the global style proxies. This approach decomposes the return difference between the global style proxy and the benchmark portfolio into currency allocation effect, market allocation effect (by sector or by country) and security selection effect. The return difference between global style proxy X and its benchmark B in domestic currency for month t is demonstrated by Equation 5.24, and the specifications of the currency allocation effect, the sector/country allocation effect and the security selection effect are depicted by Equation 5.24a, Equation 5.24b and Equation 5.24c respectively:

$$r_{(D)X,t} - r_{(D)B,t} = \sum_{j=1}^N (\phi_{j,X,t} - \phi_{j,B,t}) + \sum_{j=1}^N (\psi_{j,X,t} - \psi_{j,B,t}) + \sum_{j=1}^N (\eta_{j,X,t} - \eta_{j,B,t}) \quad \dots\dots (5.24)$$

Where:

$\sum_{j=1}^N (\phi_{j,X,t} - \phi_{j,B,t})$ represents the currency allocation effect that contributes to the return difference between style proxy X and benchmark portfolio B in month t ;

$\sum_{j=1}^N (\psi_{j,X,t} - \psi_{j,B,t})$ represents the sector/country allocation effect that contributes to the return difference between style proxy X and benchmark portfolio B in month t ;

$\sum_{j=1}^N (\eta_{j,X,t} - \eta_{j,B,t})$ represents the security selection effect that contributes to the return difference between style proxy X and benchmark portfolio B in month t ; and

N is the number of sectors/countries from which style index X and benchmark portfolio B select their constituents.

The benchmark portfolio employed for this analysis is an equally-weighted portfolio comprised of all 300 sample shares in each month to provide fair representation of all sample shares available for the construction of the global style proxies without distinctive style tilt in the benchmark. The country allocation effect and the sector allocation effect are dealt with separately in the analysis using two different factor models based on Equation 5.24. Holding the currency allocation effect constant, the remaining difference in returns between the style proxy and the benchmark is shared by the sector allocation effect and the security selection effect, or alternatively the country allocation effect and the security selection effect. Thus, the greater the ability of the country or sector allocation in explaining the return difference, the less is the remaining return difference to be explained by the security selection effect. The evaluation procedure starts by computing the monthly foreign currency returns and domestic currency returns (in U.S. dollars) for the sample shares throughout the examination period. As demonstrated by Equation 5.24a, the currency effect indicates the strength of the currencies exposed by the global style proxy relative to the currency strength of the investments held by the benchmark portfolio.

$$\sum_{j=1}^N (\phi_{j,X,t} - \phi_{j,B,t}) : \text{Currency Allocation Effect} \quad \dots\dots\dots (5.24a)$$

Where:

$\phi_{j,X,t} = \sum_{i=1}^{n_{j,t}} (w_{i,j,X,t} \times (r_{(D)i,j,t} - r_{(F)i,j,t}))$, is the part of style proxy X 's domestic currency return earned/lost due to the conversion of foreign currency return into domestic currency return in month t ;

$\phi_{j,B,t} = \sum_{i=1}^{n_{j,t}} (w_{i,j,B,t} \times (r_{(D)i,j,t} - r_{(F)i,j,t}))$, is the part of benchmark B 's domestic currency return earned/lost due to the conversion of foreign currency return into domestic currency return in month t ;

$w_{i,j,X,t}$ is the weight of the i th sample share from the j th sector/country in style proxy X in month t ;

$w_{i,j,B,t}$ is the weight of the i th sample share from the j th sector/country in benchmark B in month t ;

$r_{(D)i,j,t}$ is the domestic currency return on the i th sample share from the j th sector/country in month t ;

$r_{(F)i,j,t}$ is the foreign currency return on the i th sample share from the j th sector/country in month t ; and

$n_{j,t}$ is the number of sample shares in the j th sector/country in month t .

Equation 5.24b indicates the effect of sector/country allocation policy on the return difference between the global style proxy and the benchmark portfolio. On the other hand, the overall effectiveness of the style proxy's security selection skill within each sector/country relative to the security selection of the benchmark portfolio is demonstrated by Equation 5.24c.

$$\sum_{j=1}^N (\psi_{j,X,t} - \psi_{j,B,t}) : \text{Sector/Country Allocation Effect} \quad \dots\dots\dots (5.24b)$$

Where:

$\psi_{j,X,t} = \sum_{i=1}^{n_{j,t}} w_{i,j,X,t} \times \sum_{i=1}^{n_{j,t}} (w_{i,j,B,t} \times r_{(F)i,j,t})$, represents the part of style proxy X 's domestic currency return generated from its sector/country allocation policy in month t ; and

$\psi_{j,B,t} = \sum_{i=1}^{n_{j,t}} w_{i,j,B,t} \times \sum_{i=1}^{n_{j,t}} (w_{i,j,B,t} \times r_{(F)i,j,t})$, represents the part of benchmark B 's domestic currency return generated from its sector/country allocation policy in month t .

In order to compute the sector/country allocation effect and the security selection effect, the sector/country weights and the sector/country returns for the style proxies and the benchmark portfolio must be computed. The j th sector/country weight in style proxy X for month t is the sum of all constituent weights from the j th sector/country in month t measured as $\sum_{i=1}^{n_{j,t}} w_{i,j,X,t}$. On the other hand, the j th sector/country return for style proxy X in month t is measured as $\sum_{i=1}^{n_{j,t}} (w_{i,j,X,t} \times r_{(F)i,j,t})$, which is the sum of all constituents' return contributions to the overall style proxy return in month t . Similarly, the j th sector/country weight in benchmark B for month t is computed as $\sum_{i=1}^{n_{j,t}} w_{i,j,B,t}$, and the j th sector/country return for benchmark B in month t is computed as $\sum_{i=1}^{n_{j,t}} (w_{i,j,B,t} \times r_{(F)i,j,t})$. Note that the currency effect is removed from the analysis in Equation 5.24b and Equation 5.24c by using returns denominated in the foreign currencies since the currency effect has already been incorporated in Equation 5.24a.

$$\sum_{j=1}^N (\eta_{j,X,t} - \eta_{j,B,t}) : \text{Security Selection Effect} \quad \dots\dots\dots (5.24c)$$

Where:

$\eta_{j,X,t} = \sum_{i=1}^{n_{j,t}} w_{i,j,X,t} \times \sum_{i=1}^{n_{j,t}} (w_{i,j,X,t} \times r_{(F)i,j,t})$, represents the contribution of the securities selected by style proxy X to the domestic currency return of style proxy X in month t ; and

$\eta_{j,B,t} = \sum_{i=1}^{n_{j,t}} w_{i,j,B,t} \times \sum_{i=1}^{n_{j,t}} (w_{i,j,B,t} \times r_{(F)i,j,t})$, represents the contribution of the securities selected by benchmark B to the domestic currency return of benchmark B in month t ;

The technique of Solnik and McLeavey (2003) is not to be confused with the return-based style decomposition approach of Sharpe (1992). Solnik and McLeavey (2003)'s model attempts to explain the attribution of the return differences between the style indices rather than the style attributions of fund returns. The style indices are used as the regressors in Sharpe (1992)'s factor model while the return difference of the style indices represents the dependent variable to be explained by the currency, sector/country and security selection effects. In addition, Solnik and McLeavey (2003)'s approach focuses on the exact attributions of the return difference without leaving the unexplained part of the return difference in the error of the regression. Most importantly, Solnik and McLeavey (2003)'s approach analyses the cross-sectional attributions of the return difference in each month of the evaluation period. The average attributions over the examination period are computed from the monthly currency effect, market allocation effect and security selection effect. By contrast, Sharpe (1992) uses time-series regressions to estimate the style attributions of active fund returns with the unexplained portion of the returns in the regression error term.

5.5 Results: Performances of Global Style Indices

The performances of the global size, momentum and value indices are demonstrated in APPENDIX A, APPENDIX B and APPENDIX C respectively. In addition, the results of global loser and glamour indices that serve as the counterpart indices of the global momentum and value indices are shown in APPENDIX D and APPENDIX E respectively. The indices from the same appendix share the same characteristics of the designated investment style, and the indices formed by the same firm-specific attribute are distinguished by their weighting method and number of constituents. The results of the indices formed by different attributes of the same investment style are shown in separate pages in the appendix.

Each table of an appendix is divided into four sections. The first section displays the annualised risk and return statistics of the style indices formed by the same attribute, followed by measures of representativeness and portfolio turnover in the second and third sections respectively. The last section of the table contains information regarding the annualised risk-adjusted performances of the style indices. The results are shown over the evaluation period from 1 January 1991 to 31 December 2008 as well as the two sub-periods. The performance of the benchmark index (MSCI World) is demonstrated in the first column of the table, followed by the performance of the equally-weighted indices and the style-weighted indices. The name of each style index in the table contains its unique weighting methodology (EW or SW) and the target number of constituents. As shown in the measure of representativeness section, the average number of constituents may not be identical to the target number of constituents, since the number of available shares for the firm-specific attribute may fall short of the target at times, especially for indices targeting at all 300 sample shares.

5.5.1 Global Size Indices

There are 10 global size indices constructed for each of the indices formed by market price, market capitalisation, book value, net earnings, gross dividends, gross sales, net cash flow and the RAFI composite indicator. These indices cumulate to a total of 80 global size indices developed in this chapter. Examining the risk and return statistics in APPENDIX A reveals that the first sub-period (prior millennium period) is more bullish compared to the second sub-period (post millennium period). The drastic difference in the performances of the two sub-periods is highlighted by the average annualised geometric return of 15.67% in the first period compared to -2.69% in the second period for the MSCI World Index.

The style-weighted indices formed by price (refer to Appendix A.1) and market capitalisation (refer to Appendix A.2) exhibit significant performance drag inherent in price-sensitive indices noted by Arnott, Hsu and Moore (2005), especially during the second sub-period. This finding suggests that acquiring stocks each time the prices bounce up, in a downward trend, will only deepen the losses. However, the performance drag is less severe for the price-weighted indices compared to its impact on the cap-weighted indices because the constituents in the price-weighted indices are not necessarily large caps. Thus, the benefits of having smaller firms in the price-weighted indices partially offset the performance drag through noise trading. The performance drag inherent in price-sensitive indices, coupled with the largest caps as the constituents, lead the cap-weighted indices to be the worst performers among global size indices. This is evident in their significant negative alpha over the examination periods.

The small firm effect is also apparent among the cap-weighted indices. By including more smaller firms in the indices, the cap-weighted indices with more constituents (e.g. SW300 in Appendix A.2) outperform the more concentrated cap-weighted indices (e.g. SW30 in Appendix A.2). Similarly, the cap-weighted MSCI World Index, with roughly 1,500 constituents worldwide, outperforms all cap-weighted indices on a risk-adjusted basis over the examination periods. In summary, for price-sensitive indices, higher style tilt generally leads to underperformance of the indices.

On the other hand, equally-weighted indices formed by price and market capitalisation are price-insensitive, and their performances are competitive to the performances of the fundamental indices displayed in Appendix A.3 through Appendix A.6. Among the fundamental indices, the equally-weighted indices in general outperform their style-weighted counterparts. The performances of equally-weighted fundamental indices are more or less comparable with each other. In line with the expectation, the fundamental composite indices (RAFI indices in Appendix A.8) exhibit average performance of the individual fundamental indices in terms of their risk-return characteristics.

The results of the regression analysis indicate that the risk premium on the MSCI World Index is able to explain the time-series returns of the candidate size indices at the 1% significance level. However, the *R*-squared of the regressions are higher for the indices formed by price and market capitalisation than for the fundamental indices due to the fact that the MSCI World Index is itself a cap-weighted index. Further analysis reveals that the *R*-squared and the beta coefficients of the regressions are substantially lower during the bullish first sub-period relative to the second sub-period for the fundamental indices. The differential explanatory power of the market risk

premium is especially distinctive for the style-weighted fundamental indices. These findings are in support of Kaplan (2008)'s argument that fundamental indices outperform cap-weighted indices primarily through the embedded value bias. Most of the fundamental indices earn higher returns than the MSCI World Index with slightly higher standard deviation but lower than average beta coefficients. This results in higher risk-adjusted performance of the fundamental indices relative to the MSCI World Index. However, the abnormal returns (as measured by Jensen's alpha) for most of the global size indices appear to be insignificant, with the exceptions of the significant negative alphas for the cap-weighted indices. This result suggests that the global size indices are unable to beat their risk-adjusted returns on a consistent basis. The beta coefficients of the global size indices are around 1.0 or lower, suggesting that established firms are safer investments in the global equity market.

With regard to the mean monthly rebalancing requirements, the equally-weighted fundamental indices have lower portfolio turnover compared to their style-weighted counterparts. The 10% cap on the maximum constituent weight is applied to almost all of the style-weighted fundamental indices over the examination periods, indicating the high portfolio concentration for these indices. This is also evident in the significant differences between their average monthly actual and effective number of constituents. However, the impact of portfolio turnover on the implicit transaction costs for the style-weighted fundamental indices is insignificant, since less than 10% of the portfolio values are rebalanced, on average, over the examination periods. By contrast, the style-weighted indices formed by price and market capitalisation have the lowest monthly portfolio turnover since the constituent weights are adjusted automatically according to the price movements.

5.5.2 Global Momentum and Loser Indices

The 8 pre-specified momentum attributes generate a total of 80 candidate momentum indices and 80 candidate loser indices. Due to the fact that the monthly 300 sample shares are divided into the momentum or loser category, based on their past excess cross-sectional mean returns, indices that target at 200 or more constituents become redundant as the average number of constituents fall short of the target number substantially. In addition, the number of sample shares qualified for the development of momentum or loser indices become increasingly scarce when the formation period for the indices are 36 months or longer. Based on hindsight from the empirical studies revealed in Section 3.2.1, the focus of this research is on the momentum indices developed with relatively shorter (24 months or less) formation periods.

Examining the basic return statistics of the momentum indices (Appendix B.1 through Appendix B.8) indicates that the momentum indices earn substantially higher returns (geometric and arithmetic) than the MSCI World Index during the bullish first sub-period. The more concentrated the indices towards the momentum style, the greater the returns earned in excess of the benchmark returns. Such performance is achieved through substantially higher standard deviation, above-average beta and substantial portfolio turnover. The positive excess returns of long-term (36 months or longer) winners adhere to the finding of De Bondt and Thaler (1985), that the reversal of past long-term winners only takes place 12 months after formation, in contrast to the immediate reversals of the past long-term losers. The frequent monthly rebalancing of these indices effectively prevents the reversal effect to be reflected in their performances. The continuation of the prolonged momentum built up in the bullish market lead the long-term winners to crash in the subsequent bearish period. Such

underperformance during the second sub-period is not evident for momentum indices formed based on prior 6- and 12-month returns.

The reversals of prior 1-month winners (refer to Appendix B.1) seems to be more prompt than the reversals of prior long-term winners. No meaningful excess returns are found for the prior 1-month winners during the bullish first sub-period. In addition, their performances in the bearish second sub-period are as poor as the performances of prior long-term winners. As documented by Exley *et al* (2004), acquiring prior 1-month winners guarantees poor future performance, especially for periods of poor market sentiment. However, acquiring prior 1-month losers has the opposite effect. Indices in Appendix D.1 earn moderately higher returns than the MSCI World Index in the first sub-period, but outperform the benchmark substantially in the second sub-period. The equally-weighted 100 prior 1-month momentum index yields 4.97% annualised geometric returns, compared to -2.69% earned by the MSCI World Index. This index has also generated annualised abnormal returns (as measured by Jensen's alpha) of 8.68% during the second period, which is significant at the 5% level.

The prior 48- and 60-month losers (refer to Appendix D.6 and Appendix D.7) have achieved similar performances of the prior 1-month losers. They perform much better in bear markets than bull markets. Thus, De Bondt and Thaler (1985)'s approach that uses the average of the cumulative abnormal returns of portfolios formed at different point in time, as an indication for the average performance, inevitably results in understating the abnormal returns of past losers in the bear markets and overstating the abnormal returns of past losers in the bull markets. In general, short-term losers such as indices in Appendix D.2 and Appendix D.3 underperform the MSCI World Index in the first sub-period and perform slightly better than the MSCI World Index in

the second sub-period. Overall, the momentum indices with 6- to 12-month formation period (refer to Appendix B.2, Appendix B.3 and Appendix B.8) are the best performers in the bull market, and the prior 1-month losers achieve outstanding results in the bear market.

5.5.3 Global Value and Glamour (Growth) Indices

There are in total 50 candidate value indices developed from the 5 financial ratios, and 310 candidate value indices developed from the 31 residual composite indicators (Ures and Ores). With equal amount of glamour (growth) indices constructed based on the same set of value attributes, a total of 720 candidate value and glamour indices are developed in this chapter.

Comparing the results of the value indices displayed in APPENDIX C to their corresponding glamour indices displayed in APPENDIX E indicates that all of the value indices outperform their glamour counterparts by large margins, on a risk-adjusted basis, across all periods. Almost all the glamour indices have negative Jensen's alpha at the 5% significance level over the examination periods. Negative Sharpe ratios, M-squared, information ratio and Treynor ratios are also exhibited in the majority of the glamour indices. On the other hand, although the majority of the value indices outperform the MSCI World Index on risk-adjusted basis over the bearish second sub-period, no significant Jensen's alpha is detected for the bullish first sub-period for these indices. These findings suggest that value stocks generate their abnormal returns primarily in the bear market, and glamour stocks, on average, underperform the market proxy in both bull and bear markets.

Similar to the consequence of separating prior winners from prior losers based on their mean-adjusted returns, constructing value and glamour indices based on cross-sectional regression residuals, leads to reductions in the available number of potential constituents. As indicated by the average number of index constituents, the cross-sectional distributions of the value (Ures) and glamour (Ores) stocks are slightly skewed as there are slightly more glamour stocks than value stocks in each month. When the performances of the indices formed by individual financial ratios (refer to Appendix C.1 through Appendix C.5) are compared to the performances the indices formed by the residuals of the corresponding attributes (Appendix C.7 through Appendix C.11), it is found that almost all indices formed by financial ratios underperform their counterpart indices formed by the univariate Ures over the examination periods. However, the univariate Ores indices (refer to Appendix E.7 through Appendix E.11) only underperform their counterpart glamour indices formed by financial ratios (refer to Appendix E.1 through Appendix E.5) during the first period. These findings indicate that Yu (2008)'s technique has a better ability in ranking undervalued shares. However, Yu (2008)'s technique does not appear to be superior to the traditional ranking technique using financial ratios to classify the most expensive shares in the market.

With regard to the monthly portfolio turnover, the style-weighted value indices (refer to APPENDIX C) appear to be much more aggressive in terms of their monthly portfolio rebalancing requirements, compared to the style-weighted glamour indices (refer to APPENDIX E). Similar to the price-sensitive size indices, the monthly portfolio turnovers for the style-weighted glamour indices are lower than their equally-weighted counterpart indices due to the partial self-adjustments in constituent weights through the movements in the price component of the underlying attributes.

5.6 Results: Characteristics of the Global Style Proxies

The role of the global style proxies in this research is to represent the distinctive investment styles in the global style-based portfolios. Thus, the proxies identified for this research should adhere to the portfolio concept to avoid the formation of separate mental account for each of the size, momentum and value investment styles. Therefore, the representativeness of the underlying investment style for an index is the most important criterion in the selection of the style proxies. This selection criterion ensures that the performances of the style proxies are distinctive from each other, which mitigate the problem of multicollinearity when they are employed as factors in style-based factor models. Prioritising the representativeness requirement also implies that the style proxies should have sufficient coverage of the shares qualified for the underlying investment style and should not be overly-concentrated.

Good candidates for the global size proxy include the top 300 equally-weighted large cap index (refer to EW300 index in Appendix A.2) and the top 300 equally-weighted RAFI index (refer to EW300 index in Appendix A.8). These two indices have similar risk and return characteristics and are free of capitalisation drag exhibited by price-sensitive indices. Taking the full 300 shares in the research sample for the size proxy provides sufficient coverage of the largest firms in most of the 19 sectors in the research database, without being subject to the implicit style bias embedded in certain sectors, as discussed in Section 4.3. Due to the fact that the top 300 equally-weighted large cap index has full 300 constituents throughout the examination period, compared to around 270 constituents in the top 300 equally-weighted RAFI index, the former is regarded as a better proxy to represent the performances of the most prestigious firms in the global equity market. The style-weighted RAFI indices are not

considered in the selection process due to the extremely high portfolio concentration revealed by the drastic difference between their average actual and effective number of constituents. For instance, the average effective number of constituents for the top 300 style-weighted RAFI index is less than 30 over the examination period.

With regard to the global momentum and value proxies, style-weighted indices are considered better indices than equally-weighted indices in retaining the style orientation for the proxies. Although the style-weighted momentum and value indices appear to underperform their equally-weighted counterpart indices in terms of the cost-adjusted geometric returns, the impact of trading costs associated with individual style indices is diluted when they are employed as constituent indices in a style-based portfolio. In addition, the trading costs applied to large institutional investors are typically below 1%, which is much lower than the 2% trading costs assumed in the computation of cost-adjusted geometric returns for individual investors. The analysis of the performances of the momentum indices and value indices also reveal that momentum indices outperform value and size indices by a large margin during the bullish first sub-period. Although the intensive rebalancing requirement significantly affects the performances of the style-weighted momentum indices in the bear market, the rebalancing costs are overcome by the superior performance of the indices in the bull market.

Similarly, value indices are best performers during the bearish second sub-period, and hence the higher trading costs associated with the style-weighted value indices are justified for this period. Based on this argument, trading costs do not play an important role in a style rotation strategy that successfully tilts its performance towards the momentum investment style in the bull market, and switch to the value

investment style in the bear market. The style-weighted momentum and value indices are also expected to better replicate the underlying investment styles of actively-managed funds compared to their equally-weighted counterpart indices.

Evaluating the performances of the candidate momentum indices reveals that the indices formed by 1-month lagged 11-month prior returns (refer to Mom12-1 indices demonstrated in Appendix B.8) outperform the rival indices formed by other momentum attributes over the examination period. By excluding the reversal effects of the most recent month constituent returns, Mom12-1 indices are good representations of the shares that carry the highest short-term momentum. On the other hand, value indices developed by the undervalued residual proxy that incorporates all 5 fundamental value attributes (refer to Ures(BEDSC) indices demonstrated in Appendix C.6) are preferred candidates for the value proxy since these indices have achieved consistent outstanding performances over the examination period, and Ures(BEDSC) is the most unbiased value indicator amongst all value attributes. Since there are less than 150 shares that are qualified as potential constituents for both the momentum indices and the undervalued residual indices in any given month, the target number of constituents for the momentum and value proxies is set at 100 to offer consistent coverage of the majority of the momentum and value stocks over the examination period.

Based on the above discussions, the top 100 style-weighted Mom12-1 index and the top 100 style-weighted Ures(BEDSC) index are employed as the global momentum and value proxies. The monthly 100 constituents covered by these two proxies represent the unique style segments within the 300 prestigious shares covered by the global size proxy. The summarised performance statistics of the global style proxies

and their respective counterpart indices are presented in Table 5.4. The counterpart indices are presumed to possess opposite traits to their underlying global style proxies. The counterpart index for the global size proxy is the top 300 cap-weighted large cap index. This index is price-sensitive and thus contains the capitalisation drag in its performance, as opposed to the equally-weighted global size proxy. On the other hand, the counterpart indices for the global momentum and value proxies are developed from the same underlying attributes, weighting methodology and number of target constituents as the global momentum and value proxies. While the counterpart index for the global momentum proxy is represented the top 100 style-weighted loser index formed by the lagged prior 11-month mean-adjusted returns (refer to SW100 index in Appendix D.8), the counterpart index for the value proxy is represented by the top 100 style-weighted glamour index formed by the Ores that incorporates all 5 fundamental attributes (refer to SW100 index in Appendix E.6).

Comparing the performances of the global style proxies demonstrated in Table 5.4 reveals that the global value proxy offers the most consistent performance over the examination periods. It is also the best performer over the bearish second sub-period, and is the only global style proxy that has positive annualised Sharpe ratio during this period. By contrast, the glamour proxy is the worst performer amongst all style proxies. Although it is characterised by low standard deviation and below-average beta, its risk-adjusted return is also below average. Table 5.4 also reveals that the performances of the momentum proxy and its counterpart loser proxy are similar in terms of their aggressive rebalancing strategy and volatile returns. While such strategy enables the momentum proxy to yield the highest annualised cost-adjusted geometric returns of 20.56% over the bullish first sub-period, it adversely affects the cost-adjusted return of the momentum proxy over the bearish second sub-period (-6.09%).

Table 5.4 Performances of the Global Style Proxies

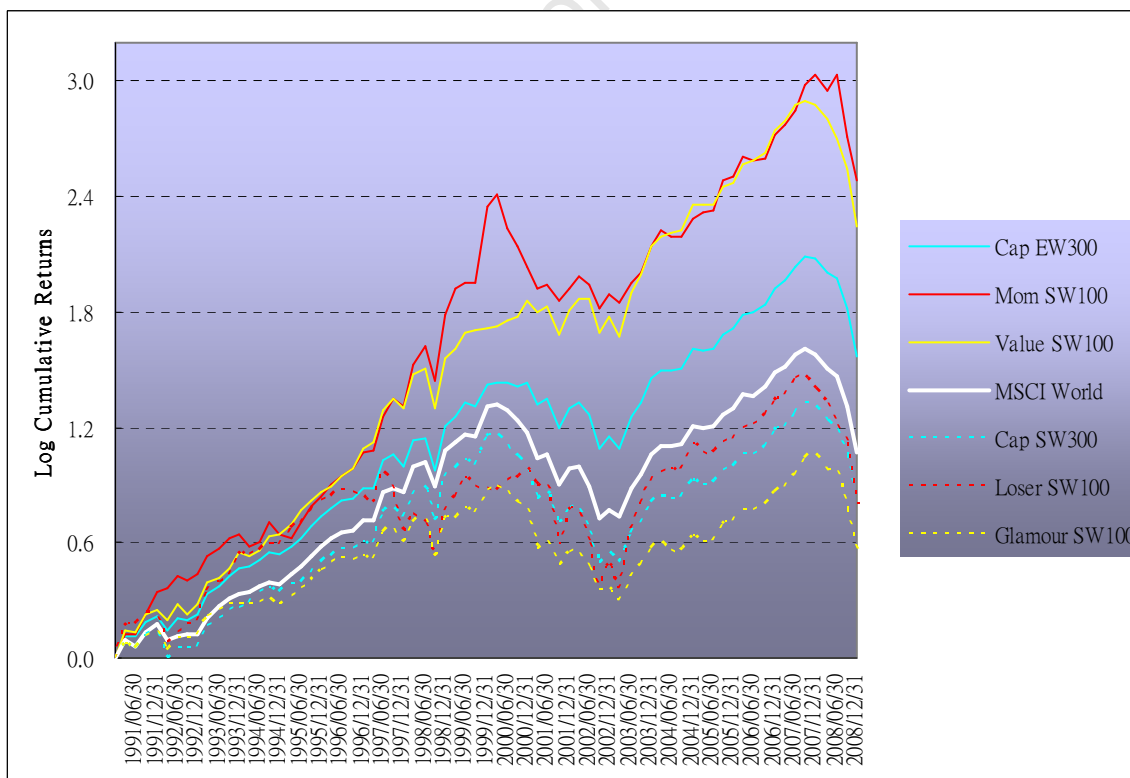
The respective style proxies representing the size, momentum and value investment styles are the top 300 equally-weighted large cap index (Cap EW300), the top 100 style-weighted momentum index (Mom12-1 SW100) and the top 100 style-weighted undervalued residual index (Value Ures(BEDCS) SW100). The performances of the counterpart indices to the style proxies based on the same attributes and number of constituents are displayed in the right-hand side panel. The counterpart indices to the above-mentioned style proxies include the top 300 style-weighted (i.e. cap-weighted) large cap index (Cap SW300), the top 100 style-weighted loser index (Loser12-1 SW100) and the top 100 style-weighted glamour overvalued residual index (Glamour Ores(BEDCS) SW100) respectively. The weighting method for the momentum/loser investment style is based on the lagged prior 11-month mean-adjusted returns of the index constituents in each month. On the other hand, the shares in the value/glamour investment category are weighted by the absolute values of their residual returns below/above the intrinsic values predicted by the 5 fundamental values per share namely, book value per share, net earnings after tax per share, gross dividends per share, gross sales per share and net cash flow per share. The benchmark for evaluating the risk-adjusted performances of the style indices is the Morgan Stanley Capital International World Index (MSCI World). The performance measures of the style proxies are annualised and denominated in U.S. dollars. The performances of the style proxies are examined over the two 108-month sub-periods and the whole 216-month period from 1 January 1991 to 31 December 2008.

Indices:		MSCI	Cap	Mom	Value	Cap	Loser	Glamour
Underlying Attribute:		Mkt. Cap	Mkt. Cap	Mom12-1	Ures (BEDCS) SW100	Mkt. Cap	Mom12-1	Ores (BEDCS) SW100
Weighting Method:		World 1500+/-	EW300	SW100		SW300	SW100	
Basic Statistics	Period							
Geometric Return	1/91-12/99	15.67%	17.16%	29.82%	20.96%	13.66%	10.27%	10.24%
Geometric Return	1/00-12/08	-2.69%	1.61%	1.46%	6.06%	-3.58%	-0.88%	-3.43%
Geometric Return	1/91-12/08	6.10%	9.11%	14.77%	13.27%	4.68%	4.55%	3.18%
Cost Adj. Geo Return	1/91-12/99	N/A	15.65%	20.56%	17.17%	12.89%	5.95%	8.48%
Cost Adj. Geo Return	1/00-12/08	N/A	0.24%	-6.09%	2.55%	-3.97%	-5.04%	-5.10%
Cost Adj. Geo Return	1/91-12/08	N/A	7.64%	6.41%	9.62%	4.12%	0.30%	1.46%
Cum. Growth of \$1	1/91-12/99	3.707	4.160	10.475	5.543	3.165	2.411	2.406
Cum. Growth of \$1	1/00-12/08	0.782	1.155	1.139	1.698	0.720	0.924	0.730
Cum. Growth of \$1	1/91-12/08	2.901	4.803	11.933	9.415	2.280	2.227	1.757
Arithmetic Return	1/91-12/99	16.57%	18.04%	31.90%	22.12%	14.69%	11.69%	11.09%
Arithmetic Return	1/00-12/08	-1.36%	2.99%	3.32%	7.96%	-2.29%	1.96%	-2.42%
Arithmetic Return	1/91-12/08	7.26%	10.28%	16.81%	14.84%	5.89%	6.72%	4.14%
Standard Deviation	1/91-12/99	12.56%	12.43%	18.40%	14.13%	13.66%	16.30%	12.50%
Standard Deviation	1/00-12/08	16.25%	16.20%	18.93%	18.50%	16.09%	23.47%	14.25%
Standard Deviation	1/91-12/08	14.69%	14.54%	18.96%	16.52%	15.07%	20.20%	13.50%
Risk-Adj. Measures	Period							
Sharpe Ratio	1/91-12/99	0.872	1.000	1.364	1.148	0.654	0.340	0.441
Sharpe Ratio	1/00-12/08	-0.354	-0.090	-0.085	0.162	-0.413	-0.168	-0.456
Sharpe Ratio	1/91-12/08	0.150	0.359	0.573	0.567	0.053	0.032	-0.053
M Squared	1/91-12/99	0.00%	1.62%	6.19%	3.48%	-2.74%	-6.67%	-5.40%
M Squared	1/00-12/08	0.00%	4.30%	4.37%	8.39%	-0.96%	3.03%	-1.65%
M Squared	1/91-12/08	0.00%	3.07%	6.22%	6.13%	-1.43%	-1.72%	-2.98%
Information Ratio	1/91-12/99	0.00%	0.325	1.234	0.650	-0.380	-0.487	-0.972
Information Ratio	1/00-12/08	0.00%	1.388	0.350	1.164	-0.423	0.156	-0.143
Information Ratio	1/91-12/08	0.00%	0.767	0.742	0.915	-0.350	-0.136	-0.540
Treynor Ratio	1/91-12/99	0.109	0.135	0.217	0.176	0.089	0.058	0.062
Treynor Ratio	1/00-12/08	-0.058	-0.015	-0.018	0.029	-0.068	-0.031	-0.078
Treynor Ratio	1/91-12/08	0.022	0.055	0.107	0.095	0.008	0.006	-0.008
Jensen's Alpha	1/91-12/99	0.00%	2.38%	13.47%	6.45%	-1.91%	-4.31%	-4.25%
Jensen's Alpha	1/00-12/08	0.00%	4.25%	4.29%	9.49%	-1.02%	4.59%	-1.80%
Jensen's Alpha	1/91-12/08	0.00%	3.18%	9.50%	7.62%	-1.33%	-1.02%	-2.63%
Beta	1/91-12/99	1.00	0.92	1.16	0.92	1.00	0.95	0.90
Beta	1/00-12/08	1.00	0.98	0.91	1.04	0.98	1.29	0.83
Beta	1/91-12/08	1.00	0.95	1.01	0.99	0.99	1.14	0.85

It is also apparent that all 3 counterpart indices underperform the respective global size, momentum and value proxies and the MSCI World benchmark over the examination period on a risk-adjusted basis. On the other hand, the global size, momentum and value proxies outperform the MSCI World Index on a risk-adjusted basis over the examination period. These findings are also documented by the log cumulative returns of the global style proxies demonstrated in Figure 5.3.

Figure 5.3 Log Cumulative Returns of the Global Style Proxies

The payoffs to the pre-specified global style proxies are examined over the period from 1 January 1991 to 31 December 2008 (a total of 216 months). The log cumulative returns of the global size (top 300 equally-weighted large caps (Cap EW300)), momentum (top 100 style-weighted excess return winners (Mom SW100)) and value (top 100 style-weighted undervalued shares (Value SW200)) proxies are represented by the solid blue, red and yellow trend lines respectively. The counterpart indices, namely the top 300 cap-weighted large caps (Cap SW300), top 100 style-weighted excess return losers (Loser SW100) and top 100 style-weighted glamour stocks (Glamour SW100), are represented by the blue, red and yellow dashed trend lines respectively. The solid white trend line demonstrates the payoffs to the Morgan Stanley Capital International World Index (MSCI World) over the examination period.



The cumulative performances of the global size, momentum and value proxies are represented by the solid blue, red and yellow trend lines while their counterpart indices are represented by dashed trend lines of the same colours in Figure 5.3. Although the MSCI World benchmark underperforms the global size, momentum and value proxies, it outperforms the 3 counterpart style indices. An interesting observation in Figure 5.3 is that significant deviations in the performances of the global momentum proxy from the performances of the remaining indices are detected just before the Asian financial crisis in 1998, the crash of the Information Technology (I.T.) bubble in 2000 and the global financial crisis in 2008. In addition, significant downward drift in the performance of the global loser proxy are also detected just before the Asian financial crisis and the crash of the I.T. bubble. Thus, significant drifts in the performances of the global momentum and loser proxies serve as early signals for the subsequent market crash.

Figure 5.4 and Figure 5.5 demonstrate the relative performances of the global style proxies against the empirical capital market line (ECML) and the empirical security market line (ESML) respectively. The ECML and the ESML demonstrate the risk-return tradeoffs for fund allocations between the risk-free proxy and the market proxy over the examination period. While the ECML uses standard deviation to measure portfolio risk, the relevant risk measure for the ESML is the sensitivity of the portfolio return to movements in the market return. Indices plotted above the ECML and the ESML yield higher returns than their risk-adjusted returns, and indices plotted below the ECML and the ESML fail to earn satisfactory returns for the levels of risk borne by the respective indices. Examining the locations of the style proxies in Figure 5.4 and Figure 5.5 indicates that the global size, momentum and value proxies earn positive excess risk-adjusted returns, while their counterpart indices earn negative

excess risk-adjusted returns against both the ECML and the ESML. The ECML and the ESML effectively separate the global style proxies from their counterpart global style indices in both Figure 5.4 and Figure 5.5.

Figure 5.4 Relative Performances of the Style Proxies Measured by the Empirical Capital Market Line (ECML)

The Empirical Capital Market Line (ECML) demonstrates the risk-adjusted returns at different levels of total risk achieved by allocating capital between the risk-free proxy and the market proxy. The return on the U.S. 3-month Treasury bill (USTB3M) is employed as the risk-free rate while the market proxy is represented by the Morgan Stanley Capital International World index (MSCI World). The total risk (the x-axis) is measured by the standard deviation of the index return over the examination period from 1 January 1991 to 31 December 2008 (a total of 216 months). The size, momentum and value proxies are represented by the top 300 equally-weighted large caps (Cap EW300), the top 100 style-weighted momentum winners (Mom SW100) and the top 100 style-weighted undervalued stocks (Value SW00). They are marked by solid blue square box, solid red dot and solid yellow triangle respectively. The counterpart indices namely the top 300 cap-weighted large caps (Cap SW300), the top 100 style-weighted losers (Loser SW100) and the top 100 style-weighted glamour stocks (Glamour SW100) are marked by empty blue square box, empty red dot and empty yellow triangle respectively.

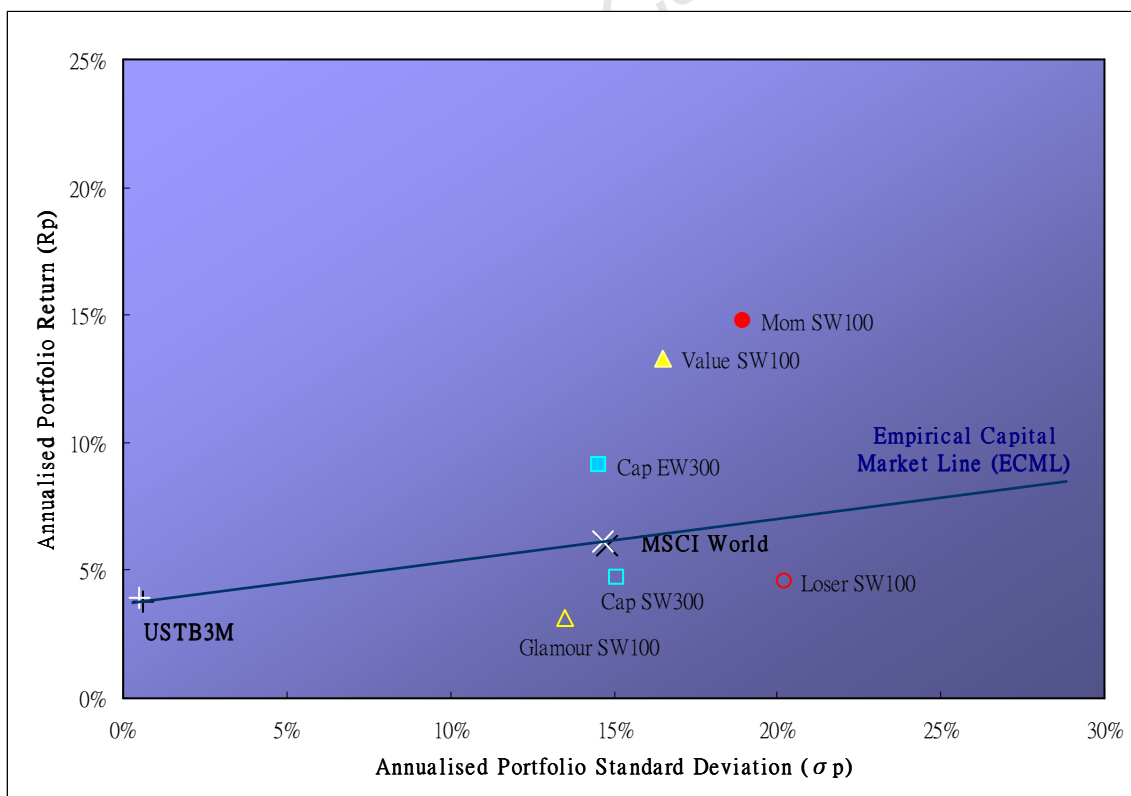
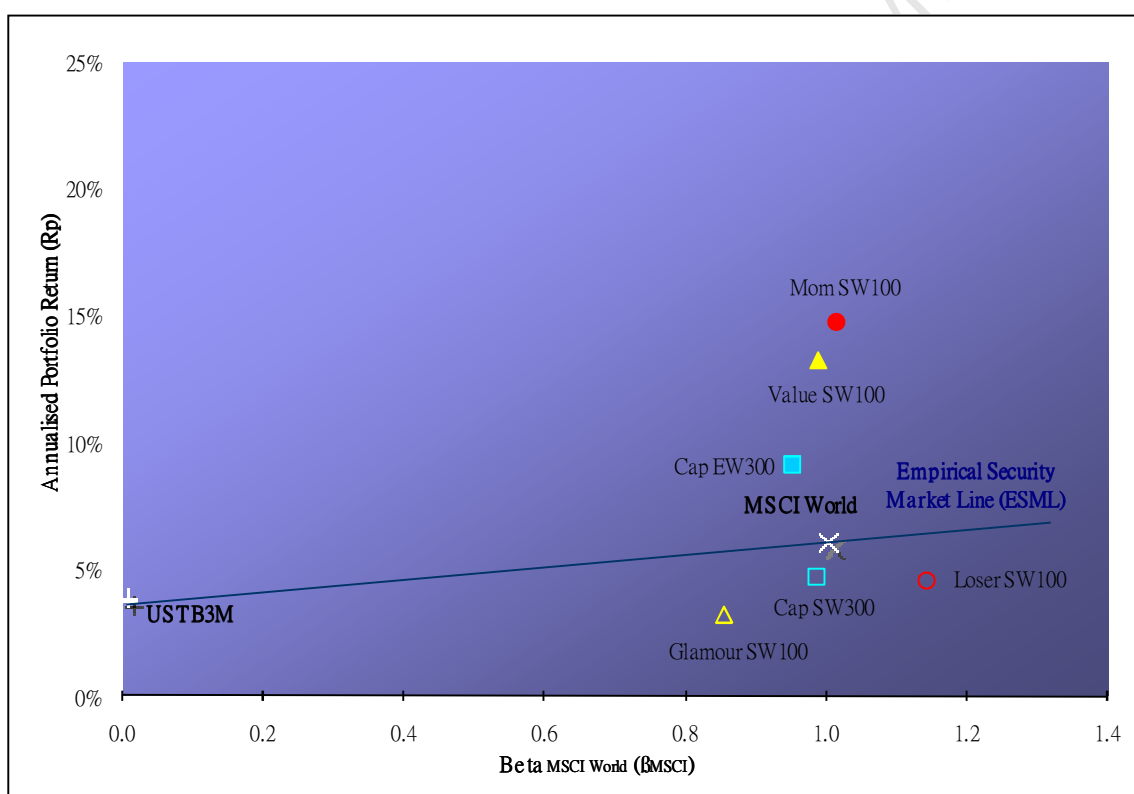


Figure 5.5 Relative Performances of the Style Proxies Measured by the Empirical Security Market Line (ESML)

The Empirical Security Market Line (ESML) demonstrates the risk-adjusted returns at different levels of systematic risk achieved by allocating capital between the risk-free proxy and the market proxy. The return on the U.S. 3-month Treasury bill (USTB3M) is employed as the risk-free rate while the market proxy is represented by the Morgan Stanley Capital International World index (MSCI World). The systematic risk (the x-axis) is measured by the beta coefficient obtained by regressing the monthly style proxy returns on the market risk premia over the examination period from 1 January 1991 to 31 December 2008 (a total of 216 months). The size, momentum and value proxies are represented by the top 300 equally-weighted large caps (Cap EW300), the top 100 style-weighted momentum winners (Mom SW100) and the top 100 style-weighted undervalued stocks (Value SW00). They are marked by solid blue square box, solid red dot and solid yellow triangle respectively. The counterpart indices namely the top 300 cap-weighted large caps (Cap SW300), the top 100 style-weighted losers (Loser SW100) and the top 100 style-weighted glamour stocks (Glamour SW100) are marked by empty blue square box, empty red dot and empty yellow triangle respectively.



Although the risks embedded in the global momentum and value proxies appear to be substantially higher than that of the market proxy in terms of their annualised standard deviations in Figure 5.4, a large portion of their risk is unsystematic in nature. As illustrated in Figure 5.5, by removing the diversifiable risk from their standard

deviations, the global size, momentum and value proxies earn higher returns than the market proxy similar level of market risk. Such risk reduction is not available for the global loser proxy, which has the highest beta coefficient of 1.14 (from Table 5.4) amongst the global style proxies as illustrated in Figure 5.5. The global loser proxy is thus characterised by above-average risk (measured by both the standard deviation and beta coefficient), low return and negative excess risk-adjusted return.

The correlation matrix of the monthly returns of the MSCI World Index and the global style proxies is demonstrated in Table 5.5. The correlation coefficients that are between 0.70 and 0.80 are highlighted in yellow, and the correlation coefficients that are greater than 0.80 are highlighted in red. All of the global style proxies are highly correlated with the MSCI World Index, indicating that the derivatives on the MSCI World Index are appropriate hedging vehicles for the global style proxies. Strong correlations are also exhibited between the pairs of most of the style proxies except the pairs involving the global momentum proxy.

Table 5.5 Correlation Matrix of the Global Style Proxies

This table demonstrates the correlation matrix of the monthly returns of the MSCI World Index and the global style proxies over the examination period from 1 January 1991 to 31 December 2008. The correlation coefficients that are greater than 0.70 but less than 0.80 are highlighted in yellow. On the other hand, the correlation coefficients that are above 0.80 are highlighted in red.

	MSCI World	Cap EW300	Mom SW100	Value SW100	Cap SW100	Loser SW100
Cap EW300	0.963					
Mom SW100	0.788	0.780				
Value SW100	0.880	0.948	0.645			
Cap SW100	0.964	0.970	0.773	0.881		
Loser SW100	0.833	0.886	0.468	0.870	0.853	
Glamour SW100	0.930	0.950	0.795	0.848	0.955	0.802

The aggressive nature of the global momentum proxy once again demonstrates its uniqueness as a distinguishable global investment class that deserves a place in addition to the existing value and size style factors in the Fama and French (1993)'s 3-factor model. The correlation coefficient between the global momentum and value proxies is less than 0.70 and the correlation coefficient between the global momentum proxy and its counterpart loser proxy is as low as 0.468 over the examination period. However, the intensive rebalancing requirement has made the global momentum proxy an undesirable investment vehicle during period of poor investor sentiment.

Table 5.6 demonstrates the effects of rebalancing frequency on the performances of the global style proxies. It is apparent that the geometric returns and the Sharpe ratios of all global style proxies deteriorate under the semi-annual rebalancing method. The global momentum proxy suffers the most from the lower rebalancing frequency. Although the mean portfolio turnover for the global momentum proxy improves to 11.47% from 31.78%, the Sharpe ratio drops by half from 0.573 to 0.295 for the semi-annual rebalancing approach. The beta for the semi-annual rebalancing approach also increases sharply to 1.10 from 1.01 for the global momentum proxy. By contrast, the mean portfolio turnover for the global size proxy indeed rises slightly under the semi-annual rebalancing approach. This is probably due to the greater adjustments of its membership under the less frequent rebalancing approach. The global value proxy seems to cope well with the lower rebalancing frequency with its Sharpe ratio maintained above 0.50 under the semi-annual rebalancing approach. This finding supports the argument of Rousseau and Van Rensburg (2004) that value investing is best employed as a long-term investment strategy.

Table 5.6 Effects of Rebalancing Frequency on the Performances of the Global Style Proxies

This table compares the monthly-rebalanced performances of the global style proxies to the semi-annually rebalanced performances. The effects of the rebalancing frequency for the global size, momentum and value indices are illustrated in Panel (a), Panel (b) and Panel (c) respectively. The respective style proxies representing the global size, momentum and value investment styles are the top 300 equally-weighted large cap index (Cap EW300), the top 100 style-weighted momentum index (Mom12-1 SW100) and the top 100 style-weighted undervalued residual index (Value Ures(BEDSC) SW100). The performance measures of the global style proxies are annualised and denominated in U.S. dollars. The performances of the global style proxies are examined over period from 1 January 1991 to 31 December 2008.

Panel (a) Global Size Proxy (Cap EW300)

Performance Statistics	Monthly Rebalancing	Semi-Annual Rebalancing
Geometric Return	9.11%	8.97%
Cost Adj. Geo Return	7.64%	7.47%
Sharpe Ratio	0.359	0.343
Avg. Effective No. of Constituents	300	300
Mean Portfolio Turnover (monthly-adjusted)	5.58%	5.82%
Beta	0.95	0.97

Panel (b) Global Momentum Proxy (Mom SW100)

Performance Statistics	Monthly Rebalancing	Semi-Annual Rebalancing
Geometric Return	14.77%	9.69%
Cost Adj. Geo Return	6.41%	6.73%
Sharpe Ratio	0.573	0.295
Avg. Effective No. of Constituents	55	55
Mean Portfolio Turnover (monthly-adjusted)	31.78%	11.47%
Beta	1.01	1.10

Panel (c) Global Value Proxy (Value SW100)

Performance Statistics	Monthly Rebalancing	Semi-Annual Rebalancing
Geometric Return	13.27%	12.91%
Cost Adj. Geo Return	9.62%	9.78%
Sharpe Ratio	0.567	0.547
Avg. Effective No. of Constituents	73	73
Mean Portfolio Turnover (monthly-adjusted)	13.85%	8.00%
Beta	0.99	0.99

5.7 Results: Performance Attributions of the Global Style Proxies

The performance attributions of the global style proxies are demonstrated in Table 5.7. The difference in the average monthly returns between the global style proxies and the benchmark is decomposed into the currency effect, the sector/country allocation effect and the security allocation effect. Coincidentally, the equally-weighted 300 large cap index is chosen as the global size style proxy as well as the benchmark for evaluating the performance attributions of the global style proxies. The return attributions of the global momentum proxy are shown in Panel (a) of Table 5.7, and the performance attributions of the global value proxy are shown in Panel (b) of Table 5.7.

Both the global momentum and the value proxies yield higher average monthly returns than the benchmark. The difference between the respective proxy returns and the benchmark return is shown as the average total effect at the bottom of the respective panels in Table 5.7. Although the average total effect is lower for the global value proxy (0.34% per month) compared to that of the momentum proxy (0.48% per month), its t -statistic for the global value proxy (2.60) is significant at the 5% level and is much higher than the t -statistic for the global momentum proxy (1.89). The highly positive, yet statistically insignificant average total effect for the global momentum proxy, is due to its high volatile returns over the examination period. It is also apparent that the currency allocation effects for both the global momentum and the value proxies are statistically insignificant and close to zero as the impacts of the movements in exchange rates are netted out in well diversified global indices.

Table 5.7 Performance Attributions of the Global Style Proxies

The global size proxy (Cap EW300) is employed as the benchmark to evaluate the performances of the global momentum proxy (Mom SW100) and the global value proxy (Value SW100). Panel (a) demonstrates the performance attributions of the global momentum proxy while the performance attributions of the global value proxy are demonstrated in Panel (b) over the examination period from 1 January 1991 to 31 December 2008. The difference between the global style proxy return and the benchmark return in each month is decomposed into the currency allocation effect, the sector/country allocation effect and the security allocation effect. The time-series means of these effects (with their *t*-statistics) are shown separately for the sector allocation analysis and the country allocation analysis.

Panel (a) Momentum Proxy vs. Size Proxy (Benchmark)

Avg. Monthly Return (Mom SW100):	1.30%	
Avg. Monthly Return (Cap EW300: Benchmark):	0.82%	
	Sector Allocation	Country Allocation
Avg. Monthly Currency Allocation Effect:	0.05%	0.05%
	<i>1.23</i>	<i>1.23</i>
Avg. Monthly Sector/Country Allocation Effect:	0.25%	0.05%
	<i>1.93</i>	<i>0.15</i>
Avg. Monthly Security Selection Effect within Sector/Country:	0.18%	0.38%
	<i>1.14</i>	<i>1.93</i>
Avg. Total Effect:	0.48%	0.48%
	<i>1.89</i>	<i>1.89</i>

Panel (b) Value Proxy vs. Size Proxy (Benchmark)

Avg. Monthly Return (Value SW100):	1.16%	
Avg. Monthly Return (Cap EW300: Benchmark):	0.82%	
	Sector Allocation	Country Allocation
Avg. Monthly Currency Allocation Effect:	0.00%	0.00%
	<i>0.02</i>	<i>0.02</i>
Avg. Monthly Sector/Country Allocation Effect:	0.08%	0.10%
	<i>0.95</i>	<i>0.74</i>
Avg. Monthly Security Selection Effect within Sector/Country:	0.26%	0.24%
	<i>2.72</i>	<i>2.60</i>
Avg. Total Effect:	0.34%	0.34%
	<i>2.60</i>	<i>2.60</i>

Holding the currency effect constant, the sector allocation effect explains the largest portion of the total effect for the global momentum proxy, as shown in Panel (a) of Table 5.7. By contrast, the country allocation effect for the global momentum proxy is close to zero. This result suggests that the uniqueness of the global momentum investment style is primarily due to its distinctive allocations across global sectors rather than countries. On the other hand, neither of the sector allocation or country allocation effect is able to successfully explain the return difference between the global value and size proxies. As a result, the average monthly security selection effects under both the sector decomposition analysis and the country decomposition analysis are statistically significant for the global value proxy.

Figure 5.6 depicts the cross-sector contributions to the global style proxy returns over the examination period. The return attributions of the global momentum and value proxies are compared to the return attributions of the global size benchmark across 19 sectors as shown in Chart (a) and Chart (b) of Figure 5.6 respectively. The sectors that are significantly overweighted by the global momentum proxy include the health care sector, the retail sector, the technology sector and the telecommunication sector. The global momentum proxy derives most of its return from the technology sector, which is 3 times of the sector's contribution to the size benchmark. Fundamental industries such as the automobile and part sector, the chemicals sector, the construction and material sector, the industrial goods and services sector and the travel and leisure sector are underweighted by the global momentum proxy. By contrast, these sectors receive considerable weights from the global value proxy. The banking sector, the insurance sector, the oil and gas sector and the real estate sector are also overweighted by the global value proxy.

Figure 5.6 Cross-Sector Contributions to the Returns of the Global Style Proxies

The average monthly cross-sector contributions to the returns of the global momentum proxy (Mom SW100) and the global value proxy (Value SW100) are compared to the average monthly cross-sector contributions to the returns of the global size proxy (Cap EW300) over the examination period from 1 January 1991 to 31 December 2008. The comparison between the global momentum proxy and the global size proxy is demonstrated in Chart (a) while the comparison between the global value proxy and the global size proxy is demonstrated in Chart (b). The 19 sectors represent the second tier of the Supersector structure defined by the Industry Classification Benchmark (ICB).

Chart (a) Momentum Proxy vs. Size Proxy (Benchmark)

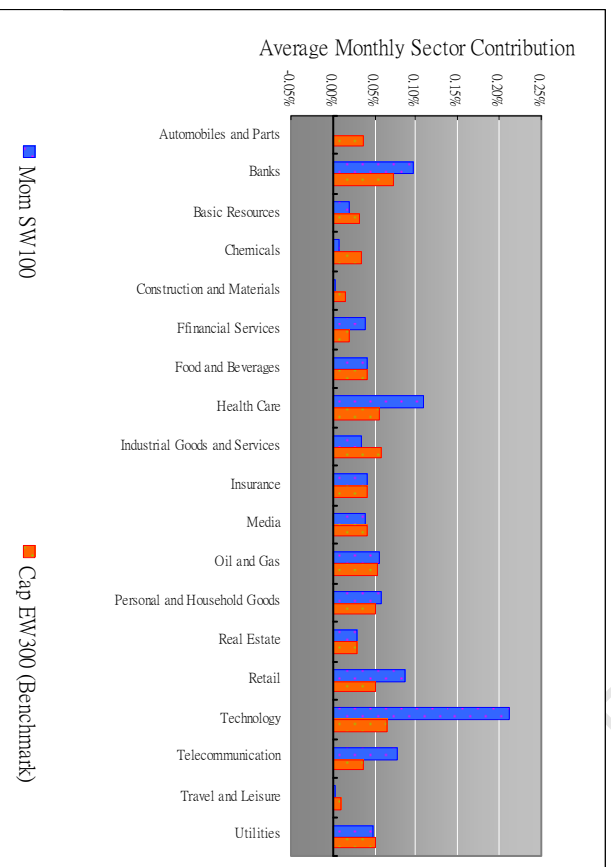
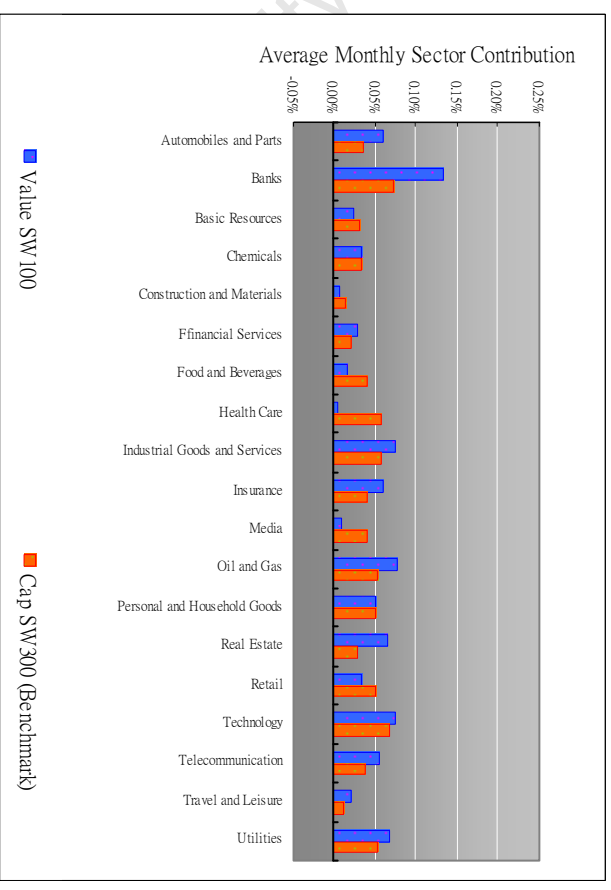


Chart (b) Value Proxy vs. Size Proxy (Benchmark)



Compared to the aggressive sector allocation policy of the global momentum proxy, the global value proxy, in general adheres, to the allocation policy of the global size benchmark across the sectors, with the exception of the banking sector which has the highest contribution to the global value proxy return over the examination period.

Figure 5.7 depicts the cross-country contributions to the global style proxy returns over the examination period. The return attributions of the global momentum and the value proxies are compared to the return attributions of the global size benchmark across 27 countries as shown in Chart (a) and Chart (b) of Figure 5.7 respectively. The cross-country allocations between the global momentum proxy and the global size benchmark are similar in that both proxies generate the majority portion of their returns from the United States. By contrast, the global value proxy significantly underweights the investments in the United Kingdom and the United States, compared to the global momentum proxy and the global size benchmark. This finding suggests that the U.K. and U.S. stocks are considered as expensive investments in the global equity markets over the examination period. This allocation policy enables the global value proxy to have a more balanced distribution of its investments across the countries. The countries that are considerably overweighted by the global value proxy include Australia, Canada, Spain, Hong Kong, Japan and Netherlands. However, the difference in the returns between the global value proxy and the global size benchmark cannot be explained by the unique country allocation policy of the global value proxy.

Figure 5.7 Cross-Country Contributions to the Returns of the Global Style Proxies

The average monthly cross-country contributions to the returns of the global momentum proxy (Mom SW100) and the global value proxy (Value SW100) are compared to the average monthly cross-country contributions to the returns of the global size proxy (Cap EW300) over the examination period from 1 January 1991 to 31 December 2008. The comparison between the global momentum proxy and the global size benchmark is demonstrated in Chart (a) while the comparison between the global value proxy and the global size benchmark is demonstrated in Chart (b).

Chart (a) Momentum Proxy vs. Size Proxy (Benchmark)

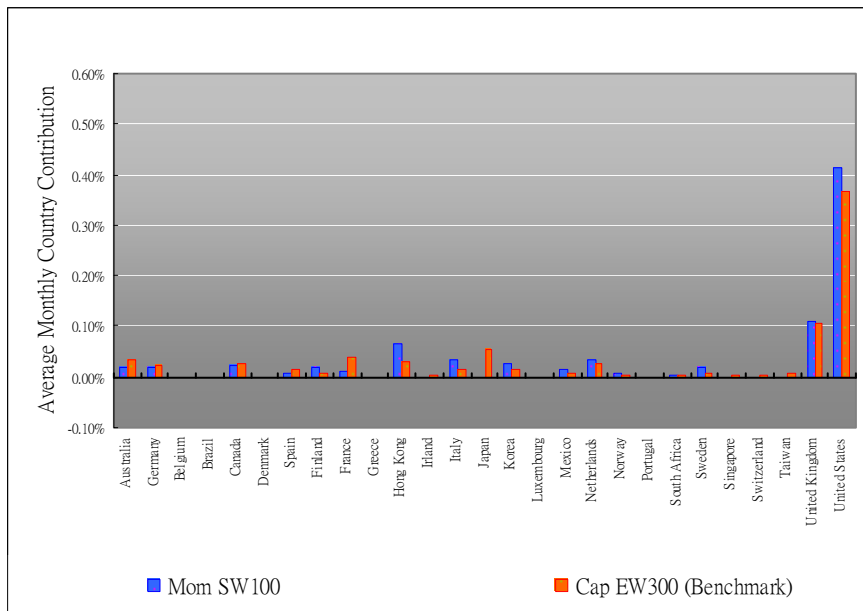
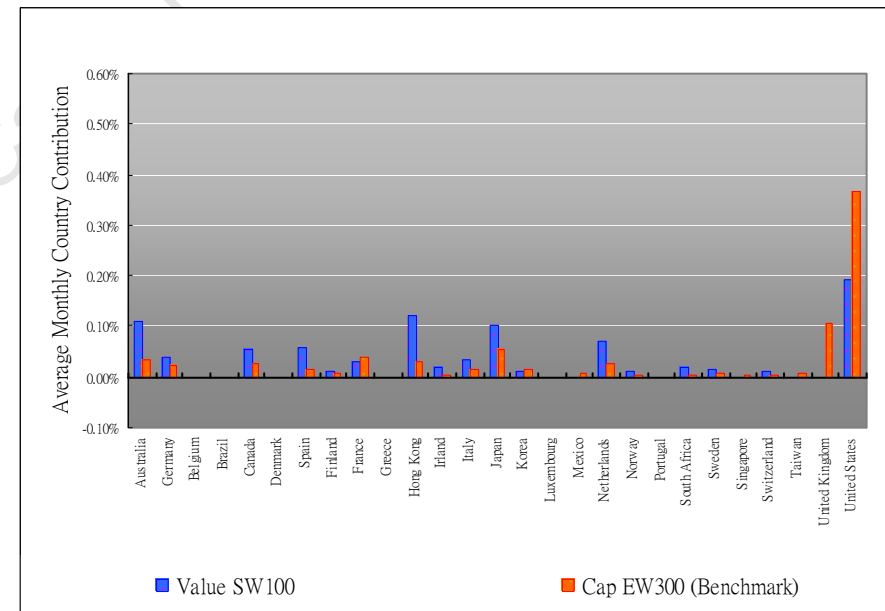


Chart (b) Value Proxy vs. Size Proxy (Benchmark)



5.8 Conclusion

There are in total 80 global size indices, 80 global momentum indices, 360 global value indices, 80 global loser indices and 360 global glamour indices developed and examined in this research. The performances of the global style indices are examined over the two sub-periods of equal length and the entire examination period from 1 January 1991 to 31 December 2008. The first sub-period of the research (prior to the millennium) represents an overheated bull market relative to the bearish second sub-period (post millennium). All of the indices perform distinctively better during the first sub-period than their performances in the second sub-period. However, indices of different investment styles are found to cope with the economic conditions differently over the two distinguishable sub-periods.

The price-sensitive size indices exhibit significant capitalisation drag, which adversely impacts on their performances during the bearish second sub-period. In general, higher style tilt leads to worse performances for the price-sensitive indices. By contrast, equally-weighted size indices and fundamental indices are price-insensitive and hence outperform the price-sensitive size indices during this period. Similar to the global value indices, the fundamental indices are found to have below average beta over the overheated first sub-period but increase substantially over the second sub-period during which stocks are less likely to be overvalued. This finding implies that the value bias is inevitably embedded in the fundamental indices.

Global value indices that undertake a defensive approach in selecting constituents are the best performers amongst the global style indices during the bearish second sub-period. The defensive approach also delivers satisfactory performances for global value indices over the bullish first sub-period, which is dominated by the global momentum (winner) indices. The excess market returns of past winners are greater for the style-weighted momentum indices with short-term (6- to 12-month) formation periods through substantially higher standard deviation, above average beta coefficients, high portfolio concentration and aggressive rebalancing. Although the past winners with 36-month or longer formation periods continue to outperform the MSCI World benchmark during the first sub-period, the prolonged momentum built up

in the bull market are substantially reversed in the subsequent bearish period. Significant reversals are also exhibited by prior 1-month winner indices. By contrast, prior 1-month, 48-month and 60-month loser indices achieve outstanding performances over the bearish second sub-period.

One of the main contributions of the studies conducted in this Chapter include the results obtained from the extended research on the effectiveness of separating the value and glamour stocks, based on the cross-sectional residuals proposed by Yu (2008) and the effectiveness of separating the past winners and losers based on the mean-adjusted returns of sample shares. The distinctive performances of the global value and glamour indices and the distinctive performances of the global winner and loser indices, over the examination periods indicate the success of the two innovative classification techniques in accomplishing their stated objectives. Yu (2008)'s approach in grouping value and glamour shares has the advantage of building unbiased value and glamour attributes based on multiple fundamental attributes, compared to financial ratios that represent univariate price multiples. On the other hand, grouping past winners and losers based on their respective mean-adjusted return, offers a method of constructing style-weighted winner and loser portfolios in situations where the majority of the sample shares yield negative returns during temporary economic shocks. The cross-sectional mean is also regarded as a better benchmark in separating past winners and losers compared to taking an equal number of winners and losers from the two ends of the cross-sectional returns.

The results of the regression analysis based on the capital asset pricing model (CAPM) indicate that the MSCI World Index is an appropriate market proxy in that all of the regressions are significant at the 1% level with high *R*-squared over the examination periods. Significant abnormal returns that cannot be explained by the risk premium on the MSCI World benchmark in this research include the negatively significant alpha of the price-sensitive size indices and the global glamour indices over the examination periods, the positively significant alpha of the global value indices over the second sub-period, the negatively significant alpha for the prior 1-month winners, the lagged prior 11-month losers in the second sub-period and the positively significant alpha for the lagged 11-month winners in the overall examination period. The rest (i.e. the

majority) of the global style indices do not earn meaningful abnormal returns over the examination periods.

The most representative proxies of the global size, momentum and value investment styles identified by this research are the top 300 equally-weighted large cap index, the top 100 style-weighted momentum index formed by lagged prior 11-month mean-adjusted returns and the top 100 style-weighted value index formed by the composite undervalued residuals, using all 5 fundamental attributes. The indices chosen to represent their counterpart indices are the top 300 cap-weighted large cap index, the top 100 style-weighted loser index formed by lagged 11-month mean-adjusted returns and the top 100 style-weighted glamour index formed by the composite overvalued residuals, using all 5 fundamental attributes. These style proxies are regarded as the best representations of their underlying investment styles in that they possess the unique risk-return characteristics of their underlying investment styles and provide the broadest coverage of the sample shares within the underlying investment style category. The global size, momentum and value proxies are found to outperform the MSCI World benchmark, which in turn outperforms the global counterpart indices over the examination periods on a risk-adjusted basis.

The global value proxy, amongst the global style proxies, offers the most consistent performance over the examination period. It is the only proxy that has a positive Sharpe ratio during the bearish second sub-period. The global value proxy is characterised by outstanding risk-adjusted returns, average beta, average standard deviation and average portfolio turnover amongst the global style indices. By contrast, the global glamour proxy is the worst performer among the global style proxies. It is characterised by poor risk-adjusted returns, below average beta, below average standard deviation and below-average portfolio turnover over the examination period. On the other hand, the risk-return characteristics of the global size proxy and its cap-weighted size counterpart index are more or less in line with the MSCI World Index. The cap-weighted size counterpart index has only 300 constituents compared to approximately 1,500 constituents for the MSCI World Index, which imposes a greater capitalisation drag for the former index.

With regard to the risk-return characteristics of the global momentum proxy and the global loser proxy, both of the proxies have aggressive rebalancing strategies and volatile returns. While such strategy enables the global momentum proxy to be the top performer during the bullish first sub-period, it adversely impacts on the performance of the global momentum proxy in the second sub-period. The results also reveal that drastic drifts in the performances of the global momentum and loser proxies provide early signals for significant global financial crises during the examination period. While the Asian financial crisis in 1998, the crash of the I.T. bubble in 2000 and the global financial crisis in 2008 are detected by the upward drifts in the performance of the global momentum proxy, the downward drifts in the performance of the global loser index successfully detect the Asian financial crisis and the burst of the I.T. bubble. In addition, the performance of the global momentum proxy is also sensitive to changes in the rebalancing frequency. The Sharpe ratio of the global momentum proxy deteriorates drastically when the rebalancing frequency is dropped from monthly to semi-annually. By contrast, the Sharpe ratio for the global value proxy remains above 50% for the semi-annual rebalancing approach. Taking into account the impact of trading costs, this result supports the argument of Rousseau and Van Rensburg (2004) that value investing is best employed as a long-term strategy.

The correlation analysis on the global style proxy returns indicates that all of the global style proxy returns are highly correlated with the MSCI World Index return. This implies that derivatives on the MSCI World Index are good hedging instruments to manage the exposures of the global style proxies without being subject to significant basis risk. Although the global momentum proxy has the highest annualised standard deviation amongst the global style proxies, it has the lowest return correlation (0.788) to the MSCI World Index, which brings down its beta coefficient to an average level of 1.01. However, this is not the case for the global loser proxy that has the highest annualised standard deviation of 20.20% and the highest beta coefficient of 1.14 amongst the global style proxies. High correlation coefficients are also exhibited between the global style proxies. Once again, the global momentum proxy has the lowest return correlation with other global style proxies. Below 0.70 correlation coefficients are exhibited between the global momentum proxy returns and the global loser proxy returns (0.468), and between the global momentum proxy returns and the global value proxy returns (0.645).

The results of the global performance attribution analysis demonstrate the importance of sector allocation in explaining the difference between the global momentum proxy return and the average return of sample shares. While the technology sector, the retail sector, the health care sector and the telecommunication sector are the most favourite choices for the global momentum proxy, the traditional industrial sectors are underweighted by the global momentum proxy. The sector allocation policies of the global value and size proxies are similar and are more evenly distributed compared to the sector allocation policy of the global momentum proxy. With regard to the country allocation effect, the global size and momentum proxies focus their country allocation in the United Kingdom and the United States over the examination period. By contrast, the global value proxy deliberately underweights its allocations in these two countries. This implies that the stocks in these two countries have relatively high price multiples compared to stocks in other countries over the examination period. Although the country allocation policies between the global momentum and value proxies are drastically different, the country allocation effect does not produce meaningful contributions to the return differences between the global style proxies.

In conclusion, the relatively low return correlation between the global momentum proxy and the global value proxy, coupled with the distinctive differences between their specific style timing, investment risks, rebalancing requirements and sector allocation policies, provide solid evidence that the momentum and value investment styles represent two distinctive investment segments in the global equity markets. On the other hand, the risk-return characteristics of the global size proxy seem to be between the MSCI World Index and the global value proxy due to its relatively high return correlations with these two indices.

PASSIVE REPLICATION OF GLOBAL EQUITY FUNDS

6.1 Introduction

The goal of this chapter is to construct style-based portfolios that replicate the underlying investment styles of the selected South African-based and internationally-domiciled global equity funds. The return-based style decomposition approach of Sharpe (1992) discussed in section 3.3.1 is adapted for this purpose. This approach decomposes the time-series returns of the fund being analysed to (i) the style return that is attributable to the returns on the pre-specified style indices and (ii) the selection return that cannot be explained by the movements in the returns of the pre-specified style indices. Thus, the style return of a fund estimated by the Sharpe (1992) factor model serves as the underlying style benchmark for the fund.

As long as the fund return is primarily attributable to its style return and the selection return is random, replicating the style return of a fund is approximately equivalent to replicating the actual fund return over time. On the other hand, significant selection return either indicates that the style indices employed by the model are misspecified, or that the fund consistently outperforms/underperforms the underlying style benchmark due to its alternative stock selection policy. Thus, the capability of the pre-specified style indices in capturing the dimensions of risk inherent in the fund plays an important role for the successful replication of the fund's performance.

This chapter presents the detailed procedure for implementing the style decomposition approach of Sharpe (1992) in this research. The return attributions of the South African-based and internationally-domiciled global equity funds are analysed to give

indications as to whether the global style proxies identified in the previous chapter have the ability to replicate and predict the underlying investment styles of the global equity funds, and whether global equity fund returns are driven mainly by their style returns or selection returns.

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6.2 Methodology and Descriptive Statistics

There are in total 6 South African-based global equity funds and 12 internationally-domiciled global equity funds selected for this research. The 6 South African-based global equity funds under examination include ABSA International Fund of Funds, Allan Gray Orbis Global Equity Fund of Funds, Coronation International Active Fund of Funds, Investec Global Equity Fund of Funds, RMB International Equity Fund of Funds and Sanlam Global Equity Fund. On the other hand, the investment styles of the 12 internationally-domiciled global equity funds to be analysed include American Capital World Growth and Income Fund, American EuroPacific Growth Fund, BlackRock International Opportunities Portfolio, C-Quadrat – ARTS Best Momentum Fund, Federated Prudent Bear Fund, Fidelity Disciplined Equity Fund, Fidelity Diversified International Fund, Fidelity VIP Contrafund, Russell International Developed Markets Fund, SEI International Equity Fund, Skandia Global Equity Fund and Templeton World Fund.

The monthly U.S. dollar-denominated returns for the selected funds are downloaded from the database of Bloomberg Limited Partnership in the research office of Salient Quantitative Investment Management (Pty) Ltd. The investments of the selected global equity funds are dominated by international equities. The selected funds are different in their intended style orientations and stated investment objectives. A major task in this chapter is to examine whether the selected global equity funds are managed in accordance with their intended style orientations and stated investment objectives.

The MSCI World Index and the global size, momentum and value proxies identified in the previous chapter are used as factor mimicking portfolios in the Sharpe (1992) factor model to synthesise the underlying investment styles of the selected global

equity funds. The MSCI World Index is used as the market proxy to track the general global equity market performance driven by the movements in the global systematic risk factors. On the other hand, the global style proxies are used to capitalise on the cross-sectional return differences of international equities based on the size, value and momentum risk premia. The first step in the style decomposition procedure is to estimate the style exposures (style weights) of the selected global equity funds. This is achieved by regressing the monthly time-series returns of the fund on the monthly time-series returns of the MSCI World Index and the global style proxies using Equation 6.1:

$$r_{i,t} = [(w_{i,MSCI} \times r_{MSCI,t}) + (w_{i,Size} \times r_{Size,t}) + (w_{i,Mom} \times r_{Mom,t}) + (w_{i,Value} \times r_{Value,t})] + \varepsilon_{i,t} \dots\dots\dots (6.1)$$

Where:

$r_{i,t}$, $r_{MSCI,t}$, $r_{Size,t}$, $r_{Mom,t}$ and $r_{Value,t}$ represent the returns on fund i , MSCI World Index, and the respective global style proxies in month t ;

$w_{i,MSCI}$, $w_{i,Size}$, $w_{i,Mom}$ and $w_{i,Value}$ represent fund i 's style weights (exposures) for the MSCI World Index and the respective global style proxies; and

$\varepsilon_{i,t}$ is the in-sample selection return for fund i in month t that is not explained by fund i 's exposures to the returns on the MSCI World Index and the global style proxies

Equation 6.1 is intended to provide an indication of the passive mix of the fund's underlying investment styles without involvements in leverage and short-selling the pre-specified indices. This objective is achieved by restricting the style exposures to be in between 0% and 100% in the equation. The sum of the terms in the squared bracket of Equation 6.1 represents the in-sample style benchmark return of the fund. The error term of the regression, on the other hand, is the in-sample selection return of the fund that is not explained by its style benchmark. Thus, the selection return

represents the deviation of the fund performance from its style benchmark, and the variance of the selection return is regarded as the fund's tracking error. Based on Equation 6.1, a series of rolling 36-month weighted least squares (WLS) regressions are performed monthly for each of the selected funds over the examination period starting from the earliest month for which the return data of the respective funds are available. The WLS regression allocates a weight to the fund return in each month equivalent to $2^{1/36}$ times the weight assigned to its predecessor in the previous month, starting with the weight of 1.0 assigned to the return in the first month. This approach effectively places greater emphasis on more recent returns relative to more distant returns. The objective of the WLS regression is to minimise the variance of the error term in Equation 6.1, which is equivalent to minimising the fund's in-sample weighted tracking error (Yu, 2008).

Once the style weights of the selected global equity funds are estimated over the examination period using Equation 6.1, the replication of the fund's underlying investment styles begins by constructing a style-based portfolio that adjusts its allocations in the pre-specified indices monthly based on the most recent prior estimates of the fund's style weights. The style-based portfolio serves as the style benchmark that mimics the underlying investment style mix of the fund. The out-of-sample style benchmark return is estimated monthly using Equation 6.2:

$$\tilde{r}_{i,Style,t} = \left(\tilde{w}_{i,MSCI,t} \times r_{MSCI,t} \right) + \left(\tilde{w}_{i,Size,t} \times r_{Size,t} \right) + \left(\tilde{w}_{i,Mom,t} \times r_{Mom,t} \right) + \left(\tilde{w}_{i,Value,t} \times r_{Value,t} \right) \dots \quad (6.2)$$

Where:

$\tilde{r}_{i,Style,t}$ represents the out-of-sample style benchmark return for fund i in month t ; and

$\tilde{w}_{i,MSCI,t}$, $\tilde{w}_{i,Size,t}$, $\tilde{w}_{i,Mom,t}$ and $\tilde{w}_{i,Value,t}$ represent the respective out-of-sample style exposure estimates for fund i in month t computed using return data from month $t-36$ through month $t-1$ based on Equation 6.1.

Based on the monthly out-of-sample style benchmark return estimated by Equation 6.2, the monthly out-of-sample selection return is the difference between the fund's actual return and its estimated style benchmark return as shown by Equation 6.3:

$$\tilde{\mathcal{E}}_{i,t} = r_{i,t} - \tilde{r}_{i,Style,t} \quad \dots\dots\dots (6.3)$$

The average out-of-sample style benchmark return and the selection return for each of the selected funds are computed and evaluated based on the significance of their respective *t*-statistics. The out-of-sample Sharpe ratios for the selected funds and their respective style benchmark are computed and compared to evaluate the fund performances on a risk-adjusted basis. In addition to this, an out-of-sample prediction model (refer to Equation 6.4) proposed by Yu (2008) is employed to evaluate the style risk-adjusted performance of the selected funds, and the ability of the style benchmark in tracking the actual fund returns over the out-of-sample period:

$$r_{i,t} = \alpha_i + b_{i,Style} \times \tilde{r}_{i,Style,t} + e_{i,t} \quad \dots\dots\dots (6.4)$$

Where:

- α_i is the regression constant that is not explained by fund *i*'s style risk;
- $b_{i,Style}$ represents the sensitivity of fund *i*'s return to movements in the style benchmark return; and
- $e_{i,t}$ is the random error of the regression that can not be explained by the style benchmark.

6.3 Results: Style Analysis of the Global Equity Funds

The results of the style analysis on the South African-based global equity funds and the internationally-domiciled global equity funds are demonstrated in APPENDIX F and APPENDIX G respectively. The performance attributions of the selected funds are presented, in separate pages, in their respective appendices. Due to the relatively high return correlations of the global size proxy with both of the MSCI World Index and the global value proxy, style replications are also performed based on the 3 pre-specified indices, exclusive of the global size proxy. The replication results based on all 4 indices (refer to Panel (a) of the table in the appendix) are compared to the results based on the 3 factors (refer to Panel (b) of the table in the appendix) to gauge the role of the global size proxy in modelling the returns of the selected global equity funds. The style compositions of the selected funds, based on their style weights estimated by the 4-factor and the 3-factor models over the out-of-sample period, are demonstrated in Chart (a) and Chart (b) of the appendices respectively. The log cumulative out-of-sample fund return, style return and selection return are depicted in Chart (c) of the appendices. Due to the fact that the replication results produced by the 3-factor model are highly resemblance of the results produced by the 4-factor model, only the cumulative performances of the 4-factor model are shown in Chart (c) of the appendices.

6.3.1 South African-Based Global Equity Funds

Collective investment schemes that aim at wide participation of investors in diversified investments with risk sharing can take forms of mutual funds or unit trusts. The main difference between a unit trust and a mutual fund lies in their governance structure. While a unit trust is overseen by a trust company, it is the responsibility of

the directors of a mutual fund company to ensure that the fund managers perform their duties according to the constituent documents (Meyer-Pretorius and Wolmarans, 2006). The unit trust industry in South Africa, which started as a single fund in 1965, provides investors with a professionally managed vehicle that offers sufficient diversification and liquidity across investments in different industries. Offshore investments were restricted for the South African unit trust industry until the deregulation of foreign investments in 1995, which significantly facilitates the diversity and range of products offered by the industry (Meyer-Pretorius and Wolmarans, 2006). The global equity funds domiciled in the South African unit trust industry generally take a form of fund of funds (FOF) that holds a portfolio of global equity funds. The selected South African-based global equity funds for this research are all FOF with the exception of the Sanlam Global Equity Fund (refer to Appendix F.6). As shown by the description section of the appendices, the selected funds generally place a cap on the investments in any particular fund at 20% of their asset values. The Investec Global Equity FOF (refer to Appendix F.4) is the fund with the longest listing history, which was registered immediately after the deregulation in 1995. The rest of the selected funds were registered after the late 1990s.

The Allan Gray Orbis Global Equity FOF (refer to Appendix F.2) is the largest fund in terms of the U.S. dollar-denominated fund value (U.S.\$771.40 million). Examining the log cumulative return attributions of the Allan Gray Orbis Global Equity FOF depicted in Chart (c) of Appendix F.2 reveals that the fund manages to accumulate value through the strong support of its selection return despite the significant accumulation of the negative style returns during the market crash. The strong pickup in the selection return towards the end of 2008 is either an indication of the manager's ability to protect the fund value through superior stock selection skills, or through the reductions in the equity exposures. However, the evaluation period for the fund only spans from 1 November 2007 to 31 December 2008 due to the limited data availability, which casts doubt on robustness of the result. The only other fund that

exhibits added value above its style benchmark return through stock selection is the Coronation International Active FOF, which also has a strong selection return during the market crash. Although other funds have failed to accumulate higher returns above their cumulative style benchmark returns, the flat log cumulative selection return of the Investec Global Equity FOF during the market crash demonstrates the manager's effort in reducing the fund's equity exposure during the period.

The strategy of the Allan Gray Orbis Global Equity FOF is dominated by the value investment style over the evaluation period (refer to Chart (a) and Chart (b) of Appendix F.2). The style compositions of the fund produced by the 4-factor model and the 3-factor model are identical, suggesting that the global size proxy is redundant in modelling the fund's return. The ABSA International FOF (refer to Appendix F.1) is another fund that does not have its return attributable to the global size proxy based on the 4-factor model. The ABSA International FOF is found to have the most frequent rotation between the value and momentum investment styles, among the selected funds, throughout the evaluation period from 1 February 2006 to 31 December 2008. Unlike the Allan Gray Orbis Global Equity FOF and the ABSA International Equity FOF, the rest of the selected South African-based global equity funds tilt their investment strategies towards the momentum investment style after 2006. The global momentum proxy alone serves as the style benchmark for the Coronation International Active FOF, the Investec Global Equity FOF, the RMB International Equity FOF and the Sanlam Global Equity Fund since 2006 (refer to Appendix F.3 through Appendix F.6). The style rotations for the Investec Global Equity FOF (refer to Appendix F.4) and the RMB International Equity FOF (refer to Appendix F.5) are similar in that their style compositions are dominated and shared by the MSCI World Index and the global size proxy prior to 2005, in terms of the results obtained from the 4-factor model. In terms of the 3-factor model results, the contribution of the global size proxy is taken over by the MSCI World Index. On the other hand, the style return of the Coronation International Active FOF (refer to Appendix F.3) is mainly

attributable to the return on the global size proxy prior to 2006 using the 4-factor model. When the global size proxy is removed from the model, the style return is dominated by the return on the MSCI World Index and the return on the global value proxy.

Regardless the role of the global size proxy in modelling the style returns of the South African-based global equity funds, the observation that the South African-based global equity funds allocate their investments mainly to the global size proxy and the MSCI World Index prior to 2006, as opposed to their momentum-oriented investment style after 2006, is a reflection of the shifts in the objectives of the South African-based global equity funds from diversification focus to performance delivery. The summarised statistics for the return attributions of the selected South African-based global equity funds are demonstrated in Table 6.1. Although the results of the selected funds are not directly comparable due to their different evaluation periods, they provide indications as to whether the underlying investment styles of the funds are replicated successfully by the style benchmarks, and whether the fund managers are able to outperform their corresponding style benchmarks in a consistent manner through their superior stock selection skills.

Table 6.1 Return Attributions of South African-Based Global Equity Funds

This table contains the summarised statistics extracted from APPENDIX F. The exposures of the selected funds to the style indices are estimated from the trailing 36-month exposures using the weighted least squares (WLS) regressions based on the style-decomposition approach of Sharpe (1992). The combined exposures are set to 100% and no negative exposure is permitted in the regression. Thus, the exposures to the style indices represent the relative weights of the fund allocated to the respective indices. The top panel demonstrates the performance attribution based on all 4 indices, namely the MSCI world index, size (Size EW300), momentum (Mom SW100) and value (Value SW100) style proxies. The bottom panel demonstrates the performance attribution based on MSCI world index, value and momentum proxies (excluding the size proxy). The statistics displayed in the style return contribution section is obtained by regressing the actual fund returns on the estimated style returns. The regression results indicate the power of the style return in explaining the actual fund returns.

	ABSA International Fund of Funds	Allan Gray Orbis Global Equity Fund of Funds	Coronation International Active Fund of Funds	Investec Global Equity Fund of Funds	RMB International Equity Fund of Funds	Sanlam Global Equity Fund
Fund Inception:	1/9/01	3/12/01	8/1/97	1/5/96	28/4/99	8/3/02
Evaluation Period:	1/2/06-31/12/08	1/11/07-31/12/08	1/5/02-31/12/08	1/9/02-31/12/08	1/5/02-31/12/08	1/4/05-31/12/08
4-FACTOR RESULTS: Performance Attribution						
Avg. Fund Return	-1.05% [-1.189]	-3.34% [-2.017]	1.24% [3.505]	0.46% [0.836]	0.14% [0.218]	-0.59% [-0.708]
Standard Deviation	5.22%	6.19%	3.09%	4.79%	5.68%	5.59%
Sharpe Ratio	-0.257	-0.561	0.332	0.050	-0.014	-0.158
(1) Avg. Style Return	-0.21% [-0.226]	-3.67% [-1.648]	0.71% [1.170]	0.84% [1.372]	0.62% [1.031]	0.41% [0.459]
Standard Deviation	5.62%	8.34%	5.42%	5.32%	5.41%	6.06%
Sharpe Ratio	-0.090	-0.457	0.091	0.116	0.075	0.020
(2) Avg. Selection Return	-0.83% [-1.792]	0.33% [0.377]	0.53% [1.135]	-0.38% [-1.653]	-0.49% [-1.257]	-1.00% [-2.758]
Standard Deviation	2.75%	3.32%	4.19%	2.00%	3.45%	2.44%
Style Return Contribution						
R Squared	76.30%	87.98%	40.73%	86.01%	65.18%	83.72%
Intercept	-0.009 [-2.004]	-0.008 [-1.189]	0.010 [3.645]	-0.002 [-1.145]	-0.004 [-1.028]	-0.009 [-2.758]
Slope Coefficient	0.811 [10.307]	0.697 [9.373]	0.363 [7.321]	0.835 [21.329]	0.848 [12.083]	0.845 [14.872]
3-FACTOR RESULTS: Performance Attribution						
Avg. Fund Return	-1.05% [-1.189]	-3.34% [-2.017]	1.24% [3.505]	0.46% [0.836]	0.14% [0.218]	-0.59% [-0.708]
Standard Deviation	5.22%	6.19%	3.09%	4.79%	5.68%	5.59%
Sharp Ratio	-0.257	-0.561	0.332	0.050	-0.014	-0.158
(1) Avg. Style Return	-0.21% [-0.226]	-3.67% [-1.648]	0.80% [1.301]	0.86% [1.410]	0.65% [1.066]	0.42% [0.467]
Standard Deviation	5.62%	8.34%	5.50%	5.33%	5.42%	6.07%
Sharpe Ratio	-0.090	-0.457	0.106	0.121	0.079	0.021
(2) Avg. Selection Return	-0.83% [-1.792]	0.33% [0.377]	0.44% [0.923]	-0.40% [-1.760]	-0.51% [-1.314]	-1.01% [-2.774]
Standard Deviation	2.75%	3.32%	4.26%	2.00%	3.45%	2.45%
Style Return Contribution						
R Squared	76.30%	87.98%	40.56%	86.06%	65.19%	83.70%
Intercept	-0.009 [-2.004]	-0.008 [1.189]	0.010 [3.528]	-0.003 [-1.241]	-0.004 [-1.075]	-0.009 [-2.774]
Slope Coefficient	0.811 [10.307]	0.697 [9.373]	0.357 [7.296]	0.834 [21.370]	0.847 [12.086]	0.844 [14.858]

The slope coefficient of the style-based regression measures the sensitivity of the fund return to movements in the style benchmark returns. The slope coefficients for all selected South African-based global equity funds are significantly positive, indicating that the style benchmarks constructed for the selected South African-based global equity funds are appropriate in modelling their respective underlying investment styles. The high R -squared of the regressions indicate that the predicted style returns are able to explain a large proportion of the out-of-sample actual fund returns. The regression intercept represents the fixed monthly deviation of the fund return from the style benchmark return as opposed to the monthly random deviation reflected in the regression residuals. The regression intercept represents the style risk-adjusted excess return of the fund. The t -statistics of the intercepts, for the majority of the funds, appear to be negatively insignificant, except the significant positive intercept of the Coronation International Active FOF and the significant negative intercept of the Sanlam Global Equity Fund. The consistent style risk-adjusted excess return earned by the Coronation International Active FOF is in direct contrast to the consistent underperformance of the Sanlam Global Equity Fund over their respective evaluation periods. Similar to the results of the style weights produced by the 4-factor model and the 3-factor model, the regression results produced by the 4-factor model and the 3-factor model are not distinguishable, providing further evidence on the insignificance of the global size proxy in modelling the style returns of the selected funds.

With the exception of the Allan Gray Orbis Global Equity FOF and the Coronation International Active FOF, the South African-based global equity funds yield lower average returns than their respective style benchmarks due to their poor alternative stock allocations. The worst selection return is detected for the Sanlam Global Equity Fund with significant negative average monthly selection return of -1%. The poor stock-picking skills of the fund manager have severely dragged down the overall fund performances over the evaluation periods. In addition, no significant positive selection returns are detected for any of the global equity funds. These findings question the

validity of the alternative stock allocations of the South African-based fund managers in creating values in addition to what is already provided by their style benchmarks. However, the professions of the fund managers cannot be totally denied. The standard deviations of the selected South African-based global equity funds are lower than the standard deviations of their respective style benchmarks, with the exception of the RMB International Equity FOF, which reflects the skill and the effort of the fund managers in minimising the volatility of their fund values. Comparing the Sharpe ratios of the South African-based global equity funds to their style benchmarks reveals that the Coronation International Active FOF is the only fund that has outperformed its style benchmark in terms of the Sharpe ratio (0.332 for the fund versus 0.091 for the style benchmark).

Although the style benchmark returns seem to be more volatile than the fund returns, the style benchmarks still manage to deliver higher risk-adjusted performances compared to their corresponding South African-based global equity funds. The Sharpe ratio, as a risk-adjusted performance measure, should be analysed with caution. The large negative style benchmark return of the Allan Gray Orbis FOF is diluted by its abnormally high standard deviation, which in turn produces a smaller negative Sharpe ratio for the style benchmark compared to the negative Sharpe ratio based on the actual fund return. The other fund that exhibits a negative Sharpe ratio, ABSA International FOF, has similar standard deviation as its style benchmark. Thus, the less negative Sharpe ratio of the style benchmark is achieved by the lower negative style return relative to the large negative fund return for the ABSA International FOF as opposed to the denominator effect exhibited by the Allan Gray Orbis FOF. As mentioned earlier, the evaluation period for the Allan Gray Orbis FOF is relatively short and the results of the style analysis might not be robust over time.

6.3.2 Internationally-Domiciled Global Equity Funds

The U.S. dollar-denominated market values of the internationally-domiciled global equity funds are much larger than the market values of the South African-based global equity funds. The largest global equity fund being analysed in this research is the American EuroPacific Growth Fund (refer to Appendix G.2), which has a market value of U.S.\$86.64 billion as of 30 June 2009. In addition, the selection of internationally-domiciled global equity funds covers a wide variety of investment styles compared to the South African-based global equity funds. While the SEI International Equity Fund, the Skandia Global Equity Fund and the Templeton World Fund (refer to Appendix G.10, Appendix G.11 and Appendix G.12) represent the global equity funds with fund assets dominated by international equities, the American EuroPacific Growth Fund, the BlackRock International Opportunities Portfolio, the Fidelity Diversified International Fund and the Russell International Developed Markets Funds (refer to Appendix G.2, Appendix G.3, Appendix G.7 and Appendix G.9) have objectives of investing primarily outside of the United States. Despite the different geographical focuses of their investments, these funds share a common goal of achieving long-term capital growth. Similar to the style compositions of the South African-based global equity funds, the internationally-domiciled global equity funds mentioned above allocate most of their investments to momentum stocks after 2006 as shown in the Chart (a) and Chart (b) of the appendices. With the exception of the BlackRock International Opportunities Portfolio and the Skandia Global Equity Fund (refer to Appendix G.3 and Appendix G.11), the internationally-domiciled global equity funds have a strong value tilt as opposed to the broad equity-orientation observed for the South African-based global equity funds prior to 2006.

In contrast to the capital growth-based global equity funds, the American Capital World Growth and Income Fund, Federated Prudent Bear Fund, the Fidelity Disciplined Equity Fund and the Fidelity VIP Contrafund (refer to Appendix G.1,

Appendix G.5, Appendix G.6 and Appendix G.8) attempt to balance the objective of capital growth with the prudent value-oriented objectives of income generation and investments in perceived undervalued stocks. While the style compositions of the American Capital World Growth and Income Fund and the Fidelity Disciplined Equity Fund and the Fidelity VIP Contrafund are similar to the style compositions of the capital growth-focused global equity funds, the strategy of the Fidelity Prudent Bear Fund (refer to Appendix G.5) is totally opposite to the rest of the global equity funds analysed by this research. The Fidelity Prudent Bear Fund has an objective of selling short stocks when the market is overheated and invests in equities when the market is depressed. The contrarian-like investment objective is reflected in its style compositions demonstrated in Chart (a) and Chart (b) of Appendix G.5. The performance of the fund depicted in Chart (c) of Appendix G.5 is also completely opposite to its style benchmark and the rest of the funds analysed in this research.

Another unique choice in the internationally-domiciled global equity fund selection, the C-QUADRAT – ARTS Best Momentum Fund (refer to Appendix G.4), is an Austrian-based investment vehicle that invests in the highly volatile short- and medium-term momentum stocks based on a trend-following program. The aggressive momentum investing objective is reflected in its style composition over the evaluation period (refer to Chart (a) and Chart (b) in Appendix G.4).

Examining the log cumulative return attributions of the selected internationally-domiciled global equity funds in Chart (c), of the respective appendices, reveals that the majority of the funds add values to their existing style returns as their log cumulative returns are plotted above their cumulative style returns. Although this is not the case for the BlackRock International Opportunities Portfolio, the Skandia Global Equity Fund and the Templeton World Fund (refer to Appendix G.3, Appendix G.11 and Appendix G.12), these funds exhibit significant drift in their log cumulative selection returns during the market crash, reflecting the managers' efforts in reducing

the impacts of the global financial crisis. Comparing the style composition produced by the 4-factor model (Chart (a) of the respective appendices) to the style composition produced by the 3-factor model (Chart (b) of the respective appendices) for the selected funds reveals that the weight carried by the global size proxy is generally replaced by either the MSCI World Index or the global value proxy.

The summarised results for the return attributions of the selected internationally-domiciled global equity funds are demonstrated in Table 6.2. No clear distinction can be drawn between the statistics produced by the 4-factor model and the 3-factor model, reflecting the insignificance of the global size proxy in modelling fund returns. With the exception of the Federated Prudent Bear Fund, the regression slope coefficients for all of the selected internationally-domiciled global equity funds are significantly positive. In addition, most of the selected funds have high *R*-squared, reflecting the appropriateness of the style benchmark in replicating the underlying investment styles of the selected funds.

However, the replication for the Federated Prudent Bear Fund is unsuccessful, since the synthetic style benchmark delivers return that is significant, yet opposite to the actual fund return. The examination of the regression intercepts reveal that none of the funds yields significant style risk-adjusted excess returns over their respective evaluation periods. In addition, the only significant average selection return detected in Table 6.2 is the significant negative selection return produced by the Templeton World Fund. The American Capital World Growth and Income Fund, the American EuroPacific Growth Fund and the C-Quadrat ARTS Best Momentum Fund are the only funds that outperform their respective benchmarks in terms of the Sharpe ratio.

Table 6.2 Return Attribution of Internationally-Domiciled Global Equity Funds

This table contains the summarised statistics extracted from APPENDIX F. The exposures of the selected funds to the style indices are estimated from the trailing 36-month exposures using the weighted least squares (WLS) regressions based on the style-decomposition approach of Sharpe (1992). The combined exposures are set to 100% and no negative exposure is permitted in the regression. Thus, the exposures to the style indices represent the relative weights of the fund allocated to the respective indices. The top panel demonstrates the performance attribution based on all 4 indices, namely the MSCI world index, size (Size EW300), momentum (Mom SW100) and value (Value SW100) style proxies. The bottom panel demonstrates the performance attribution based on MSCI world index, value and momentum proxies (excluding the size proxy). The statistics displayed in the style return contribution section is obtained by regressing the actual fund returns on the estimated style returns. The regression results indicate the power of the style return in explaining the actual fund returns.

	American Capital World Growth and Income Fund	American EuroPacific Growth Fund	BlackRock International Opportunities Portfolio	C-Quadrat ARTS Best Momentum Fund	Federated Prudent Bear Fund	Fidelity Disciplined Equity Fund
Fund Inception:	26/3/93	16/4/84	26/9/97	4/1/99	28/12/95	28/12/88
Evaluation Period:	1/9/02-31/12/08	1/9/02-31/12/08	1/2/03-31/12/08	1/9/02-31/12/08	1/9/02-31/12/08	1/9/02-31/12/08
4-FACTOR RESULTS:						
<u>Performance Attribution</u>						
Avg. Fund Return	1.60% [1.963]	1.51% [1.733]	0.55% [0.937]	2.11% [2.299]	0.88% [1.243]	0.55% [0.736]
Standard Deviation	7.09%	7.59%	4.91%	7.99%	6.14%	6.48%
Sharpe Ratio	0.194	0.170	0.065	0.236	0.107	0.050
(1) Avg. Style Return	0.97% [1.642]	1.03% [1.730]	0.98% [1.575]	0.88% [1.457]	0.53% [0.885]	0.75% [1.289]
Standard Deviation	5.17%	5.18%	5.22%	5.28%	5.20%	5.10%
Sharpe Ratio	0.146	0.156	0.143	0.126	0.059	0.105
(2) Avg. Selection Return	0.62% [1.215]	0.48% [0.875]	-0.43% [-1.640]	1.22% [1.704]	0.35% [0.295]	-0.21% [-0.412]
Standard Deviation	4.47%	4.79%	2.20%	6.26%	10.25%	4.38%
<u>Style Return Contribution</u>						
R Squared	60.46%	61.16%	82.27%	38.74%	39.99%	54.60%
Intercept	0.006 [1.065]	0.003 [0.594]	-0.003 [-1.138]	0.013 [1.742]	0.013 [2.299]	-0.002 [-0.315]
Slope Coefficient	1.067 [10.637]	1.146 [10.795]	0.854 [17.894]	0.941 [6.841]	-0.747 [-7.022]	0.939 [9.433]
3-FACTOR RESULTS:						
<u>Performance Attribution</u>						
Avg. Fund Return	1.60% [1.963]	1.51% [1.733]	0.55% [0.937]	2.11% [2.299]	0.88% [1.243]	0.55% [0.736]
Standard Deviation	7.09%	7.59%	4.91%	7.99%	6.14%	6.48%
Sharp Ratio	0.194	0.170	0.065	0.236	0.107	0.505
(1) Avg. Style Return	1.01% [1.683]	1.08% [1.791]	0.98% [1.578]	0.92% [1.501]	0.52% [0.871]	0.79% [1.350]
Standard Deviation	5.24%	5.25%	5.22%	5.32%	5.19%	5.12%
Sharpe Ratio	0.151	0.164	0.144	0.131	0.058	0.112
(2) Avg. Selection Return	0.58% [1.130]	0.43% [0.781]	-0.43% [-1.647]	1.19% [1.658]	0.36% [0.303]	-0.25% [-0.490]
Standard Deviation	4.51%	4.81%	2.20%	6.26%	10.24%	4.39%
<u>Style Return Contribution</u>						
R Squared	59.57%	60.61%	82.27%	38.78%	39.93%	54.29%
Intercept	0.005 [1.018]	0.003 [0.525]	-0.003 [-1.145]	0.013 [1.707]	0.013 [2.286]	-0.002 [-0.376]
Slope Coefficient	1.045 [10.441]	1.126 [10.672]	0.854 [17.896]	0.935 [6.846]	-0.747 [-7.013]	0.931 [9.375]

Table 6.2 Return Attribution of International Global Equity Funds - Continued

	Fidelity Diversified International Fund	Fidelity VIP Contrafund	Russell International Developed Markets Fund	SEI International Equity Fund	Skandia Global Equity Fund	Templeton World Fund
Fund Inception:	27/12/91	3/1/95	31/1/83	20/12/89	13/9/00	17/1/78
Evaluation Period:	1/9/02-31/12/08	1/9/02-31/12/08	1/9/02-31/12/08	1/9/02-31/12/08	1/10/03-31/12/08	1/9/02-31/12/08
4-FACTOR RESULTS:						
<u>Performance Attribution</u>						
Avg. Fund Return	1.36% [1.447]	0.82% [1.087]	1.12% [1.206]	0.63% [0.632]	0.21% [0.357]	0.46% [0.877]
Standard Deviation	8.22%	6.60%	8.11%	8.72%	4.73%	4.57%
Sharpe Ratio	0.139	0.091	0.111	0.047	-0.007	0.053
(1) Avg. Style Return	0.97% [1.618]	0.93% [1.539]	0.95% [1.628]	0.94% [1.636]	0.74% [1.082]	1.03% [1.730]
Standard Deviation	5.20%	5.25%	5.11%	5.03%	5.40%	5.18%
Sharpe Ratio	0.143	0.135	0.144	0.144	0.091	0.156
(2) Avg. Selection Return	0.40% [0.670]	-0.10% [-0.215]	0.17% [0.283]	-0.31% [-0.472]	-0.52% [-1.671]	-0.57% [-2.047]
Standard Deviation	5.20%	4.24%	5.12%	5.75%	2.49%	2.42%
<u>Style Return Contribution</u>						
R Squared	62.72%	58.81%	62.64%	60.66%	78.80%	78.22%
Intercept	0.002 [0.266]	-0.001 [-0.143]	-0.001 [-0.132]	-0.006 [-1.000]	-0.004 [-.288]	-0.003 [-1.362]
Slope Coefficient	1.250 [11.158]	0.964 [10.280]	1.255 [11.138]	1.352 [10.681]	0.777 [15.060]	0.781 [16.301]
3-FACTOR RESULTS:						
<u>Performance Attribution</u>						
Avg. Fund Return	1.36% [1.447]	0.82% [1.087]	1.12% [1.206]	0.63% [0.632]	0.21% [0.357]	0.46% [0.877]
Standard Deviation	8.22%	6.60%	8.11%	8.72%	4.73%	4.57%
Sharp Ratio	0.139	0.091	0.111	0.047	-0.007	0.053
(1) Avg. Style Return	1.00% [1.652]	0.95% [1.572]	0.98% [1.642]	0.98% [1.664]	0.74% [1.081]	1.05% [1.690]
Standard Deviation	5.27%	5.29%	5.19%	5.12%	5.41%	5.42%
Sharpe Ratio	0.148	0.139	0.146	0.148	0.091	0.153
(2) Avg. Selection Return	0.37% [0.615]	-0.13% [-0.269]	0.14% [0.242]	-0.34% [-0.520]	-0.52% [-1.664]	-0.59% [-2.040]
Standard Deviation	5.18%	4.24%	5.15%	5.77%	2.50%	2.52%
<u>Style Return Contribution</u>						
R Squared	62.41%	58.81%	61.78%	59.65%	78.70%	78.52%
Intercept	0.001 [0.226]	-0.001 [-0.181]	-0.001 [-0.134]	-0.007 [-1.003]	-0.004 [-1.281]	-0.003 [-1.304]
Slope Coefficient	1.232 [11.083]	0.957 [10.278]	1.227 [10.937]	1.316 [10.459]	0.776 [15.012]	0.748 [16.447]

6.4 Conclusion

The majority of the South African-based global equity funds are collective portfolios of other funds. This branch of collective investment scheme is known as fund of funds (FOF). Among the 6 selected South African-based global equity funds, the Allan Gray Orbis global Equity FOF and the Coronation International Active FOF are the only funds that manage to create values above what is offered by their style benchmark. The Coronation International Active FOF is the only fund that yields significant style risk-adjusted excess return. The rest of the South African-based global equity funds do not deliver values in addition to the values provided by their respective style benchmarks in absolute terms and in style risk-adjusted terms. The Sanlam Global Equity FOF appears to be the worst performer with significant negative style risk-adjusted excess return and significant negative average selection return, which severely drags down the fund performance.

Although it can be argued that the fund managers' efforts in controlling risk are reflected in the lower standard deviations of the funds compared to the standard deviations of their respective style benchmark, the Coronation International Active FOF is the only South African-based global equity fund that beats its benchmark in terms of the Sharpe Ratio. On the other hand, the internationally-domiciled global equity fund managers seem to be better in delivering added value compared to the South African-based global equity fund managers. There are 7 out of 12 internationally-domiciled global equity funds that have their log cumulative fund returns plotted above their respective log cumulative style returns. The American Capital World Growth and Income Fund, the American EuroPacific Growth Fund, The C-Quadrat ARTS Best Momentum Fund and the Federated Prudent Bear Fund outperform their respective style benchmarks in terms of the Sharpe ratio. However, none of the internationally-domiciled global equity funds analysed in this research yields significant style risk-adjusted excess return.

The *R*-squared and the slope coefficients of the out-of-sample prediction models for all of the selected global equity funds are highly significant, indicating that the style benchmark constructed are appropriate in replicating the underlying investment styles of the selected global equity funds. The analysis of the style compositions of the funds reveals that most of the South African-based and internationally-domiciled global equity funds pursue aggressive momentum-oriented investment strategies after 2006. Prior to 2006, the style compositions are different between the South African-based and internationally-domiciled global equity funds in that the South African-based funds undertakes a broad-based equity investment style while the internationally-domiciled funds invest mostly in value stocks. This observation reflects the shift in the objectives of South African-based funds from diversification focus to performance delivery.

The C-Quadrat ARTS Best Momentum Fund and the Federated Prudent Bear Funds represent the two unique choices with strong style-orientation. The C-Quadrat ARTS Best Momentum Fund has a strong momentum style orientation throughout the evaluation period, while the Federated Prudent Bear Fund operates totally opposite to the investment styles of the selected global equity funds. These findings suggest that both of the funds have strictly followed their stated investment objectives over their respective evaluation periods. When the global size proxy is removed from the replication process, its contributions are replaced by either the MSCI World Index or the global value proxy. This finding confirms that the momentum investment style is a unique strategy that is not substitutable for any other investment style. In addition, the statistics produced by the 4-factor model are not distinguishable from the results produced by the 3-factor model, indicating that the global size proxy is redundant in mapping the performances of global equity funds due to its high return correlations with the MSCI World Index and the global value proxy.

In conclusion, the passive replications of the underlying investment styles of the selected global equity funds, based on the Sharpe (1992) style decomposition approach, are successful, with the exception of the replication for the Federated Prudent Bear Fund. With limited contribution from the selection return to the actual fund return, the performance of the style benchmark serves as an unbiased estimate of the performance of the fund being replicated. The inability of the Sharpe (1992)'s approach in mimicking the underlying investment styles of the Federated Prudent Bear Fund that involves short selling securities supports the argument of Fung and Hsieh (1998) and Baghai-Wadji and Klockner (2007) that more advanced techniques, in addition to the traditional asset classes are required to explain the dynamics of hedge fund returns. Although no clear evidence that the managers of the global equity funds are able to outperform their respective style benchmarks in terms of the style risk-adjusted excess return and the Sharpe ratio, the internationally-domiciled global equity funds, in general, demonstrates a better ability in creating value in addition to the style benchmark returns, compared to the South African-based global equity funds.

ACTIVE GLOBAL STYLE PORTFOLIO OPTIMISATION

7.1 Introduction

The focus of this chapter shifts from passive fund replication to active portfolio optimisation, based on the global style proxies identified in Chapter 5. The primary objective of this chapter is to evaluate potential benefits of style-based portfolio optimisation in active portfolio management.

The details of the optimisation procedure is based on the existing works of Yu (2008), who performs style-based portfolio optimisation on the JSE Securities Exchange (JSE) over the period from 1 January 1998 to 31 December 2006. The portfolio optimisation procedure of Yu (2008) includes the developments of style-based optimal portfolios for the four pre-specified investment strategies, namely the long-only mean-variance optimised strategy with no leverage, the long-only mean-tracking error optimised strategy with no leverage, the long-short mean-variance optimised strategy with leverage and the market neutral optimised strategy with leverage. By relaxing the no leverage and long-only constraints for the last two strategies, the potential benefits exclusive to hedge funds are explored in this research. The details of the optimisation procedure are discussed in Section 7.2.

The same set of pre-specified indices employed in the previous chapter, namely the MSCI World Index, the global size proxy, the global momentum proxy and the global value proxy are employed as constituent indices of the style-based optimised portfolios in this chapter. Due to the observed minimal contribution of the global size proxy in replicating the style returns of global equity funds, the extent of its

involvement in the optimisation process is to be closely monitored. Section 7.3 presents the result of the optimisation procedure for each of the four pre-specified investment strategies. The performances of the Sharpe ratio-optimised portfolio for each of the four investment strategies are evaluated and analysed in Section 7.4. Section 7.5 consolidates the empirical findings of the studies conducted in this chapter. With the extended period from 1 January 1991 to 31 December 2008 based on indices comprised of international stocks, the results of this research provide new insights into strategies in active portfolio management in addition to the existing findings discovered by Yu (2008).

7.2 Methodology and Descriptive Statistics

Mean-variance optimisation is a procedure that searches for the optimal asset allocation that minimises the portfolio variance/standard deviation at each level of portfolio return. The return on the style-based portfolio P comprised of the pre-specified indices in month t is computed using Equation 7.1:

$$r_{P,t} = \left(w_{P,MSCI}^* \times r_{MSCI,t} \right) + \left(w_{P,Size}^* \times r_{Size,t} \right) + \left(w_{P,Mom}^* \times r_{Mom,t} \right) + \left(w_{P,Value}^* \times r_{Value,t} \right) \dots \quad (7.1)$$

Where:

$r_{P,t}$, $r_{MSCI,t}$, $r_{Size,t}$, $r_{Mom,t}$ and $r_{Value,t}$ represent the returns on style-based portfolio P , MSCI World Index, and the respective global style proxies in month t ; and

$w_{P,MSCI,t}^*$, $w_{P,Size,t}^*$, $w_{P,Mom,t}^*$ and $w_{P,Value,t}^*$ represent the optimal weights of the MSCI World Index and the respective global style proxies in style-based portfolio P .

On the other hand, the T -month standard deviation for the style-based portfolio P is computed using Equation 7.2.

$$\sigma_P = \sqrt{\frac{\sum_{t=1}^T (r_{P,t} - R_P)^2}{T-1}} \quad \dots \dots \dots (7.2)$$

Where:

$r_{P,t}$ is the return for style-based portfolio P in month t ;

R_P is the T -month arithmetic average return for style-based portfolio P ; and

T is the number of months in the holding period.

The research begins by developing the basic long-only, mean-variance optimised portfolios with no leverage. The no leverage and the long-only constraints restrict the weight of each of the constituent indices to be between 0% and 100%, and to sum to

100%. Based on the stipulated constraints, a series of long-only optimised portfolios with no leverage are constructed by solving for the optimal constituent weights that minimise portfolio standard deviation at each level of portfolio return. The optimised portfolio returns are bound by the highest annualised geometric constituent return of 14.77% offered by the global momentum proxy and the lowest annualised constituent return of 6.10% offered by the MSCI World Index over the examination period, under the no leverage and long-only constraints.

The mean-tracking error optimisation is different from the mean-variance optimisation in that it attempts to minimise the portfolio tracking error instead of the portfolio standard deviation. The mean-tracking error optimised portfolios are constructed based on the same constraints placed on the long-only, mean-variance optimisation procedure with no leverage. The portfolio's tracking error is the standard deviation of the portfolio's return in excess of its benchmark. The benchmark portfolio in this research is the MSCI World Index. The T -month tracking error for the style-based portfolio P is computed using Equation 7.3:

$$\sigma_{P-B} = \sqrt{\frac{\sum_{t=1}^T (r_{P-B,t} - R_{P-B})^2}{T-1}} \quad \dots\dots\dots (7.3)$$

Where:

- $r_{P-B,t}$ is return of the style-based portfolio P in excess of the return on its benchmark B in month t ; and
- R_{P-B} is the T -month arithmetic average excess benchmark return for style-based portfolio P .

Once a series of mean-variance and mean-tracking error optimal portfolios with no leverage are developed at each incremental level of portfolio returns, the no leverage and long-only constraints are lifted to develop mean-variance efficient portfolios for the long-short hedge fund strategy and the market-neutral hedge fund strategy. The

leverage for both hedge fund strategies are capped at 200% of the total exposures (long and short) in the constituent indices. The 200% leverage constraint requires the sum of the absolute values of the constituent weights to be equal to, or less than, 200% during the optimisation process. Similar to the 10% to 15% capped allocation constraint in any particular investment, the 200% leverage constraint is considered as a general discipline in the hedge fund industry (Maestro Investment Consulting, 2009).

The short positions for the two hedge fund strategies are only permitted in the MSCI World Index to allow sufficient liquidity for implementing the strategies. This means that the weights for the global style proxies remain positive in the optimisation process. When the sum of the weights in the constituent indices is less than 100% of the original capital, the excess capital is invested in the risk-free proxy represented by the U.S. 3-month Treasury bills. On the other hand, when the sum of the weights in the constituent indices is less than 100% of the original capital, the short fall is financed by borrowing at the risk-free rate. Thus, the risk-free rate serves as a balancing item that equates the overall weight in the risky and risk-free asset to 100% of the original capital.

Both the long-short hedge fund strategy and the market neutral hedge fund strategy are bound by the above portfolio constraints. The difference between the long-short hedge fund strategy and the market neutral hedge fund strategy lies on the additional constraint placed on the latter that requires the investment held long in the global style proxies to equate to the investment held short in the MSCI World Index. As a result, a series of zero investment portfolios, similar to the one discussed under the arbitrage pricing theory (APT), are created for the market neutral hedge fund strategy.

Due to the fact that the global style proxies are well-diversified indices with their beta coefficients close to 1.0 (discussed in Chapter 5), creating equal exposures for the short position in the MSCI World Index and the long positions in the global style

proxies effectively hedge against any market-related risk. Therefore, the relevant risk to the market neutral hedge fund strategy is purely firm-specific in nature, and the return generated by the market neutral hedge fund strategy is entirely an abnormal return that cannot be explained by the market risk.

Once the best asset allocations for the style-based portfolios under each of the four investment strategies are determined at each given level of portfolio returns or tracking error, the portfolio composition that produces the highest attainable Sharpe ratio is identified for each of the investment strategies. The Sharpe ratio-optimised portfolio for each investment strategy represents the style-based portfolio that achieves the highest risk-adjusted return bound by the specific constraints of the investment strategy. Thus, the combinations of the Sharpe ratio-optimised portfolio and the risk-free asset dominate all other asset mixes between the risk-free asset and other optimal portfolios constructed under the same investment constraints on a risk-adjusted basis, using standard deviation as the measure of risk.

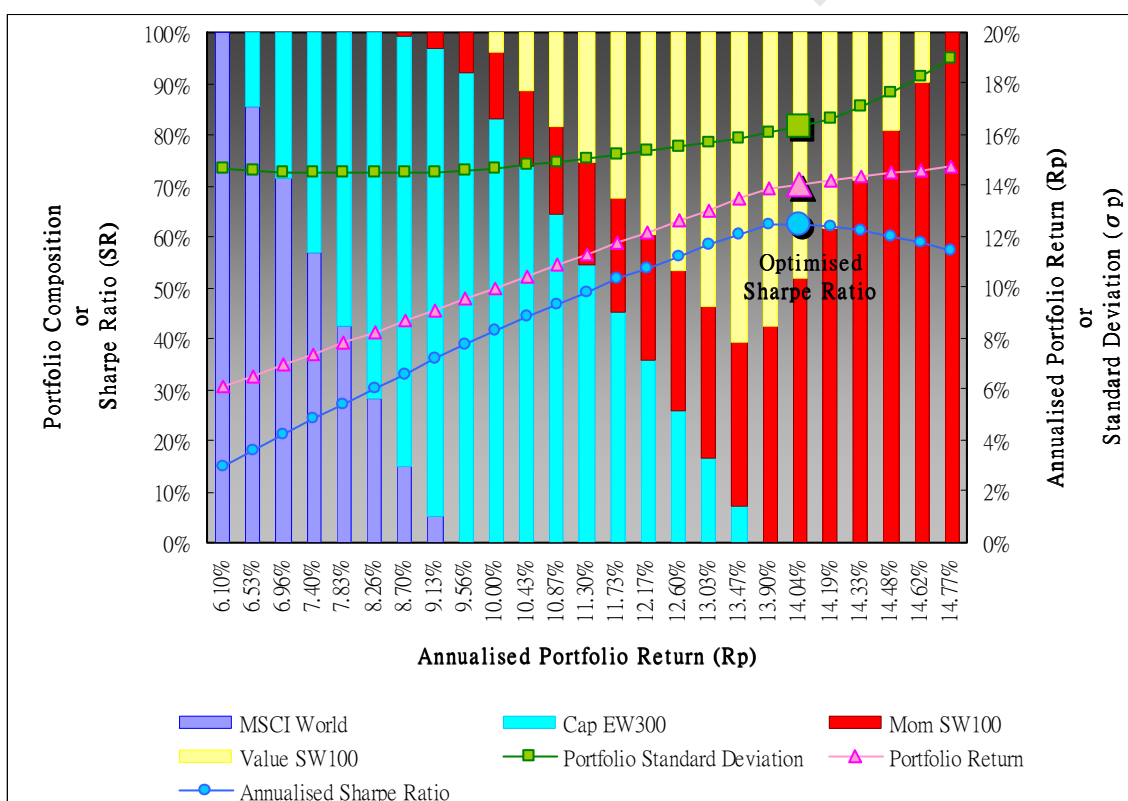
7.3 Results: Optimal Global Style-Based Portfolios

The risk-return characteristics and portfolio compositions of the long-only, mean-variance optimised portfolio with no leverage at each level of portfolio returns is illustrated in Figure 7.1. The portfolio compositions are represented by the weights allocated to the constituent indices in the form of histograms at different levels of annualised (geometric) portfolio returns. The annualised portfolio return, standard deviation and Sharpe ratio at each level of portfolio returns are depicted by the pink, green and blue trend lines respectively. When 100% of the capital is invested in the MSCI World Index, the portfolio return is at its lowest level. As the portfolio return increases, the investments in the MSCI World Index is gradually replaced by the global size proxy first, and then replaced by the global momentum proxy and the global value proxy. In order to improve the portfolio return at the lowest expense of increasing portfolio standard deviation, the global size proxy and the global value proxy are invested in, in conjunction with the investment in the global momentum proxy.

When the global size proxy eventually becomes redundant in the optimisation process, the weight of the global value proxy is gradually replaced by the global momentum proxy, in order to achieve higher levels of portfolio returns. The annualised Sharpe ratio is optimised at 62.29% when 51.86% of the capital is invested in the global momentum proxy and 48.14% of the capital is invested in the global value proxy. The annualised portfolio return and portfolio standard deviation for the Sharpe-optimised portfolio are 14.04% and 16.30% respectively. Beyond this point, the Sharpe ratio deteriorates as the portfolio return for the strategy is increasing, at a decreasing rate, while the portfolio standard deviation starts to increase at an increasing rate.

Figure 7.1 Long-Only Mean-Variance Portfolio Optimisation with No Leverage

The optimisation procedure is implemented over the examination period from 1 January 1991 to 31 December 2008. The constituent indices comprising the mean-variance optimised portfolios include the MSCI World Index, the global size proxy (Cap EW300), the global momentum proxy (Mom SW100) and the global value proxy (Value SW100). The portfolios are optimised by altering the weights of the constituent indices with the goal to minimise the portfolio standard deviation at each level of portfolio returns. The no leverage and the long-only constraints in the optimisation procedure restrict the individual constituent weights to be between 0% and 100%, and the sum of the constituent weights to be set at 100%. The optimised portfolio returns are bound by the highest annualised constituent return of 14.77% offered by Mom SW100 and the lowest annualised constituent return of 6.10% offered by MSCI World Index due to the long-only constraint. The portfolio compositions are represented by the different weights allocated to the constituent indices in the form of histograms at different levels of annualised portfolio returns. The annualised portfolio returns, standard deviations and Sharpe ratios at different levels of portfolio returns are indicated by the pink, green and blue trend lines. The annualised Sharpe ratio is optimised when 51.86% of the capital is allocated to Mom SW100 and 48.14% of the capital is allocated to Value SW100. The annualised Sharpe ratio, portfolio return and portfolio standard deviation for the optimal portfolio composition are 62.29%, 14.04% and 16.30% respectively.



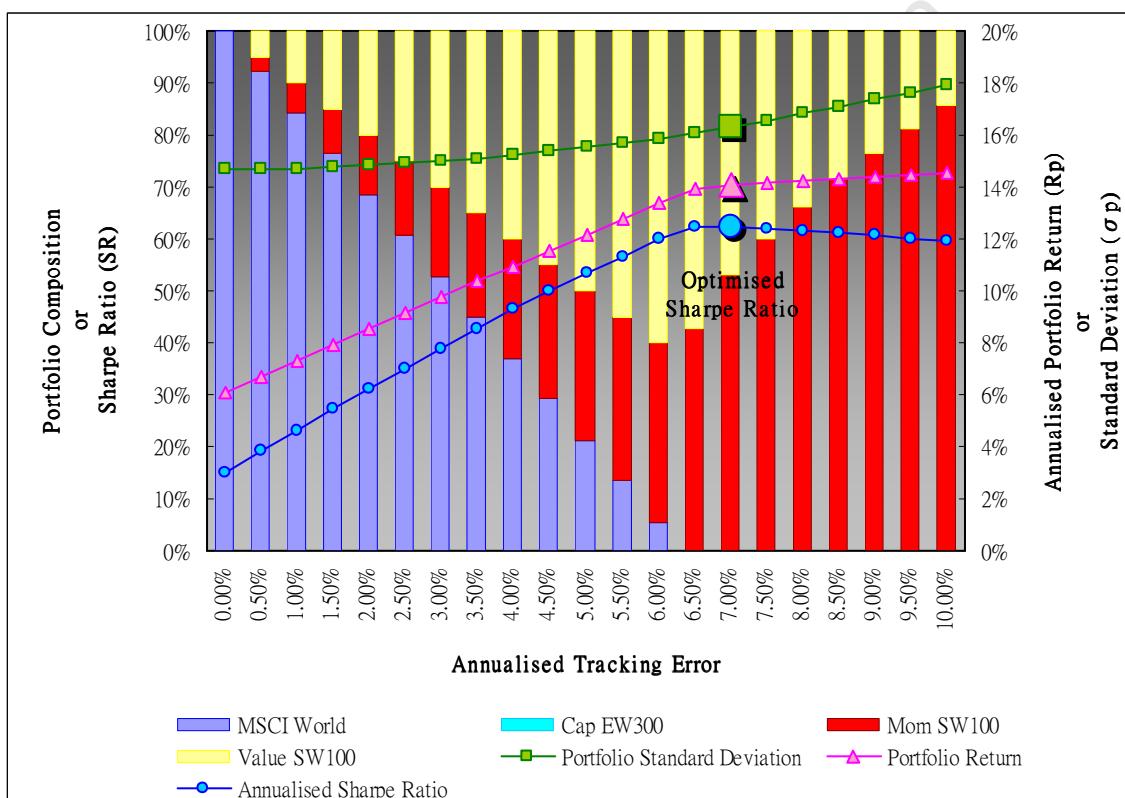
The results of the long-only mean-tracking error optimised portfolios with no leverage are demonstrated in Figure 7.2. The main difference between the long-only mean-tracking error optimisation and the long-only mean-variance optimisation is that the global size proxy does not have play a role in the mean-tracking error optimisation process. The global size proxy is a less efficient index with annualised Sharpe ratio of 35.90% compared to the Sharpe ratio for the global momentum proxy of 57.30% and the Sharpe ratio for the global value proxy of 56.70% over the examination period (refer to the summarised performance results in Table 5.4 in Section 5.6).

Similar to the mean-variance optimisation, the mean-tracking error optimisation gradually replaces the investment in the MSCI World Index with more efficient global momentum and value proxies. The composition that yields the highest Sharpe ratio allocates 52.95% of the capital to the global momentum proxy and 47.05% of the capital to the global value proxy. This composition is similar to the composition for the Sharpe ratio-optimised long-only portfolio.

The annualised Sharpe ratio, portfolio return and portfolio standard deviation for the Sharpe-ratio optimised mean-tracking error portfolio are 62.27%, 14.06% and 16.33% respectively. This performance is achieved when the annualised tracking error for the portfolio return from the MSCI World Benchmark is set at 7.00%. Additional deviations from the benchmark unnecessarily increase the portfolio standard deviation, without any improvement in the portfolio return, which lead to deteriorations in the Sharpe ratio.

Figure 7.2 Long-Only Mean-Tracking Error Portfolio Optimisation with No Leverage

The optimisation procedure is implemented over the examination period from 1 January 1991 to 31 December 2008. The constituent indices comprising the mean-tracking error optimised portfolios include the MSCI World Index, the global size proxy (Cap EW300), the global momentum proxy (Mom SW100) and the global value proxy (Value SW100). The portfolios are optimised by altering the weights of the constituent indices with the goal to minimise the portfolio's tracking error at each level of portfolio returns. Short sale and leverage remain prohibited in the optimisation process. As indicated by the blue trend line, the annualised Sharpe ratio is maximised when 52.95% of the capital is allocated to Mom SW100 and 47.05% of the capital is allocated to Value SW100. This is achieved when the annualised tracking error is set at 7.00%. At the optimised level of tracking error, the annualised Sharpe ratio, portfolio return and portfolio standard deviation are 62.27%, 14.06% and 16.33% respectively.

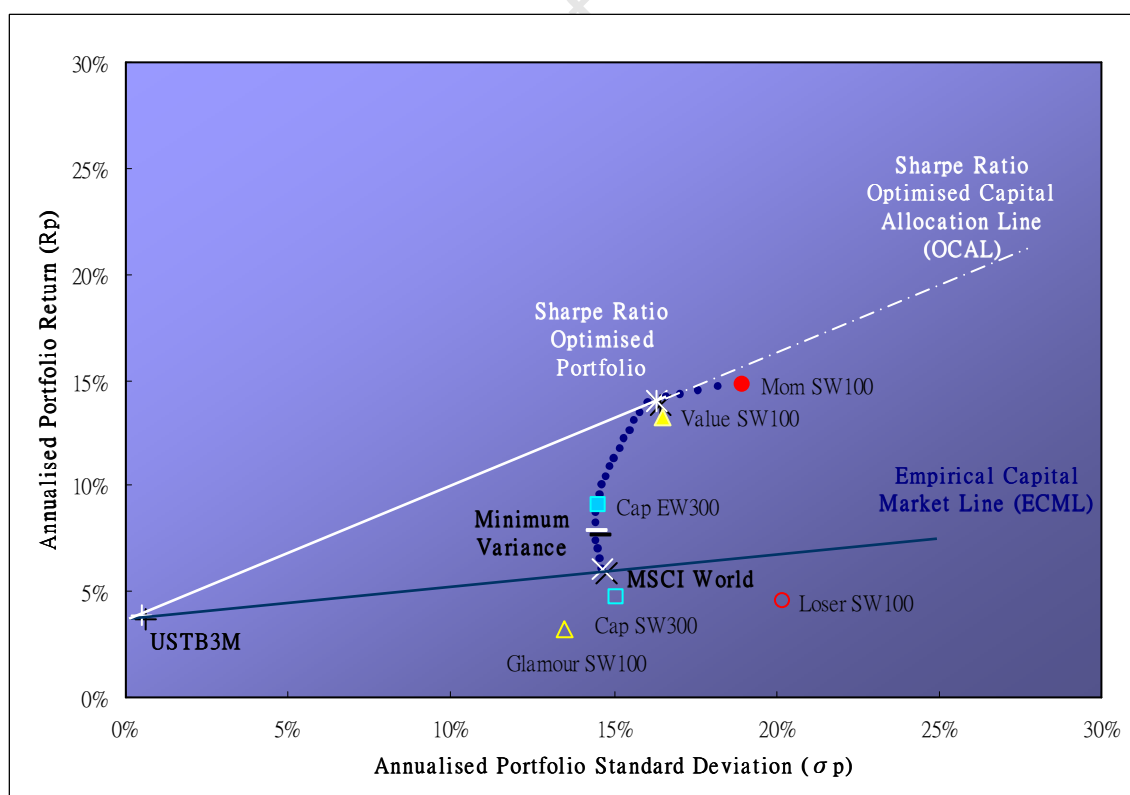


The mean-variance efficient frontier for the long-only portfolios with no leverage is illustrated in Figure 7.3. The constituent indices comprising the efficient frontier and their counterpart indices are also plotted in the diagram. The lowest point of the frontier is represented by the MSCI World Index while the portfolio that achieves the highest attainable return on the efficient frontier is represented by the global momentum proxy.

The Sharpe ratio-optimised portfolio, marked by the white asterisk, is the portfolio on the efficient frontier that has earned the highest risk premium per unit of standard deviation. The reward-to-risk ratio for asset mixes between the Sharpe ratio-optimised portfolio and the risk-free proxy is represented by the white trend line termed the Sharpe ratio-optimised capital allocation lines (OCAL). Portfolios plotted on the OCAL dominate the reward-to-risk ratios of any other portfolios bound by the long-only and no leverage constraints, which includes the asset mixes between the risk-free proxy and the market proxy (MSCI World Index) represented by the empirical capital market line (ECML). Portfolios plotted on the dashed portion of the OCAL beyond the Sharpe ratio-optimised portfolio are unattainable due to the long-only and no leverage constraints. By relaxing the constraints placed on the traditional fund operations, the reward-to-risk ratio for the optimal portfolios can be further improved beyond the OCAL.

Figure 7.3 The Mean-Variance Efficient Frontier for the Long-Only Portfolios with No Leverage

The optimisation procedure is implemented over the examination period from 1 January 1991 to 31 December 2008. The constituent indices that comprise the no leverage, long-only optimised portfolios on the efficient frontier include the MSCI World Index, the global size proxy (Cap EW300), the global momentum proxy (Mom SW100) and the global value proxy (Value SW100). The counterpart indices, namely, the global cap-weighted size proxy (Cap SW300), the global loser proxy (Loser SW100) and the global glamour proxy (Glamour SW100) are also depicted in the diagram. The portfolio on the efficient frontier that achieves the highest risk premium per unit of total risk, as measured by standard deviation, is termed the Sharpe ratio-optimised portfolio (marked by the white asterisk). The Sharpe ratio-optimised portfolio invests 51.86% of the capital in Mom SW100 and 48.14% of the capital is invested in Value SW100. The annualised Sharpe ratio, portfolio return and portfolio standard deviation for this composition are 62.29%, 14.04% and 16.30% respectively. The white capital asset allocation line that connects the risk-free proxy (U.S. 3-month Treasury bill (USTB3M)) and the Sharpe ratio-optimised portfolio, is termed the Sharpe ratio optimised capital allocation line (OCAL). The portfolios on the extended portion of the OCAL beyond the Sharpe ratio-optimised portfolio (i.e. the white dashed line) are unattainable due to the no leverage and short sale constraints. The portfolios on the OCAL represent the investment splits between the USTB3M and the Sharpe ratio-optimised portfolio. Due to the fact that the OCAL is the highest attainable capital allocation line, portfolios on the OCAL dominates any other combinations between the USTB3M and portfolios on the efficient frontier, other than the Sharpe ratio-optimised portfolio, at any given level of portfolio risk. This includes the various combinations of the USTB3M and the MSCI World Index represented by the empirical capital market line (ECML).



The optimisation results of the long-short leverage hedge fund strategy are illustrated in Figure 7.4. For the long-short leverage hedge fund strategy, the lowest possible return is offered by the risk-free rate of 3.89% when the entire capital is invested in the risk-free proxy. This return is improved by increasing the exposures in the constituent indices, which simultaneously improves the Sharpe ratio of the strategy at a decreasing rate until 200% leverage is used. The Sharpe ratio is optimised at 121.57% when 37.08% of the capital is allocated to the global momentum proxy, 66.20% of the capital is allocated to the global value proxy, 93.44% of the capital is allocated to the risk-free proxy and 96.72% of the capital is held short in the MSCI World Index.

The annualised portfolio return and portfolio standard deviation for the Sharpe ratio-optimised portfolio for the strategy are 12.00% and 6.67% respectively. The improvement in the Sharpe ratio is benefited from expanding the exposures in the global momentum and value proxies with its risk being controlled by increasing the amount held short in the MSCI World Index and the steady cash reserve in the risk-free proxy. After the maximum leverage allowance is reached, higher portfolio returns are achieved by shifting risk-free lending to risk-free borrowing and simultaneously reducing the amount held short in the MSCI World Index. These adjustments drastically raise the standard deviation of the portfolio with limited improvements in portfolio returns, which cause the Sharpe ratio for the strategy to decline at an increasing rate. The highest attainable return is reached when twice the amount of the original capital is invested in the global momentum and value proxies with 100% of the original capital being financed by the extensive borrowing at the risk-free rate.

Figure 7.4 Long-Short Mean-Variance Portfolio Optimisation with Leverage Capped at 200%

The optimisation procedure is implemented over the examination period from 1 January 1991 to 31 December 2008. The constituent indices comprising the mean-variance optimised portfolios include the MSCI World Index, the global size proxy (Cap EW300), the global momentum proxy (Mom SW100) and the global value proxy (Value SW100). The portfolios are optimised by altering the weights of the constituent indices with the goal to minimise the portfolio standard deviation at each level of portfolio returns. The short position is only permitted in the MSCI World Index and hence the weights for the style proxies remain positive. The leverage is allowed up to 200% of the original exposures (long and short) in the constituent indices, and hence the constraint that the sum of the absolute values of the constituent weights to be capped at 200% is placed in the optimisation process. When the sum of the weights in the constituent indices is less than 100% of the original capital, the excess capital is invested in the risk-free proxy (U.S. 3-month Treasury bill (USTB3M)). On the other hand, when the sum of the weights in the constituent indices is greater than 100% of the original capital, the short fall is financed by borrowing at the risk-free rate. Thus, the risk-free rate serves as a balancing item that equates the overall weight in the risky and risk-free asset to 100%. The orange trend line depicts the level of leverage utilised at each level of portfolio returns. As indicated by the blue trend line, the Sharpe ratio is optimised when the full 200% leverage is utilised. This is achieved when 37.08% of the capital is allocated to Mom SW100, 66.20% of the capital is allocated to Value SW100, 93.45% of the capital is allocated to USTB3M and 96.73% of the capital held short in MSCI World Index. The annualised Sharpe ratio, portfolio return and portfolio standard deviation for the optimal portfolio composition are 121.57%, 12.00% and 6.67% respectively.

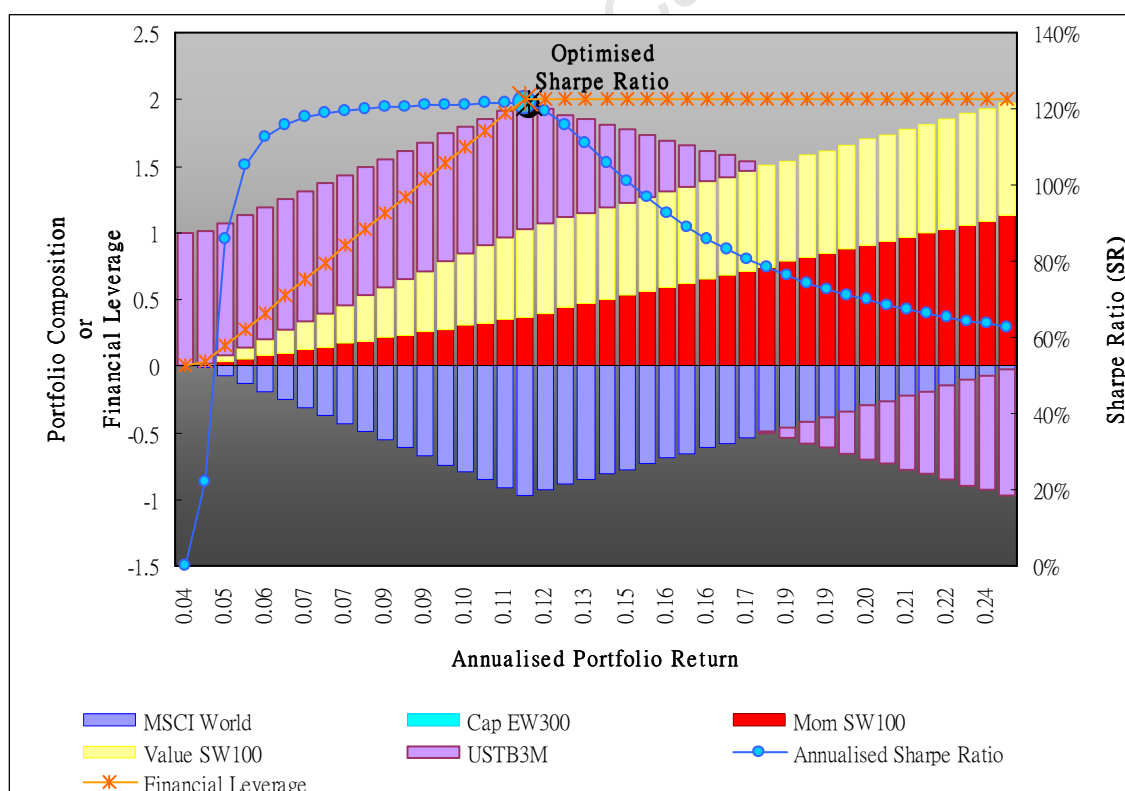


Figure 7.5 demonstrates the changes in the reward-to-risk ratio when short positions in the MSCI World Index and 200% leverage are permitted in the optimisation process. The new OCAL is represented by the white dotted curve while the original long-only OCAL with no leverage is represented by the solid white line. In line with the changes in Sharpe ratio depicted by the blue trend line in Figure 7.4, the new Sharpe ratio-optimised portfolio represents the kinked point on the new OCAL, indicating the instant deterioration of the reward-to-risk ratio beyond the point when the 200% capped leverage is reached. The second part of the OCAL is flatter than the first part of the OCAL and the long-only OCAL, indicating that the asset allocations in the second part of the OCAL have lower reward-to-risk ratios than the asset allocations in the first part of the OCAL and the long-only OCAL.

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Figure 7.5 The Mean-Variance Efficient Frontier for the Long-Short Portfolios with Leverage Capped at 200%

The optimisation procedure is implemented over the examination period from 1 January 1991 to 31 December 2008. The constituent indices comprise the long-short optimised portfolios with leverage capped at 200% on the efficient frontier include the MSCI World Index, the global size proxy (Cap EW300), the global momentum proxy (Mom SW100) and the global value proxy (Value SW100). The counterpart indices namely, the global cap-weighted size index (Cap SW300), the global loser proxy (Loser SW100) and the global glamour proxy (Glamour SW100) are also depicted in the diagram. The short position is only permitted in the MSCI World Index. The relaxation of the short sale and the leverage constraints extends the long-only Sharpe ratio-optimised capital allocation line (represented by solid white line) to the new Sharpe ratio-optimised capital allocation line (OCAL) represented by the white dotted curve. The portfolios on the OCAL represent the mix between the risk-free proxy (USTB3M) and the new Sharpe ratio-optimised portfolio (marked by white asterisk). The new Sharpe ratio-optimised portfolio has an annualised Sharpe ratio, portfolio return and portfolio standard deviation of 121.57%, 12.00% and 6.67% respectively. This is achieved when 37.08% of the capital is allocated to Mom SW100, 66.20% of the capital is allocated to Value SW100, 93.45% of the capital is allocated to USTB3M and 96.73% of the capital is held short in MSCI World index. The OCAL is kinked at the Sharpe ratio-optimised portfolio with flatter slope for the second part of the OCAL due to the 200% leverage constraint. The asset allocations in the second part of the OCAL have lower reward-to-risk ratios than the asset allocations in the first part of the OCAL.

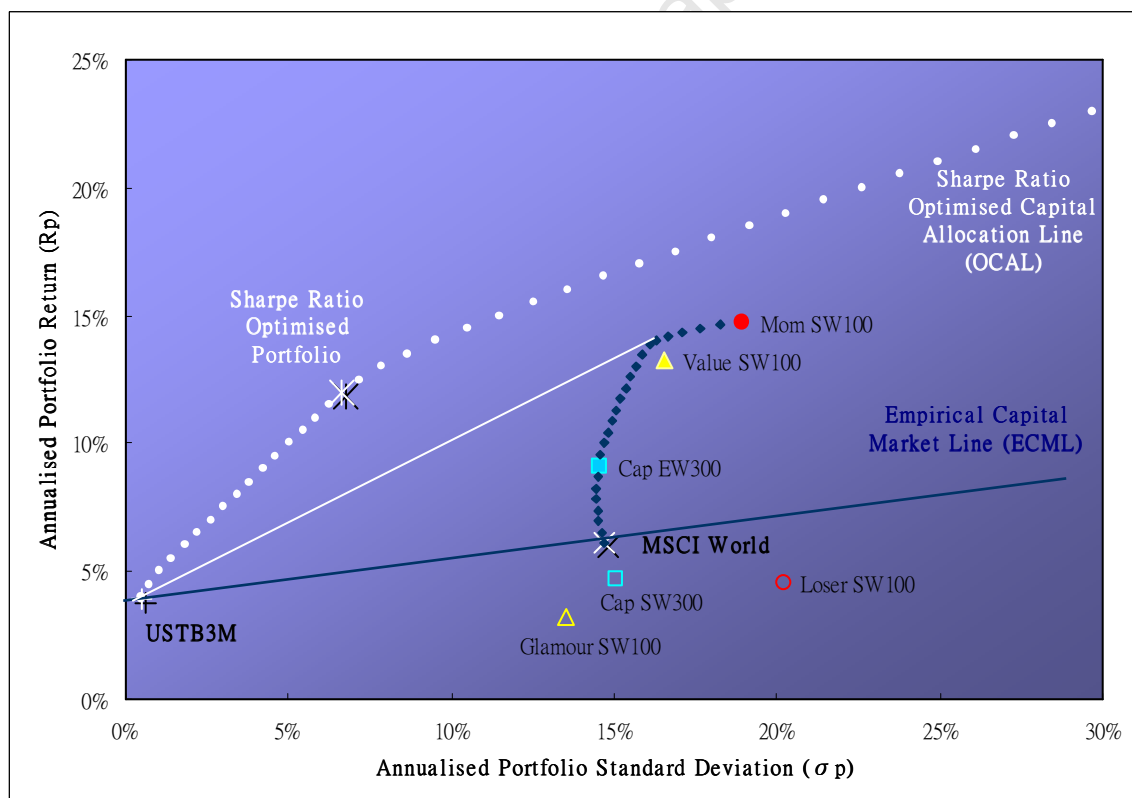


Figure 7.6 demonstrates the risk-return characteristics and portfolio compositions of the market neutral hedge fund strategy. Similar to the long-short hedge fund strategy, the optimisation process of the market neutral strategy begins by allocating the entire capital to the risk-free proxy. The Sharpe ratio is subsequently improved by increasing the strategy's exposures in the more efficient global growth and value proxies and simultaneously short selling the less efficient MSCI World Index. The constraint that requires the market neutral strategy to have zero net exposure in the constituent indices, forces the investments in the global style proxies to be entirely financed by the proceeds from the short position in the MSCI World Index. This also results in a rapid replacement of the global value proxy by the global momentum proxy in the process of achieving higher portfolio returns beyond the 200% capped leverage point. In addition, since no investment is required for the market neutral hedge fund strategy, the entire capital is allocated to the risk-free proxy at all times. The Sharpe ratio for the market neutral hedge fund strategy is optimised at 120.59% when 191% leverage is used to achieve an annualised portfolio return of 11.25% with annualised portfolio standard deviation of 6.10%. The portfolio compositions for the Sharpe ratio-optimised market neutral portfolio include 34.18% of the capital invested in the global momentum proxy, 61.26% of the capital invested in the global value proxy, 100% of the capital invested in the risk-free proxy and 95.44% of the capital held short in the MSCI World Index.

Figure 7.7 depicts the OCAL for the market neutral hedge fund strategy (white dotted curve). Similar to the OCAL for the long-short hedge fund strategy, the OCAL for the market neutral hedge fund strategy kinks at the Sharpe ratio-optimised portfolio. The market neutral constraints with the 200% capped leverage lead to inefficient asset allocations beyond the kinked point. However, the first part of the OCAL achieves higher reward-to-risk ratio than the long-only OCAL and the ECML, as it has relatively higher slope compared to the slopes for the long-only OCAL and ECML respectively.

Figure 7.6 Market Neutral Mean-Variance Portfolio Optimisation with Leverage Capped at 200%

The optimisation procedure is implemented over the examination period from 1 January 1991 to 31 December 2008. The constituent indices comprising the market neutral mean-variance optimised portfolios include the MSCI World Index, the global size proxy (Cap EW300), the global momentum proxy (Mom SW100) and the global value proxy (Value SW100). The portfolios are optimised by altering the weights of the constituent indices with the goal of minimising the portfolio standard deviation at each given level of portfolio return. The short position is only permitted in the MSCI World Index and hence the weights for the style proxies remain positive. The market neutral strategy by definition equates the investment held long in the style proxies to the investment held short in the MSCI World Index. The leverage is allowed up to 200% of the original exposure (long and short) in the constituent indices as long as the weights in the long and short positions are equal. The risk-free rate provided by the U.S. 3-month Treasury bill (USTB3M) serves as a balancing item that equates the overall weight in the risky and risk-free asset to 100% by assuming risk-free lending and borrowing. The orange trend line depicts the level of leverage utilised at each level of portfolio return. As indicated by the blue trend line, the Sharpe ratio is optimised when the 191% leverage is utilised. This is achieved when 34.18% of the capital is allocated to Mom SW100, 61.26% of the capital is allocated to Value SW100, 100% of the capital is allocated to USTB3M and 95.44% of the capital is held short in the MSCI World Index. The annualised Sharpe ratio, portfolio return and portfolio standard deviation for the optimal portfolio composition are 120.59%, 11.25% and 6.10% respectively.

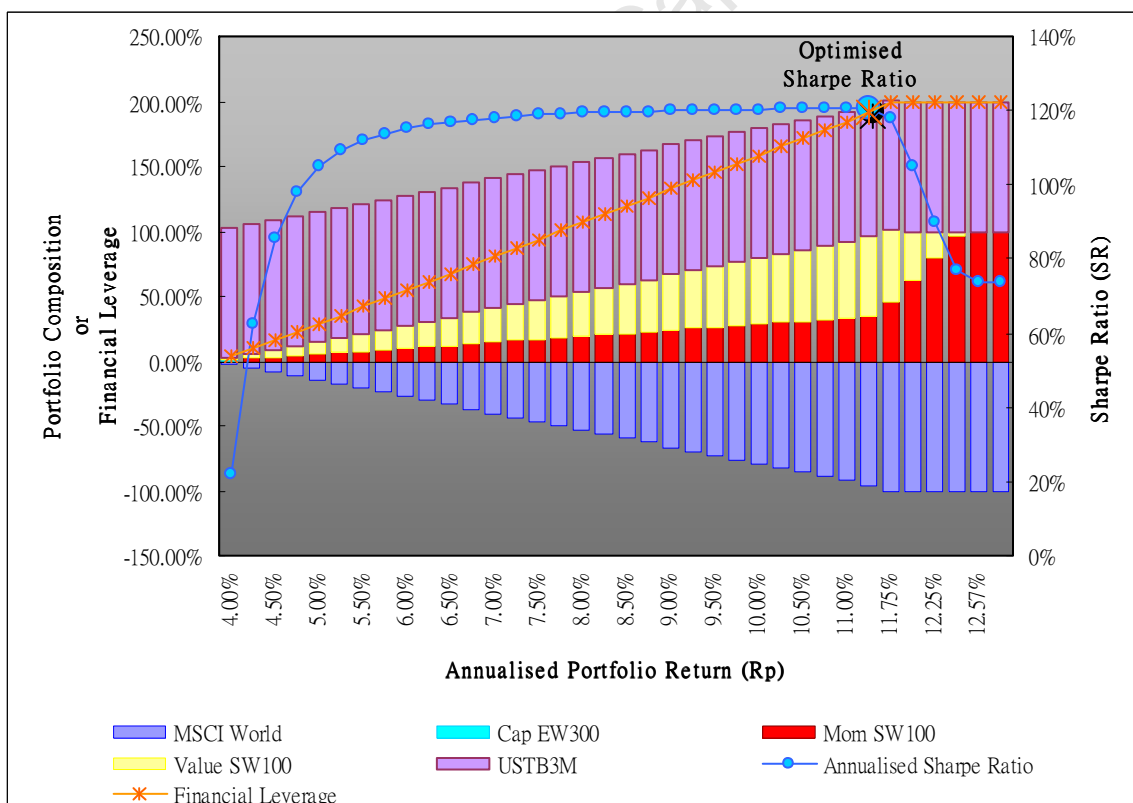
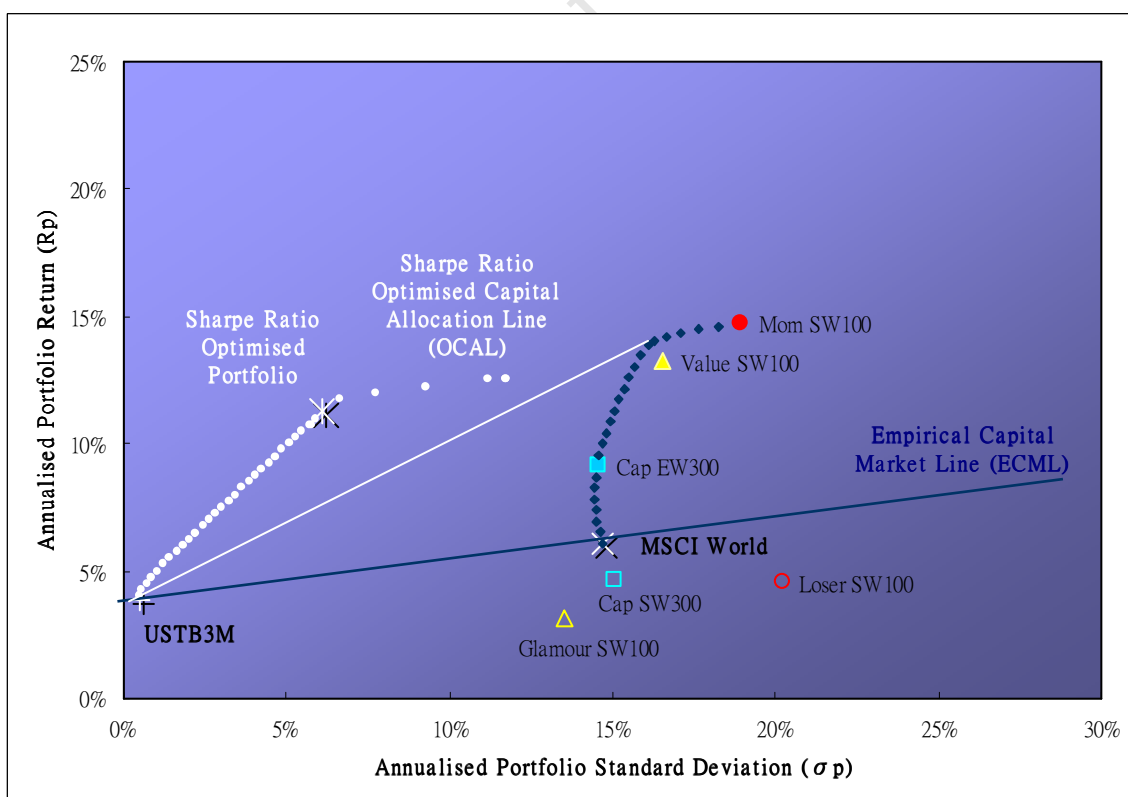


Figure 7.7 The Mean-Variance Efficient Frontier for the Market**Neutral Portfolios with Leverage Capped at 200%**

The optimisation procedure is implemented over the examination period from 1 January 1991 to 31 December 2008. The constituent indices comprising the long-short market neutral optimised portfolios with leverage capped at 200% on the efficient frontier include the MSCI World Index, the global size proxy (Cap EW300), the global momentum proxy (Mom SW100) and the global value proxy (Value SW100). The counterpart indices, namely, the cap-weighted size proxy (Cap SW300), the global loser proxy (Loser SW100) and the global glamour proxy (Glamour SW100) are also depicted in the diagram. The short position is only permitted in the MSCI World Index. The relaxation of the short sale and leverage constraints extends the long-only Sharpe ratio-optimised capital allocation line (represented by solid white line) to the new Sharpe ratio-optimised capital allocation line (OCAL), represented by the white dotted curve. The new constraint that the long and short positions have equal weights for the market neutral strategy nevertheless limits the potential for the OCAL. The portfolios on the OCAL represent the mix between the risk-free proxy (USTB3M) and the new Sharpe ratio-optimised portfolio (marked by white asterisk). The new Sharpe ratio-optimised portfolio has an annualised Sharpe ratio, portfolio return and portfolio standard deviation of 120.59%, 11.25% and 6.10% respectively. This is achieved when 34.18% of the capital is allocated to Mom SW100, 61.26% of the capital is allocated to Value SW100, 100% of the capital is allocated to USTB3M and 95.43% of the capital is held short in MSCI World index. The OCAL is kinked at the Sharpe ratio optimised portfolio, with flatter slope for the second part of the OCAL, due to the market neutral constraint and the 200% leverage constraint. The asset allocations in the second part of the OCAL are less efficient than the asset allocations in the first part of the OCAL because the proceeds from short selling the MSCI World Index is limited at 100% beyond the kinked point.



7.4 Results: Global Sharpe Ratio-Optimised Portfolios

The summarised statistics for the global Sharpe ratio-optimised portfolios, constructed under various optimisation constraints, are displayed in Table 7.1. The first two portfolios represent the traditional long-only funds with no leverage as opposed to the long-short leverage hedge funds represented by the last two portfolios. Examining the performance statistics and the portfolio compositions of portfolio 1 (mean-variance optimised) and portfolio 2 (mean-tracking error optimised) indicate that the two portfolios closely resemble each other, despite their different optimisation criteria. This observation is due to the high correlations between the portfolios comprised of the global momentum and value proxies and the MSCI World benchmark. This is evident from the beta coefficients of 1.00 for both portfolio 1 and portfolio 2. As a result, the objective of minimising the portfolio's variance is equivalent to minimising the portfolio's tracking error.

Comparing the performance statistics of the Sharpe ratio-optimised long-only portfolios with no leverage (refer to portfolio 1 and portfolio 2) to the Sharpe ratio-optimised hedge fund strategies (refer to portfolio 3 and portfolio 4), reveals that the hedge fund strategies effectively double the attainable Sharpe ratio of the traditional long-only strategies. Although the Sharpe ratio-optimised hedge fund strategies (refer to portfolio 3 and portfolio 4) yield slightly lower returns compared to the Sharpe ratio-optimised long-only strategies (refer to portfolio 1 and portfolio 2), the standard deviations for the hedge fund strategies are less than half of the standard deviations for the long-only strategies. In addition, the hedge fund strategies have beta coefficients that are close to zero, compared to the average beta coefficients for the long-only strategies. These findings imply that the major advantage of hedge funds over traditional funds lies in the ability to lower risk, rather than the potential of reaping higher returns.

Table 7.1 Summarised Statistics for the Global Sharpe Ratio-Optimised Portfolios

The optimisation strategies, under which the global Sharpe ratio-optimised portfolios are developed, include the long-only mean-variance optimisation with no leverage, the long-only mean-tracking error optimisation with no leverage, the long-short mean-variance optimisation with 200% capped leverage and the long-short mean-variance market neutral optimisation with 200% capped leverage. The MSCI World Index is the only index which is allowed to be held short in the optimisation procedure. The Sharpe ratio-optimised portfolios are the portfolios that achieve the highest return in excess of the return on the risk-free proxy per unit of total risk, as measured by standard deviation. The market proxy and the risk-free proxy are represented by the MSCI World Index and the U.S. 3-month Treasury bill (USTB3M) respectively.

Portfolio No.	(1) Long-Only	(2) Long-Only	(3) Long-Short	(4) Market Neutral
Constraints:	Mean-Variance No Leverage	Mean-Tracking Error No Leverage	Mean-Variance 200% Leverage	Mean-Variance 200% Leverage
Performance Statistics:				
Geometric Return p.a.	14.04%	14.06%	12.00%	11.25%
Std. Deviation p.a.	16.30%	16.33%	6.67%	6.10%
Sharpe Ratio p.a.	62.29%	62.27%	121.57%	120.59%
Beta	1.000	1.000	0.062	0.000
Portfolio Composition:				
MSCI World Index	0%	0%	-96.73%	-95.44%
Cap EW300	0%	0%	0%	0%
Mom SW100	51.86%	52.95%	37.08%	34.18%
Value SW100	48.14%	47.05%	66.20%	61.26%
USTB3M	0%	0%	93.45%	100%
Leverage:	N/A	N/A	200%	191%

A common observation across the Sharpe ratio-optimised portfolios is that none of the portfolios has exposure in the global size proxy (Cap EW300). This indicates that the global size proxy is relatively less mean-variance efficient, compared to the global momentum and value proxies. The most inefficient index with the lowest Sharpe ratio amongst the constituent indices is the MSCI World Index, which is used as a hedging instrument, to offset the risk in the global momentum and value proxies, without sacrificing their returns. The Sharpe ratios for both hedge fund strategies are

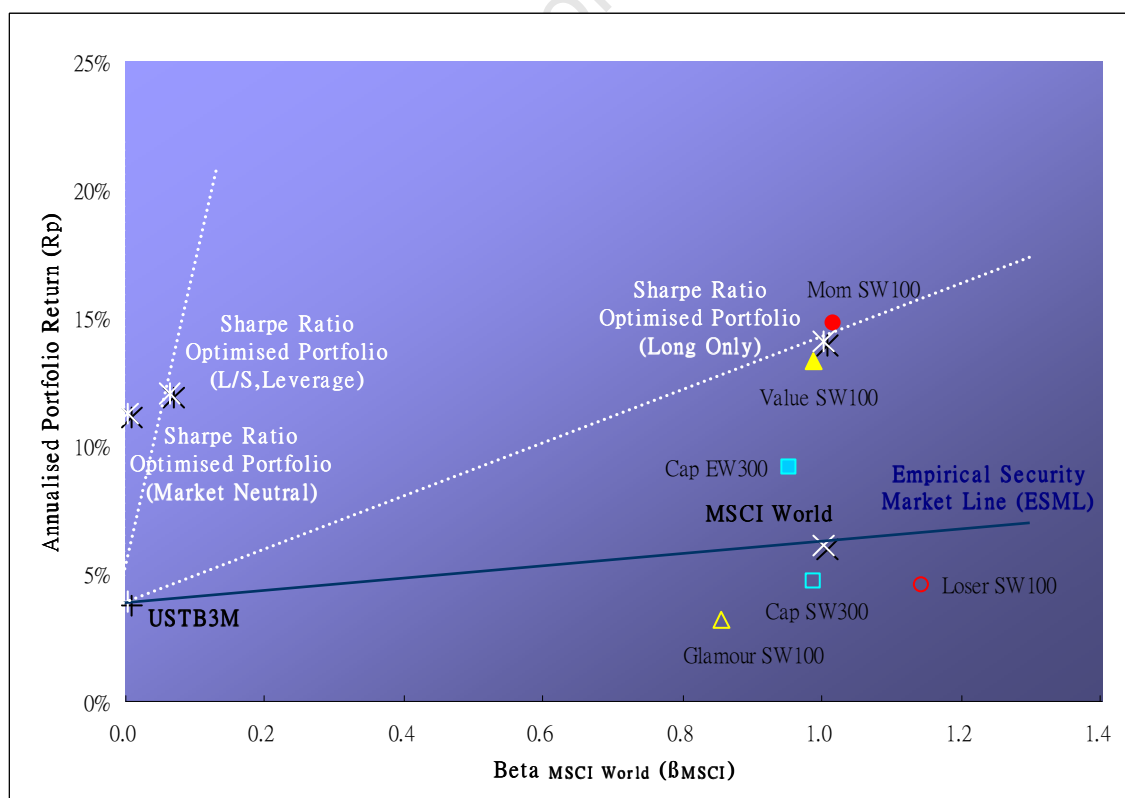
optimised by investing approximately 100% of the capital in the global momentum and value proxies, and simultaneously short selling the MSCI World Index to finance the acquisition of the risk-free proxy.

Figure 7.8 demonstrates the relative risk-adjusted performances of the Sharpe ratio-optimised portfolios using CAPM beta as the measure of risk. Examining the relative locations of the constituent indices reveals that although all of the constituent indices have beta coefficients of around 1.0, the global size proxy and the MSCI World Index yield much lower returns compared to the global momentum and value proxies. In addition, the global momentum and value proxies are found to share similar risk-return characteristics with the long-only Sharpe ratio-optimised portfolio with no leverage. This observation suggests that no solid benefits can be obtained from optimising the asset allocations between the global momentum and value proxies, without engaging in short selling securities and leverage. On the other hand, the risk-return characteristics of the Sharpe ratio-optimised portfolios, constructed under the long-short hedge fund strategy and the market neutral strategy are similar in terms of their locations in Figure 7.8. The main advantage of implementing the market neutral strategy over the long-short hedge fund strategy lies in its ability to completely hedge away the systematic risk in the portfolio.

The Treynor measure for the Sharpe ratio-optimised portfolios are indicated by the slopes of the dotted lines connecting the risk-free proxy to the respected Sharpe ratio-optimised portfolios. The market neutral Sharpe ratio-optimised portfolio has the highest Treynor measure amongst the Sharpe ratio-optimised portfolios, since its beta coefficient is closed to zero, with almost no exposure to systematic risk. The annualised return for the market neutral Sharpe ratio-optimised portfolio is 11.25%, which is approximately triple of the risk-free rate of 3.89%. The excess return of 7.36% represents the potential arbitrage return available to the market neutral funds that invest in the constituent indices and follow the same set of constraints.

Figure 7.8 Relative Performances of the Sharpe Ratio-Optimised Portfolios Measured by the Empirical Security Market Line (ESML)

The optimisation procedure is implemented over the examination period from 1 January 1991 to 31 December 2008. The 3 Sharpe ratio-optimised portfolios under evaluation are the long-only Sharpe ratio-optimised portfolio with no leverage, the long-short Sharpe ratio-optimised portfolio with 200% capped leverage and the long-short market neutral Sharpe ratio-optimised portfolio with 200% capped leverage. The constituent indices comprising the Sharpe ratio-optimised portfolios include the MSCI World Index, the global size proxy (Cap EW300), the global momentum proxy (Mom SW100) and the global value proxy (Value SW100). The counterpart indices namely, the cap-weighted size proxy (Cap SW300), the global loser proxy (Loser SW100) and the global glamour proxy (Glamour SW100) are also depicted in the diagram. The long-only Sharpe ratio-optimised portfolio has an annualised portfolio return of 14.04% and a beta of 1.0, due to the well-diversified nature of its constituent indices. The long-short leveraged Sharpe ratio-optimised portfolio has an annualised portfolio return of 12% and a beta as low as 0.06, due to the permission to short sell the market proxy (the MSCI World Index). Due to the fact that the amounts invested in the well-diversified style proxies are entirely matched by the proceeds from short selling the MSCI World Index for the market neutral strategy, the market neutral Sharpe ratio-optimised portfolio contains no systematic risk as its beta is close to zero. The annualised portfolio return for the market neutral Sharpe ratio-optimised portfolio has an annualised portfolio return of 11.25%, which outperforms the risk-free rate (USTB3M) of 3.89% by 7.36% per annum. The Treynor measures for the optimised portfolios are indicated by the slopes of the lines connecting the USTB3M to the respective Sharpe ratio-optimised portfolios.



7.5 Conclusion

In line with the findings of Yu (2008), all the Sharpe ratio-optimised portfolios developed under the four investment strategies generate their returns from the global momentum and value proxies. The Sharpe ratio-optimised portfolios for the long-short hedge fund strategy and the market neutral strategy have additional investments held in the risk-free proxy, which are financed by the proceeds from short selling the MSCI World Index. The fact that the global size proxy does not take part in any of the Sharpe ratio-optimised portfolio indicates that it is less efficient, compared to the global momentum and value proxies. The most inefficient constituent index is the MSCI World Index, which is held short in approximately the same amount as the combined positions held long in the global momentum and value proxies to hedge the risks inherent in the Sharpe ratio-optimised hedge fund strategies, at the least expense of their upside potentials. Although all the constituent indices are exposed to average systematic risk, the global size proxy and the MSCI World Index yield much lower returns compared to the global momentum and value proxies.

The most important finding of the studies conducted in this chapter is the realisation that the hedge fund strategies that engage in short sale of securities and leverage, drastically improve their risk-adjusted performances above the long-only strategies with no leverage, primarily through the reduction in risk rather than boosting portfolio returns. The optimal Sharpe ratios for the two hedge fund strategies are double the optimal Sharpe ratios for the long-only strategies with no leverage at a minimal sacrifice of portfolio returns. In addition, the standard deviations of the Sharpe ratio-optimised hedge fund strategies are only half of the standard deviations of the Sharpe ratio-optimised long-only strategies with no leverage. The beta coefficients of the hedge fund strategies are close to zero, which bring their Treynor measures to near infinity. Without engaging in short sale and leverage, the Sharpe ratio-optimised portfolio developed from the global momentum and value proxies fail to distinguish

its performance from the constituent indices. Due to the fact that beta coefficients for the global style proxies are close to the market average of 1.0, using the MSCI World Index as the market proxy, the objective of minimising portfolio tracking error is in line with the objective of minimising portfolio variance in the optimisation process.

ACTIVE GLOBAL STYLE TIMING STRATEGIES

8.1 Introduction

The examination of the characteristics of the global style proxies in Chapter 5 indicates that momentum and value investment styles represent two distinctive investment segments in the global equity markets, especially for their specific timing throughout the business cycle. In addition, the replication of global equity funds demonstrated in Chapter 6 and the style-based portfolio optimisation conducted in Chapter 7 reveal the active involvements of the global momentum and value proxies in the replication and optimisation processes. These observations motivate for the development of a style rotation strategy between the global momentum and value proxies to capture the specific timing of the two pronounced investment styles.

The drastic improvements in the risk-adjusted performances of the hedge fund strategies documented in Chapter 7, through the relaxations of the long-only and no leverage constraints, also provide motivations for the re-examination of the out-of-sample performances of the Sharpe-optimised portfolios with various portfolio constraints.

The goal of this chapter is to develop style timing models that dynamically forecast the style tilt of the portfolio over the out-of-sample period. The style timing strategies employed by this study include a value-momentum rotation strategy that switches between the global value and momentum proxies and four tactical style allocation

(TSA) strategies that predict the optimal style compositions, based on their respective portfolio constraints.

Section 8.2 of this chapter discusses the methodology employed to develop style timing strategies in this research. Section 8.3 presents and analyses the results of the style rotation strategy and the TSA strategies over the examination period. Section 8.4 consolidates the findings and provides insights into the empirical studies conducted in this research.

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8.2 Methodology and Descriptive Statistics

Both the value-momentum style timing model and the TSA models are designed to update the style tilt monthly, based on the model outputs trained in the prior 36 months. The first training (in-sample) period is from 1 January 1991 to 31 December 1993 to forecast the style tilt in January 1994, which represents the first month in the out-of-sample period from 1 January 1994 to 31 December 2008 (a total of 180 months). Thus, the monthly style tilts for the out-of-sample period are forecasted by the model trained in the 180 corresponding overlapping 36-month in-sample periods. The portfolio developed from a successful style timing strategy should achieve better risk-adjusted performance results compared to its constituent indices.

8.2.1 Value-Momentum Rotation Strategy

In order to predict the timing to switch between the global value and momentum proxies, a macroeconomic timing model that employs common arbitrage pricing theory (APT) factors as its regressors is developed for this research. The macroeconomic variables examined by this research include the monthly growth rate for the industrial production of advanced economies, the U.S. dollar return relative to the currency composite of advanced economies, the market risk premium, the U.S. term structure of interest rate and the year-on-year percentage change in the consumer price index (CPI) of advanced economies, of which the term structure of interest rate is found to significantly determine the forward value-growth spread in the studies conducted by Kao and Shumaker (1999) and Mutooni and Muller (2007).

The time-series data of the selected macroeconomic variables are downloaded from the official website of the International Monetary Fund (IMF) monthly over the examination period from 1 January 1991 to 31 December 2008. The market risk premium is the return difference between the MSCI World Index and the U.S. 3-month Treasury bill. The U.S. term structure is computed as the 10-year U.S. Treasury bond yield less the U.S. 3-month Treasury bill yield. The choice of the U.S.-based term structure is due to the fact that U.S. dollar is used as the base currency for this research. On the other hand, the growth rate of industrial production and the percentage change in CPI are based on advanced economies, to provide more realistic indications regarding the current global economic conditions, without being subject to abnormal economic shocks inherent in less developed economies in the training process. Similarly, the U.S. dollar return is computed relative to the currency composite of advanced economies. The advanced economies defined by the IMF include Australia, Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Greece, Hong Kong, Iceland, Ireland, Italy, Japan, Luxembourg, Malta, Netherlands, New Zealand, Norway, Portugal, San Marino, Singapore, Slovakia, Slovenia, South Korea, Spain, Sweden, Switzerland, Taiwan, the United Kingdom and the United States.

In order to prevent look-ahead bias, the variables are lagged for 3 months in the macroeconomic timing model to forecast the forward value-momentum spread, as suggested by Mutooni and Muller (2007). The power of each variable in predicting the forward value-momentum spread is examined by a univariate test using ordinary least squares (OLS) regression technique over the examination period.

Only the variables with significant slope coefficients from the univariate test are employed as regressors in the macroeconomic timing model. The model is trained monthly, based on a series of rolling 36-month OLS regressions performed in each of the 180 overlapping in-sample periods to estimate the regression constants and slope coefficients as shown in Equation 8.1:

$$r_{Value-Mom,t} = \alpha_{Value-Mom} + \sum_{k=1}^K b_{Value-Mom,k} \times F_{k,t-3} + \varepsilon_{Value-Mom,t} \quad \dots\dots\dots (8.1)$$

Where:

- $\alpha_{Value-Mom}$ is the regression constant;
- $F_{k,t-3}$ is the value of the k th significant macroeconomic variable in month $t-3$;
- K is the number of significant macroeconomic variables identified in the univariate test;
- $b_{Value-Mom,k}$ is the sensitivity of the value-momentum spread to the movement in the lagged 3-month k th significant macroeconomic variable;
- $\varepsilon_{Value-Mom,t}$ is the random error of the regression in month t that cannot be explained by movements in the lagged 3-month significant macroeconomic variables.

The regression constant and slope coefficients estimated over the in-sample period from $t-36$ through $t-1$ are used as estimates to forecast the value-momentum spread in month t based on the macroeconomic timing model demonstrated in Equation 8.2:

$$\hat{r}_{Value-Mom,t} = \hat{\alpha}_{Value-Mom} + \sum_{k=1}^K \hat{b}_{Value-Mom,k} \times F_{k,t-3} \quad \dots\dots\dots (8.2)$$

Where:

$\hat{r}_{Value-Mom,t}$ is the forecasted value-momentum spread in month t ; and
 $\hat{\alpha}_{Value-Mom,k}$ and $\hat{b}_{Value-Mom,k}$ represent the regression constant estimate and the slope coefficient estimate computed from the OLS regression from month $t-36$ through $t-1$;

Based on the monthly out-of-sample prediction of the value-momentum spread, the value-momentum rotation strategy is designed to hold the global value proxy at the beginning of the out-of-sample period (January 1994), and switch to the global momentum proxy if the model predicts that the value-momentum spread is narrowing. Similarly, the strategy holds the entire investments in the global value proxy, as long as the estimated value-momentum spread is expanding.

8.2.2 Tactical Style Timing (TSA) Strategies

The portfolio compositions of the TSA strategies are optimised, based on similar constraints as the Sharpe ratio-optimised portfolios developed in Chapter 7. Thus, the out-of-sample results of the TSA style timing strategies serve to ascertain the robustness of the performances of the Sharpe ratio-optimised portfolios developed in

Chapter 7. The constituent indices for the TSA portfolios include the risk-free proxy, the market proxy and the global size, momentum and value proxies developed in Chapter 5. The risk-free proxy and the market proxy are represented by the U.S. 3-month Treasury bill and the MSCI World Index respectively. The Sharpe ratio-optimised portfolios constructed in Chapter 7 include a long-only portfolio with no leverage, a long-short portfolio with 200% capped leverage and a market neutral portfolio with 200% capped leverage. Due to the active involvements of the risk-free proxy for the long-short hedge fund strategies observed in Chapter 7, an additional long-only Sharpe ratio-optimised portfolio, that includes the risk-free proxy as its constituent in the optimisation process, is developed in this chapter to determine whether the risk-free proxy (cash) can effectively protect the downside risk of the long-only portfolio without sacrificing its upside return potential.

The objective of the training process for the TSA strategies is to find the portfolio compositions that maximise the in-sample Sharpe ratios for the respective TSA strategies. The Sharpe ratio is computed using Equation 5.10 while the monthly portfolio return and standard deviation are computed using Equation 7.1 and Equation 7.2 respectively. Once the optimal portfolio compositions for each of the TSA strategies are identified over the 180 overlapping in-sample periods, the same portfolio compositions are replicated for the immediate months following the corresponding in-sample periods. Performing TSA in this manner is equivalent to replicating the hypothetical Sharpe-ratio optimised portfolios for the TSA strategies. Following the same methodology of the replication procedure in Chapter 6, the monthly portfolio compositions are estimated by the weighted least squares (WLS) regressions that allocate a weight to the returns of the constituent indices in each month equivalent to $2^{1/36}$ times of their predecessors in the previous month.

8.3 Results: Global Style Timing Strategies

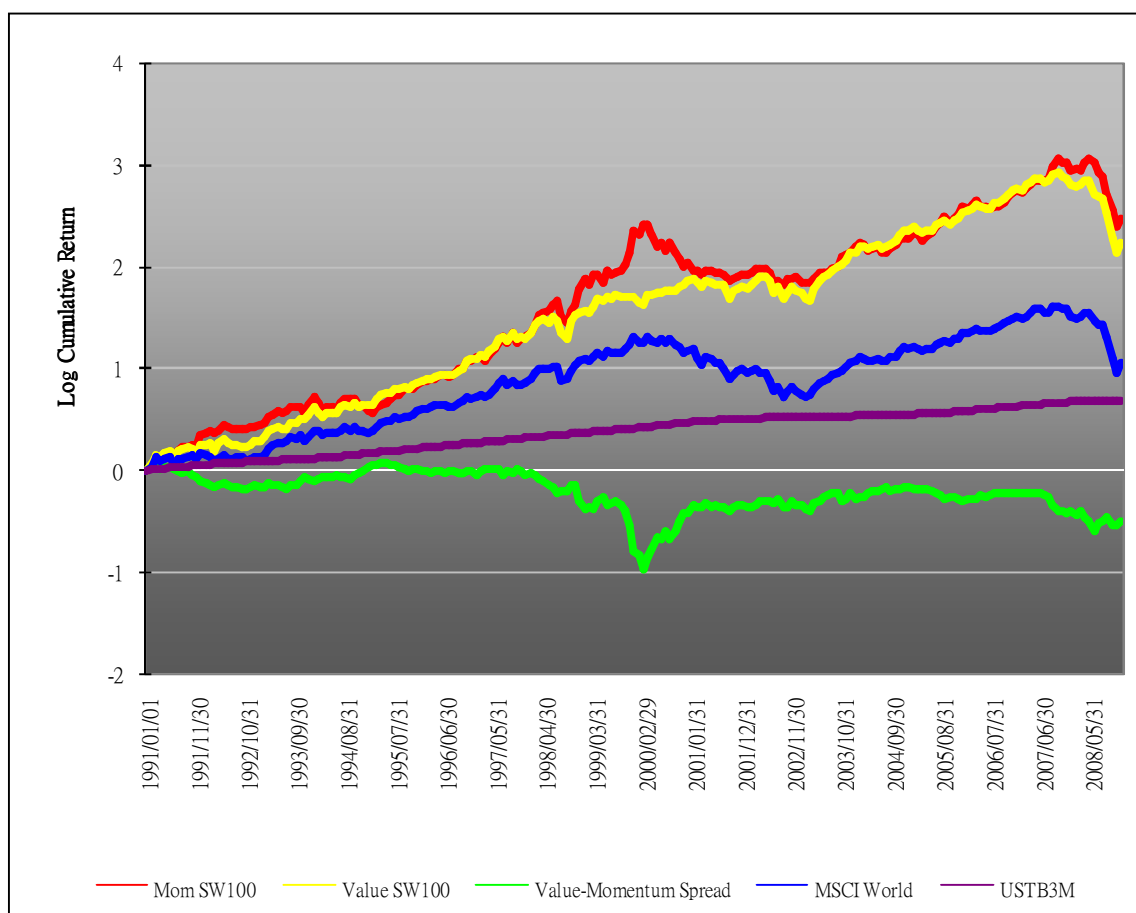
The log cumulative performance of the global value-momentum spread over the examination period from 1 January 1991 to 31 December 2008 is depicted in Figure 8.1. The log cumulative returns for the MSCI World Index, the U.S. Treasury bill and the global momentum and value proxies are also depicted in the diagram. The significant drift in the performance of the global momentum proxy towards the market peak in 2000 can be seen from the drastic decline in the global value-momentum spread. However, significant recovery in the global value-momentum spread is detected immediately after the burst of the information technology (I.T.) bubble.

By contrast, the movements in the global value-momentum spread are less drastic for the financial market crisis in 2008. This is because the majority of the constituents in the global momentum proxy are I.T. shares before the crash of the I.T. bubble. Thus, the global value proxy serve as a good hedge against the market decline in the early 2000s, since it holds less proportion of its assets in the I.T. shares. By contrast, although momentum shares react more drastically to the financial market crisis in 2008, the impacts of the crisis spill over all asset classes across sectors and countries.

Besides the significant swings of the global value-momentum spread around the major turning points of the global economic cycle, no significant movements in the global value-momentum spread are detected during normal course of the economy. This phenomenon suggests that the global value-momentum rotation strategy that frequently switches between the two investment styles might be fruitless in acquiring abnormal return.

Figure 8.1 Performance of the Global Value-Momentum Spread

The log cumulative returns of the global momentum index (Mom SW100), the global value index (Value SW100), the MSCI World Index (MSCI World), the U.S. Treasury bill (USTB3M) and the value-momentum spread over the examination period from 1 January 1991 to 31 December 2008 are represented by red, yellow, blue, purple and green trend lines respectively. The value-momentum spread strategy is designed to invest in Value SW100 and hold an equivalent short position in Mom SW100 in each month of the examination period.



Since the global value-momentum spread declines significantly towards the market peak and recovers rapidly at the beginning of the market downturn, factors that correlate positively with the value-momentum spread are contractionary indicators of the global economic activities. On the other hand, factors that correlate negatively with the value-momentum spread are regarded as expansionary indicators of the global economic activities.

Figure 8.2 illustrates the scatter plots of the univariate regressions between the global value-momentum spread and the values of the respective trailing 3-month macroeconomic variables. The lagged 3-month monthly growth rate for the industrial production of advanced economies and the lagged 3-month U.S. dollar return relative to the currency composite of advanced economies are the only two variables that significantly explain the forward value-momentum spread over the examination period. While the monthly growth rate for the industrial production of advanced economies are negatively correlated with the forward value-momentum spread, the U.S. dollar return relative to the currency composite of the advanced economies are positively correlated with the value-momentum spread.

Table 8.1 displays the regression statistics when the lagged 3-month values of these two variables are regressed on the global value-momentum spread over the examination period. The p -value of the regression indicates that the explanatory power of the 2-factor regression is significant at the 5% level. The slope coefficient for the lagged 3-month industrial production growth rate is negatively significant at a 1% level while the lagged 3-month U.S. dollar return is positively significant at a 10% level. Overall, the R -squared of the regression is only 4.25%, casting serious doubt on the ability of the 2-factor model in forecasting the forward value-momentum spread.

Figure 8.2 The Influences of Economic Forces on the Global Value-Momentum Spread

The macroeconomic variables analysed in this study include the monthly growth rate for the industrial production of advanced economies, the U.S. dollar return relative to the currency composite of advanced economies, the market risk premium, the term structure of interest rates and the year-on-year percentage change in the CPI of advanced economies. The influences of these variables on the global value-momentum spread are determined by regressing the monthly global value-momentum spread on the monthly values of each of the variables over the examination period from 1 January 1991 to 31 December 2008. In order to determine the relative forecasting power of the selected variables, their values are lagged for 3 months in the univariate regressions. The regression statistics with the scatter plots between the global value-momentum spread and the lagged values of the selected variables are presented in Chart (a) through Chart (e) respectively. The global value-momentum spread is computed as the return difference between the global value and momentum proxies. The advanced economies defined by the International Monetary Fund include Australia, Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Greece, Hong Kong, Iceland, Ireland, Israel, Italy, Japan, Luxembourg, Malta, Netherlands, New Zealand, Norway, Portugal, San Marino, Singapore, Slovakia, Slovenia, South Korea, Spain, Sweden, Switzerland, Taiwan, the United Kingdom and the United States.

Chart (a) Monthly Growth Rate for the Industrial Production of Advanced Economies

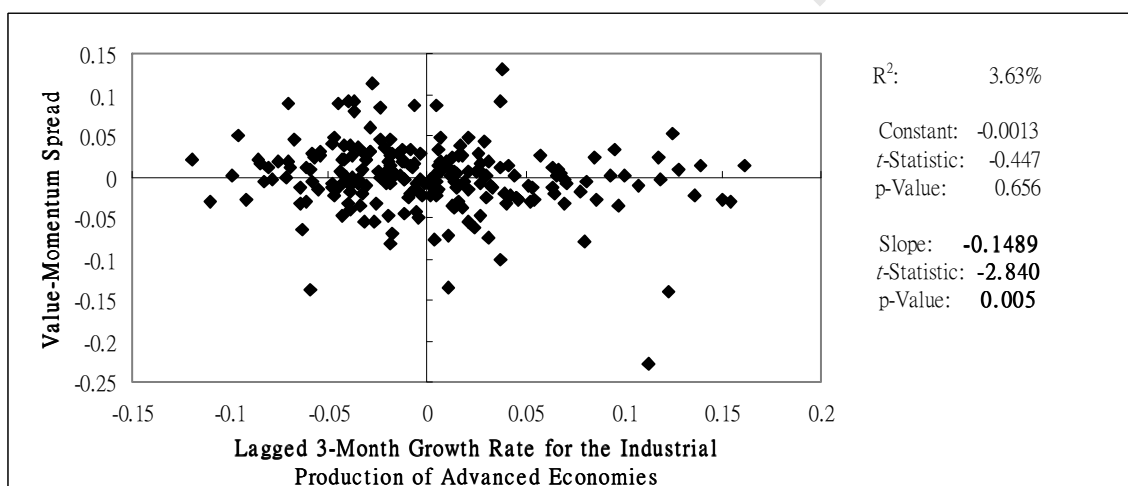


Chart (b) U.S. Dollar Return Relative to the Currencies of Advanced Economies

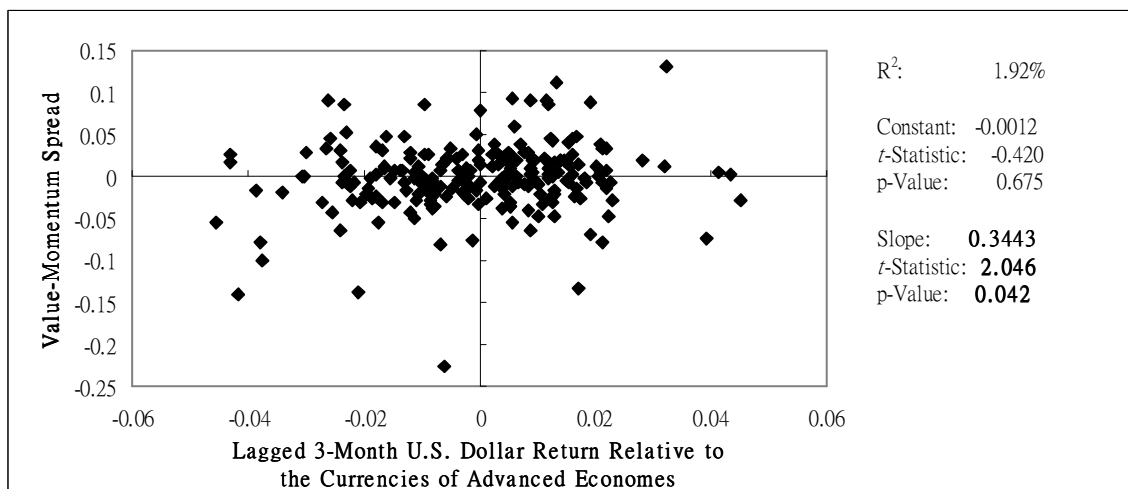


Figure 8.2 The Influences of Economic Forces on the Global Value-Momentum Spread - Continued

Chart (c) Market Risk Premium (Return Difference between MSCI World and USTB3M)

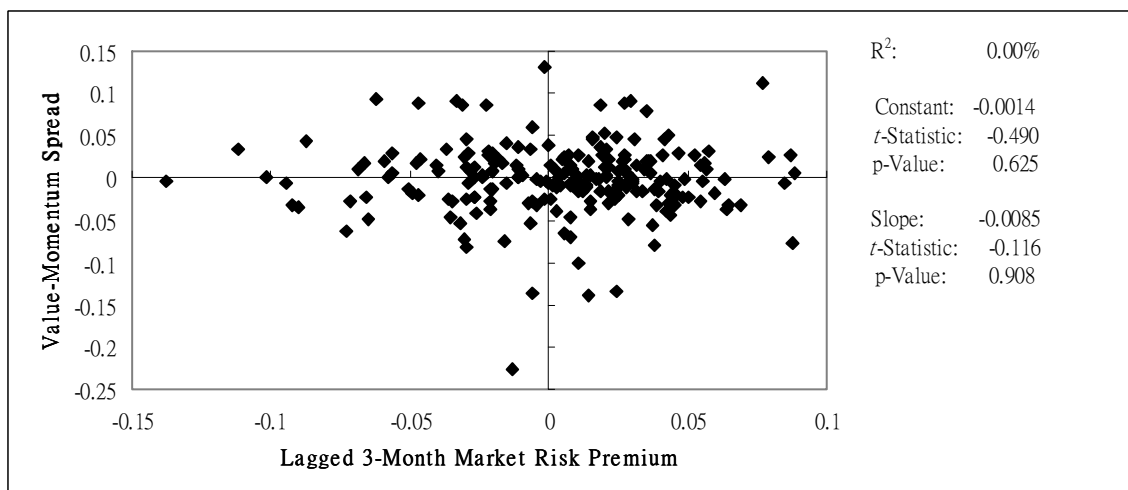


Chart (d) Term Structure (10-year U.S. Treasury Bond Yield – USTB3M)

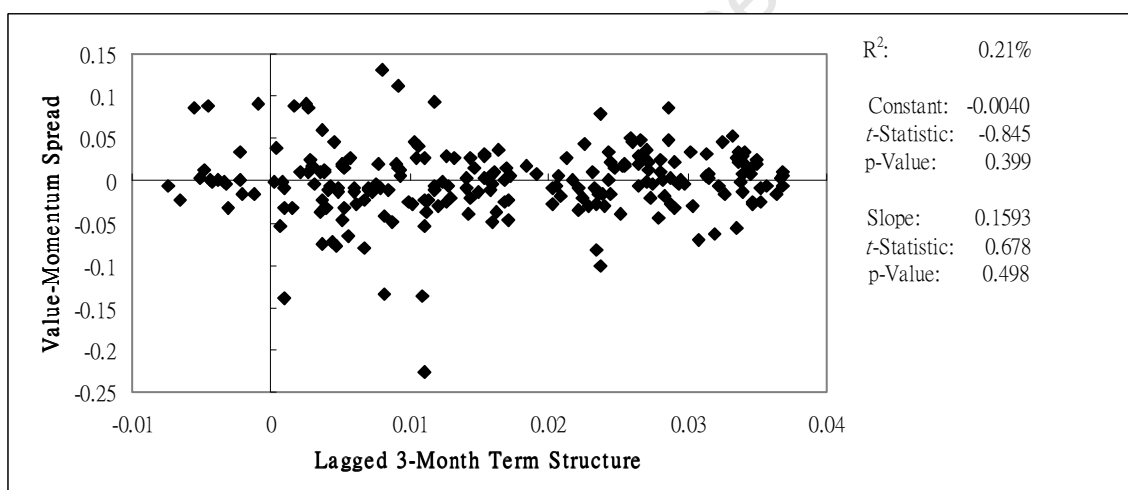


Chart (e) Percentage Change in CPI of Advanced Economies (Year on Year)

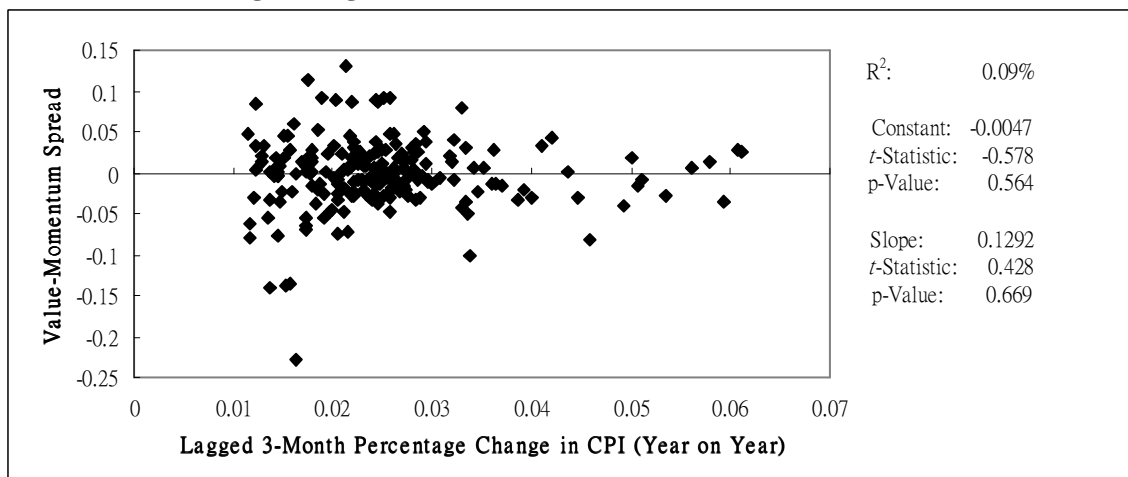


Table 8.1 Regression Statistics for the 2-Factor Global Value-Momentum Spread Forecasting Model

The 2 significant variables in forecasting the global value-momentum spread identified in the univariate tests include the monthly growth rate for the industrial production of the advanced economies (GIP) and the U.S. dollar return relative to the currencies of advanced economies (RUSD). The 3-month lagged values of these two variables are regressed on the monthly global value-momentum spread over the examination period from 1 January 1991 to 31 December 2008 to estimate the collective strength of these two macroeconomic variables in forecasting the global value-momentum spread over the examination period.

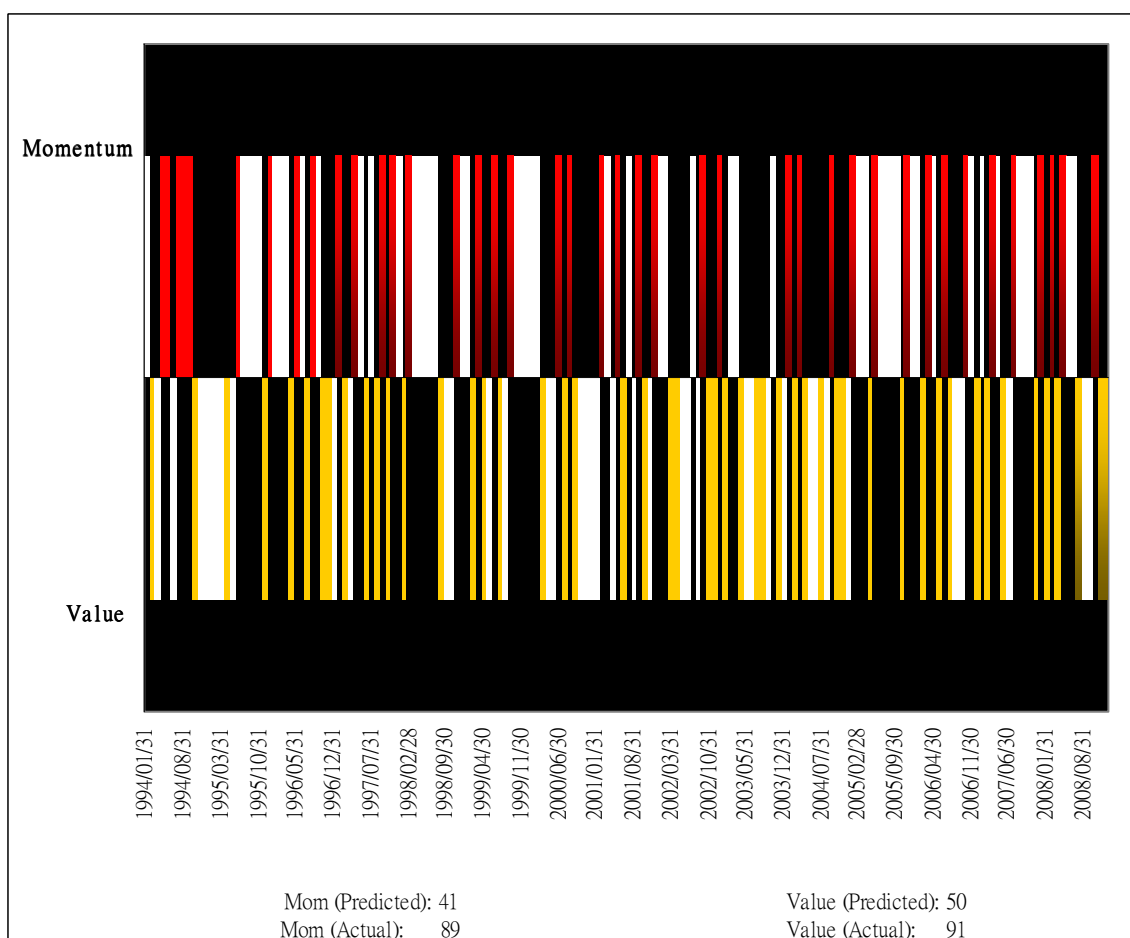
R ²	:	5.15%			
Adjusted R ²	:	4.25%			
Standard Error	:	4.09%			
Observations	:	216			
<hr/>					
ANOVA		Df	SS	MS	F-Statistic
					p-Value
Regression	:	2	0.0193	0.0097	5.7774
Residual	:	213	0.3560	0.0017	
Total	:	215	0.3753		
<hr/>					
		Coefficient	Standard Error	t-Static	p-Value
Constant	:	-0.0010	0.0028	-0.3724	0.7100
GIP _{t-3}	:	-0.1408	0.0523	-2.6918	0.0077
RUSD _{t-3}	:	0.3070	0.1665	1.8440	0.0666

The out-of-sample forecasting accuracy of the global value-momentum rotation strategy developed from the 2-factor macroeconomic timing model is demonstrated in Figure 8.3. The time-series outperforming index (momentum or value) is first plotted in the form of white histograms with the correct predictions for the momentum and value investment styles being coloured in red and yellow respectively. The global momentum and value proxies outperform each other approximately half of the time over the 180 months out-of-sample period. Overall, the predictions of the 2-factor macroeconomic timing model are random as the success rate for predicting the forthcoming outperforming investment style is approximately 50%.

The 2-factor macroeconomic timing model seems unreliable in predicting the correct switching point between the global momentum and value proxies. This is perhaps due to the complex interactions of the international parity relations in developing global trend following models. In addition, the term structure of interest rates that is found to be significant in predicting the value-glamour spread in the U.S. equity market has lost its forecasting power in this research (it is not included in the 2-factor model). This highlights the complexity of the choices of parameters in developing global trend following models. Another reason that contributes to the poor forecasting power of the 2-factor macroeconomic timing model pointed out earlier, is that the global value-momentum spread does not exhibit significant trends besides around the major turning point of the global economic cycle. Thus, it seems impractical to develop a trend-following model for style rotation strategies in the global equity market. The TSA strategies developed through in-sample portfolio optimisation that hold on to the most recent optimal style allocations could potentially be better alternatives to the style rotation strategies in generating abnormal returns in the global equity market.

Figure 8.3 Time-Series Predictions for the Global Value-Momentum Rotation Strategy

The global momentum proxy (Mom SW100) and the global value proxy (Value SW100) are viewed as alternative investment strategies over the out-of-sample period from 1 January 1994 to 31 December 2008. This diagram is developed by first plotting the actual outperforming index in the form of white histograms monthly over the out-of-sample period, and subsequently comparing the actual results to the predictions of the macroeconomic timing model. The correct predictions regarding Mom SW100 are coloured in red and the correct predictions regarding Value SW100 are coloured in yellow. The statistics for the respective actual versus predicted outperforming investment styles are depicted at the bottom of the diagram.



The out-of-sample time-series portfolio composition for the global long-only no leverage TSA strategy is illustrated in Figure 8.4. Due to the fact that this TSA strategy does not apply financial leverage, the orange trend line that depicts the level of financial leverage used by the portfolio remains at 1.0, as the combined exposures for the strategy is equal to 100% of the original and reinvested capital over the examination period. The long-only TSA does not propose significant holding of the momentum stocks during the drift of the global momentum proxy towards the peak of the I.T. bubble, which is an indication of the abnormally high volatility for the global momentum proxy during the drift. In fact, the long-only TSA strategy invests heavily in the global momentum proxy in the late 1990s prior to the significant drift of the global momentum proxy.

Another period of heavy allocations in the global momentum proxy is during the late 2000s. However, the long-only TSA strategy does not pull out its investment in momentum shares during the market crash in 2008, indicating that the global momentum proxy is more mean-variance efficient compared to the global value proxy. The global momentum proxy achieves higher returns for similar risk as the global value proxy prior to the market crash. The impact of the market crash in 2008 is not exclusive to momentum shares as it is during the burst of the information technology (I.T.) bubble in 2000, but rather a spill over phenomenon. Thus, the portfolio compositions obtained from the global long-only optimisation have failed to protect the portfolio value during the global financial crisis in 2008. The inclusion of cash in the optimisation procedure has a potential to avoid unwanted exposures in the equity market during the global financial crisis.

Figure 8.4 Time-Series Portfolio Composition of the Global Long-Only Tactical Style Allocation (TSA) Strategy with No Leverage

The global long-only TSA strategy with no leverage (exclusive of the risk-free proxy) performs style allocation in month t based on the model predictions of the Sharpe ratio-optimised portfolio compositions over the period from $t-36$ to $t-1$ using the weighted least squares technique (WLS). The model is trained monthly for the out-of-sample period from 1 January 1994 to 31 December 2008. The constituent indices for the TSA strategy includes the market proxy (MSCI World Index), the risk-free proxy (USTB3M), the global size proxy (Cap EW300), the global momentum proxy (Mom SW100) and the global value proxy (Value SW100). The long-only constraint restricts the weights of the constituent indices to stay positive and sum to 1.0 (100%). The strategy does not apply financial leverage and the financial leverage depicted by the orange trend line remains at 1.0 as the combined exposures equal to 100% of the original and reinvested capital.

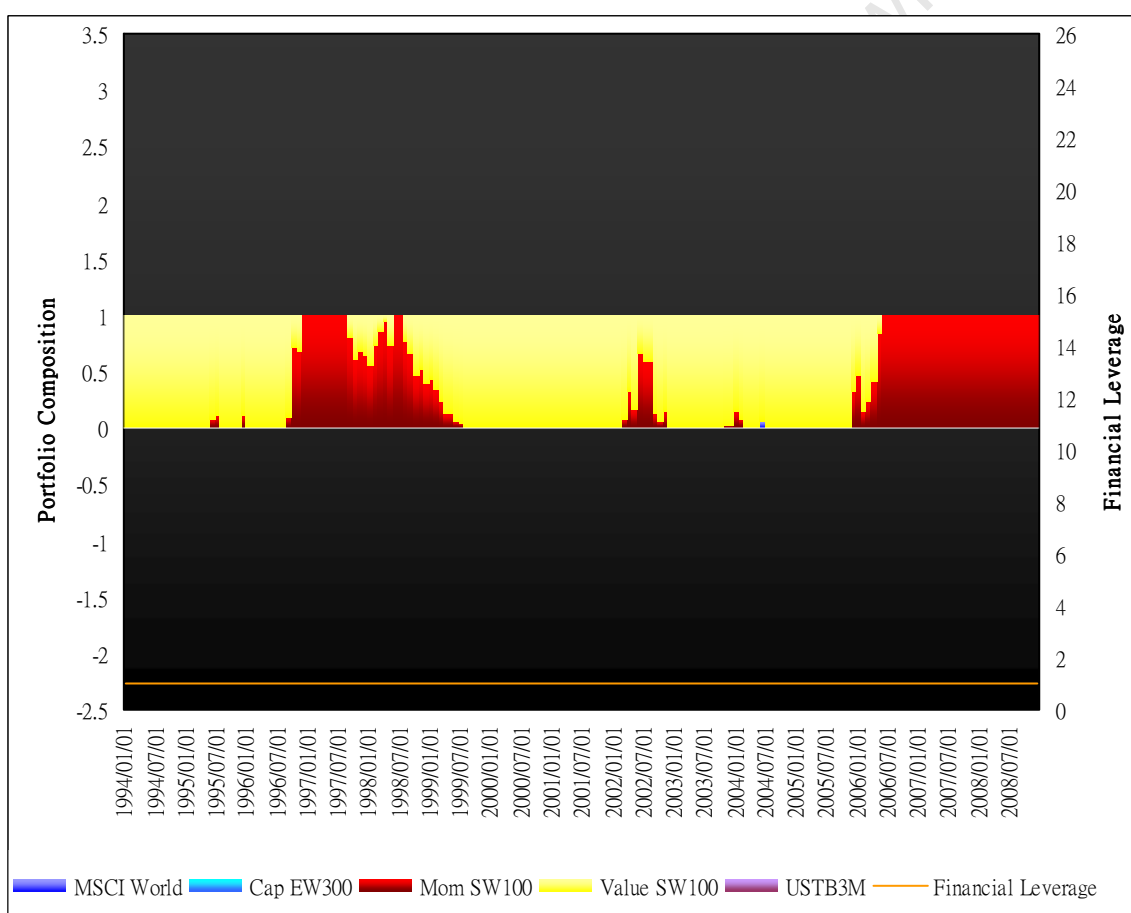


Figure 8.5 demonstrates the out-of-sample time-series portfolio composition for the global long-only TSA strategy with the inclusion of the risk-free proxy (cash) in the optimisation procedure. By incorporating the risk-free proxy in the optimisation procedure, the cash-protected long-only TSA strategy allocates significant amounts of capital to cash during major declines of the global equity markets, which includes the Asian financial crisis in 1998, the global downturn led by the crash of the I.T. bubble in early 2000s and the subprime crisis which led to the global downturn in 2007 and 2008.

The similarity between the long-only TSA strategies with and without the risk-free proxy in the optimisation procedure is that the portfolio compositions rely heavily on the global value proxy over the examination period. Although there are no major movements in the global value-momentum spread during the normal course of the economic cycle, the global value proxy is proven to be more mean-variance efficient during normal times. The global momentum proxy only plays a role in the long-only optimisation procedure closer to the peak of the global equity market. Before the relaxation of the long-only constraint, cash holding is regarded as the most mean-variance efficient allocation during economic downturns. On the other hand, the global size proxy and the MSCI World Index are regarded as less efficient investments relative to the global momentum proxy, the global value proxy and the risk-free proxy, and hence do not have active roles in the long-only optimisation procedure. The inclusion of cash in the long-only optimisation procedure has the potential to reduce the portfolio variance through diversification since the return on the risk-free proxy is not correlated with the returns of the remaining index constituents in the portfolio. Further improvements in the risk-adjusted return can be achieved by relaxing the long-only and no leverage constraints.

Figure 8.5 Time-Series Portfolio Composition of the Cash-Protected Global Long-Only Tactical Style Allocation Strategy (TSA) with No Leverage

The cash-protected global long-only TSA strategy with no leverage performs style allocation in month t based on the model predictions of the Sharpe ratio-optimised portfolio compositions over the period from $t-36$ to $t-1$ using the weighted least squares (WLS) technique. The model is trained monthly for the out-of-sample period from 1 January 1994 to 31 December 2008. The constituent indices for the TSA strategy includes the market proxy (MSCI World Index), the risk-free proxy (USTB3M), the global size proxy (Cap EW300), the global momentum proxy (Mom SW100) and the global value proxy (Value SW100). The long-only constraint restricts the weights of the constituent indices to stay positive and sum to 1.0 (100%). The strategy does not apply financial leverage and the financial leverage depicted by the orange trend line remains at 1.0, as long as the capital stays fully invested in the risky constituents (i.e. MSCI World Index, Cap EW300, Mom SW100 and Value SW100). Capital allocation in USTB3M is considered risk-free and serves to reduce the financial leverage of the strategy.

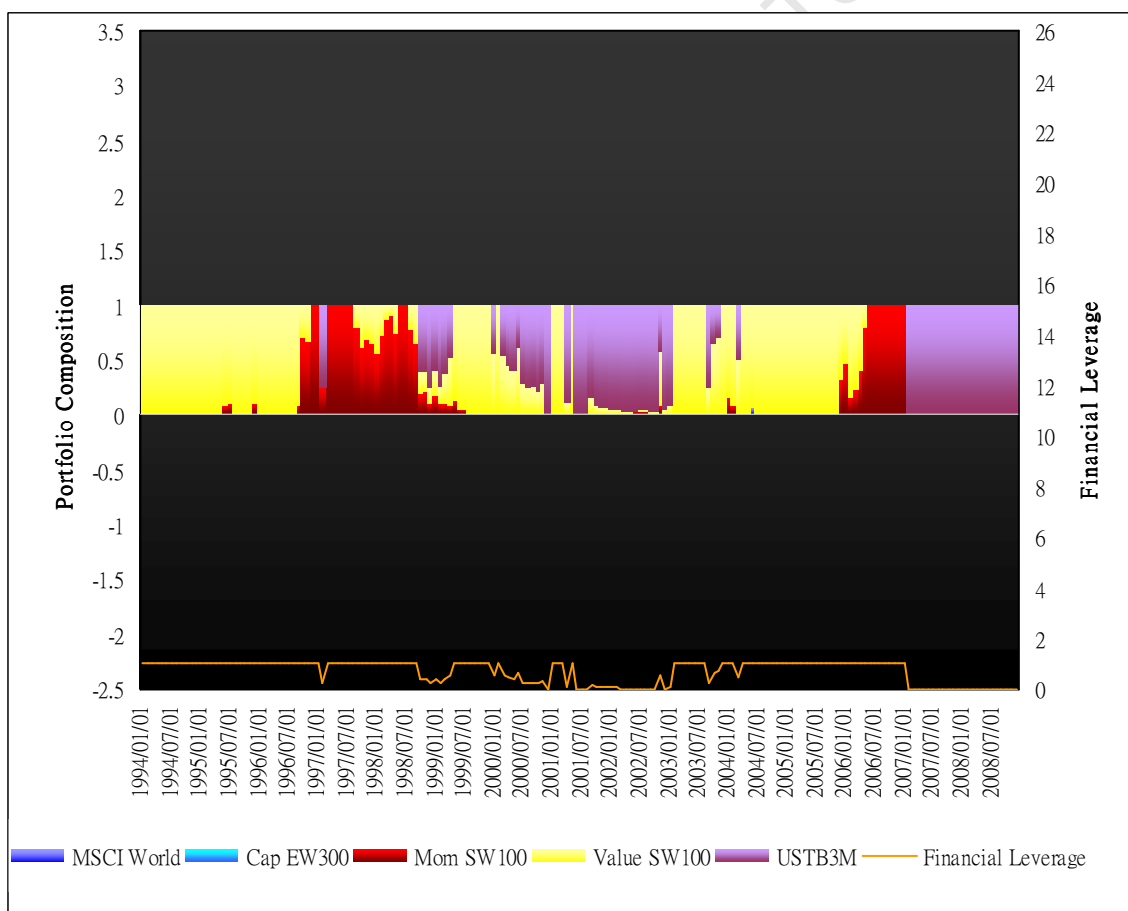


Figure 8.6 presents the out-of-sample time-series portfolio compositions for the long-short TSA strategies with 200% capped leverage. By relaxing the long-only constraint, the long-short TSA strategy is able to hedge against systematic risk by holding a short position in the MSCI World Index. To completely eliminate the systematic risk of the portfolio, yet earn a decent return above the risk-free rate, the out-of-sample optimal portfolio composition for the market neutral TSA strategy is illustrated in Figure 8.7. The relaxation of the no leverage constraint offers the long-short TSA strategy and the market neutral TSA strategy an opportunity to double their exposures to movements in the constituent indices, which effectively doubles the potentials for the return and the risk for the hedge fund TSA strategies compared to the long-only TSA strategies.

Besides the requirement that the market neutral TSA strategy must have a net exposure of zero, the allocations in the global style indices are similar for both the long-short TSA strategy and the market neutral TSA strategy. The major observation in the portfolio compositions of the two hedge fund TSA strategies is that the global size proxy plays an important role in the optimisation procedure. More specifically, the investment in the global size proxy dominates the portfolio compositions for both of the hedge fund TSA strategies during the market crash in the early 2000s and before and after the market crash in 2008. Another way of analysing this observation is that the combination of the long position in the global size proxy and the short position in the MSCI World Index partially replaces the cash protection initiated by the long-only TSA strategy. Thus, holding an equally-weighted portfolio and simultaneously selling short the cap-weighted large cap portfolio can be viewed as an alternative to holding the risk-free proxy, which has the potential to generate an absolute return above the risk-free rate during low interest rate regime.

Figure 8.6 Time-Series Portfolio Composition of the Global Long-Short Tactical Style Allocation Strategy with 200% Capped Leverage

The global long-short TSA strategy with 200% capped leverage performs style allocation in month t based on the model predictions of the Sharpe ratio-optimised portfolio compositions over the period from $t-36$ to $t-1$ using the weighted least squares (WLS) technique. The model is trained monthly for the out-of-sample period from 1 January 1994 to 31 December 2008. The constituent indices for the TSA strategy includes the market proxy (MSCI World Index), the risk-free proxy (USTB3M), the global size proxy (Cap EW300), the global momentum proxy (Mom SW100) and the global value proxy (Value SW100). The short position is only permitted in the MSCI World Index. The combined weights of the constituent indices is restricted to 1.0 (100%) using USTB3M as the balancing item. When the net weight of the risky assets (i.e. MSCI World Index and the global style proxies) is less than 100%, the excess cash is invested in USTB3M. When the net weight of the risky assets exceeds 100% of the capital, additional allocations are financed by borrowing at the risk-free rate. The 200% capped financial leverage restricts the absolute values of the weights for the risky constituents to sum to 200% of the original and reinvested capital. The exposure to USTB3M is assumed to be zero and therefore is not relevant for the 200% capped leverage constraint.

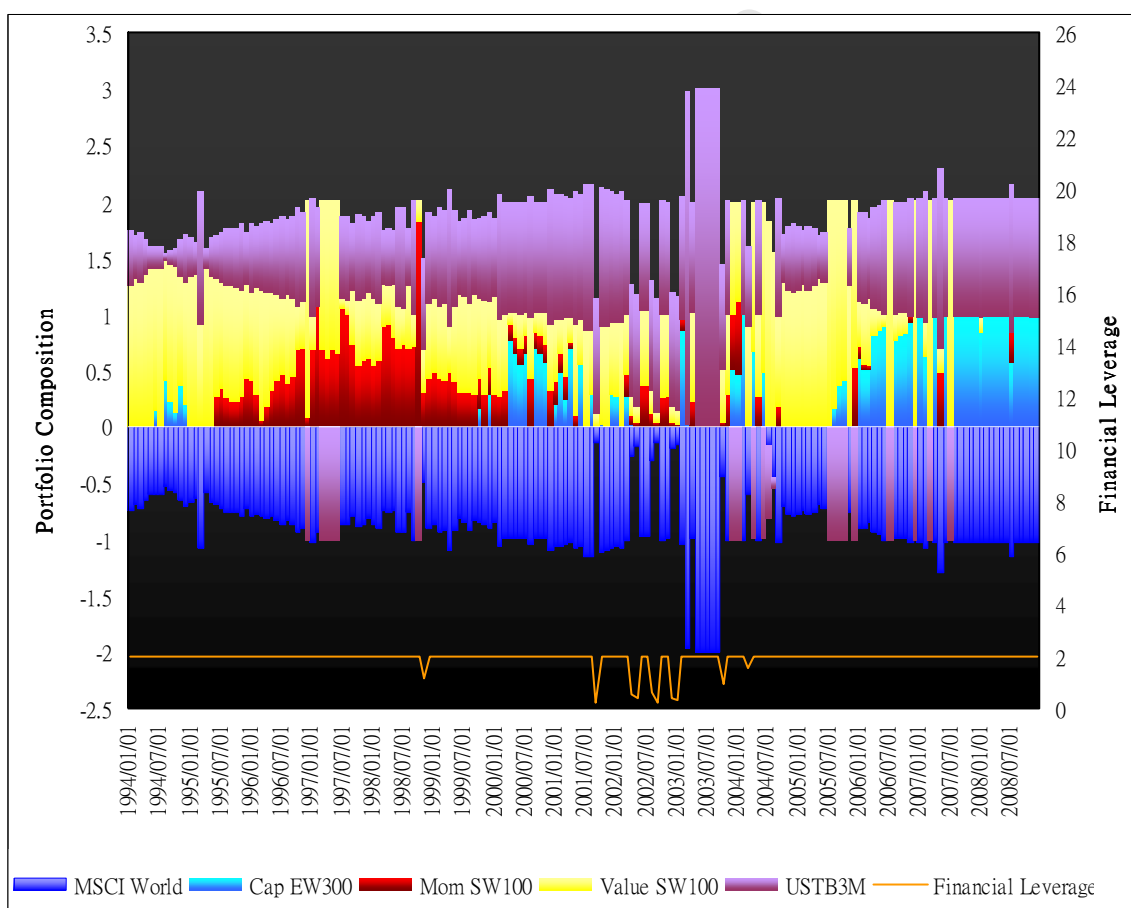
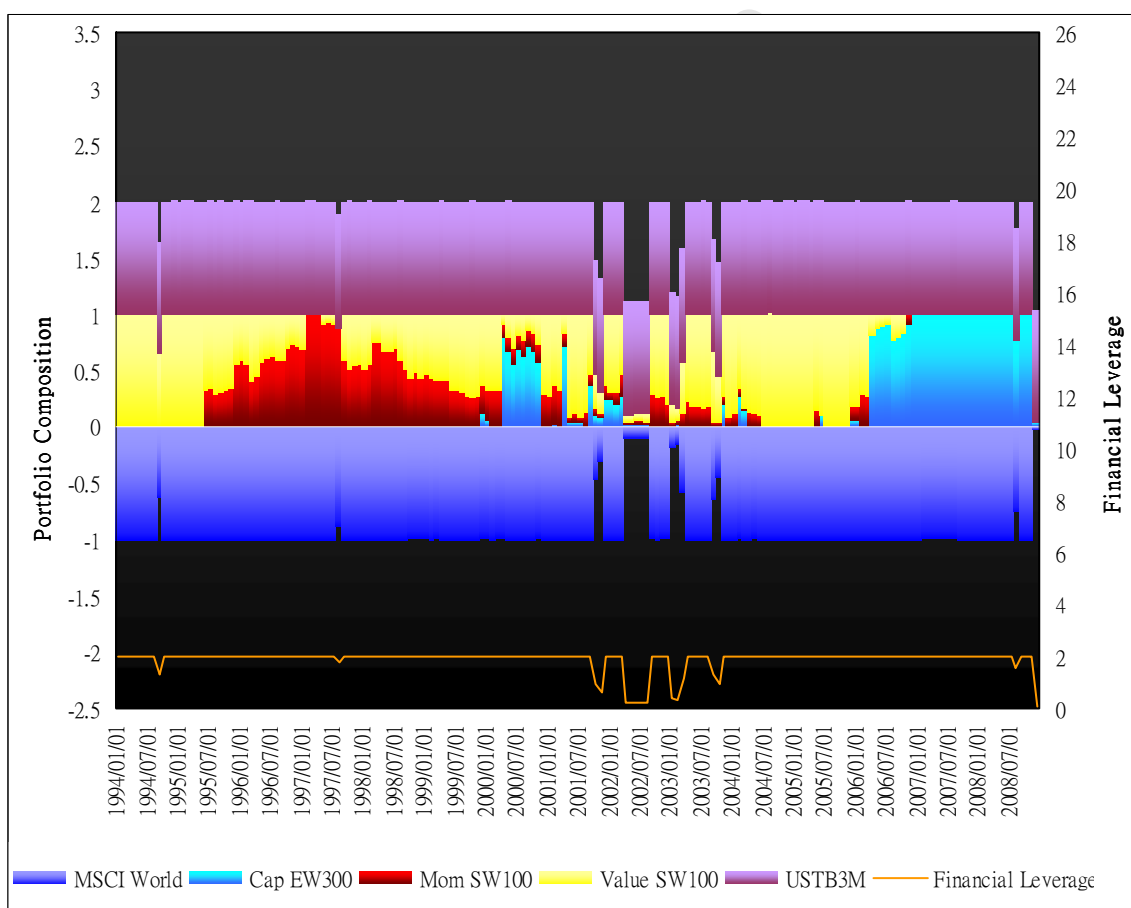


Figure 8.7 Time-Series Portfolio Composition of the Global Market Neutral Tactical Style Allocation Strategy with 200% Capped Leverage

The global market neutral TSA strategy with 200% capped leverage performs style allocation in month t based on the model predictions of the Sharpe ratio-optimised portfolio compositions over the period from $t-36$ to $t-1$ using the weighted least squares (WLS) technique. The model is trained monthly for the out-of-sample period from 1 January 1994 to 31 December 2008. The constituent indices for the TSA strategy includes the market proxy (MSCI World Index), the risk-free proxy (USTB3M), the global size proxy (Cap EW300), the global momentum proxy (Mom SW100) and the global value proxy (Value SW100). The short position is only permitted in the MSCI World Index, which is used to offset the exposures of the long positions in the global style proxies for the strategy to remain market neutral. The 200% capped financial leverage restricts the absolute values of the weights for the risky constituents to sum to 200% of the original and reinvested capital. Thus, the maximum investment in the global style proxy is equal to 100% of the original and reinvested capital as additional investments in the global style proxy will not be covered by sufficient exposures in the MSCI World Index. The investment in USTB3M is equal to 100% of the original and reinvested capital since the combined weight of the risky investments is to stay at zero at all times.



The performance statistics of the five global style timing strategies over the out-of-sample period are displayed in the right-hand side panel in Table 8.2. The left-hand side the panel of Table 8.2 displays the performance statistics of the constituent indices of the style timing strategies. The geometric return, arithmetic return, standard deviation, Sharpe ratio, Treynor measure and Jensen's alpha are annualised statistics. With the exception of the global value-momentum rotation strategy, the style timing strategies outperform their respective benchmarks on a risk-adjusted basis. Both of the long-only TSA strategies and the long-short TSA strategy achieve higher geometric return, cumulative return, arithmetic return, Sharpe ratio, Treynor measure and Jensen's alpha compared to the MSCI World market proxy and the constituent global style proxies. On the other hand, the market neutral TSA strategy with market beta as low as 0.018 earns 11.67% annualised geometric return compared to 3.86% annualised return earned by the risk-free proxy.

The annualised standard deviations and the beta coefficients for the TSA strategies decline significantly once the risk-free proxy is incorporated in the optimisation procedure. Further reductions in the beta coefficients are observed for the two hedge fund TSA strategies compared to the two long-only strategies. Although the cash-protected, long-only TSA strategy obtains higher Sharpe ratio compared to the long-short TSA strategy, the long-short TSA strategy outperforms the cash-protected, long-only TSA strategy in terms of the Treynor measure and Jensen's alpha, due to its substantially lower beta coefficient. All of the TSA strategies earn significant alpha over the out-of-sample period. The explanatory power of the market model, indicated by the *R*-squared of the regressions, declines sharply when the risk-free rate is incorporated in the optimisation procedure and also through the permission for short selling and financial leverage.

Table 8.2 Performances of the Global Style Timing Strategies

The annualised performance statistics of the market proxy (MSCI World Index), the risk-free proxy (USTB3M) and the constituent global style proxies in the optimisation procedure are demonstrated on the left-hand side of the table. The performance statistics of the global style timing strategies are demonstrated on the right-hand side of the table. The style allocations of the global style timing strategies in month t are estimated based on the outputs of the respective style timing models trained using information available from $t-36$ to $t-1$. The first in-sample (training) period is from 1 January 1991 to 31 December 1993 to predict the style allocations for 1 January 1994. The training process is repeated monthly until the style allocations for 1 December 2008 are estimated. Thus, the out-of-sample period is from 1 January 1994 to 31 December 2008 (a total of 180 months). The global style timing strategies include a value-momentum rotation strategy and 4 tactical style allocation (TSA) strategies. The value-momentum rotation strategy is designed to hold Value SW100 at the beginning of the out-of-sample period, and to switch to Mom SW100 if the macroeconomic timing model predicts the value-momentum spread is narrowing, and vice versa. The macroeconomic timing model uses the lagged 3-month growth rate in industrial production of advanced economies and the lagged 3-month U.S. dollar return relative to the currency composite of advanced economies as model inputs to predict the monthly value-momentum spread over the out-of-sample period. On the other hand, the TSA strategies are trained to predict the best style allocations monthly based on the Sharpe ratio-optimised portfolio compositions in the prior 36-month period using the weighted least squares (WLS) technique.

	Benchmarks (Constituent Indices)					Global Style Timing Strategies					
	Market Proxy Proxy	Risk-Free Proxy	Global Style Proxies			Rotation	v.s.	Tactical Style Allocation (TSA)			
	MSCI World	USTB3M	Size EW300	Mom SW100	Value SW100	Value Momentum Rotation		Long-Only TSA (USTB3M Exclusive)	Cash- Protected Long-Only TSA (USTB3M Inclusive)	L/S TSA 200% Capped Leverage	Market Neutral TSA 200% Capped Leverage
Basic Statistics:											
Geometric Return	4.99%	3.86%	7.61%	13.03%	11.91%	10.65%		14.90%	15.31%	15.32%	11.67%
Cumulative Return	2.077	1.765	3.006	6.282	5.410	4.562		8.03	8.47	8.49	5.24
Arithmetic Return	6.22%	3.86%	8.87%	15.31%	13.58%	12.36%		16.63%	16.04%	16.24%	11.85%
Standard Deviation	15.10%	0.49%	15.16%	20.15%	17.08%	17.68%		17.31%	11.40%	13.00%	5.69%
Risk-Adj. Measures											
Sharpe Ratio	7.52%	N/A	24.78%	45.53%	47.15%	38.42%		63.79%	100.43%	88.22%	137.31%
Treynor Measure	1.14%	N/A	3.87%	8.69%	8.08%	6.97%		11.20%	24.48%	52.25%	438.62%
Jensen's Alpha t -Statistic	0.00% <i>0.000</i>	N/A <i>N/A</i>	2.72% <i>1.131</i>	8.95% <i>1.298</i>	7.36% <i>1.434</i>	6.20% <i>1.950</i>		10.44% 2.508	11.07% 3.566	11.86% 3.074	7.95% 5.006
Beta	1.00	0.00	0.971	1.056	1.00	0.974		0.986	0.468	0.219	0.018
R-Squared	100%	0.00%	93.64%	62.61%	78.21%	70.28%		74.16%	37.75%	6.56%	0.25%

The relative performances of the five style timing strategies developed in this chapter are plotted against the empirical capital market line (ECML) and the empirical security market line (ESML) as illustrated in Figure 8.8 and Figure 8.9 respectively. When the risks of the portfolios are measured by standard deviation in Figure 8.8, the cash-protected, long-only TSA strategy outperforms the long-short TSA strategy. However, when the risks of the portfolios are measured by the beta coefficient in Figure 8.9, the long-short TSA strategy achieves similar returns as the cash-protected, long-only TSA strategy with much lower systematic risk. The permission for short position in the MSCI World Index significantly reduces the beta coefficient of the long-short TSA strategy.

Although the long-only TSA strategy without cash protection achieves higher return than its constituent indices, it does not benefit from the risk reduction that is available to other TSA strategies through cash protection and the short position in the market proxy. As a result, the long-only TSA strategy has approximately the same risk measured by standard deviation or beta coefficients as its constituent indices. By contrast, the market neutral TSA strategy fully utilises the financial leverage and short position in the market proxy to control its risk. The market neutral TSA strategy has the lowest risk measured by both standard deviation and beta coefficient, yet it earns approximately the same level of return as the global momentum and value indices.

Figure 8.8 Relative Performances of the Global Style Timing Strategies Measured by the Empirical Capital Market Line (ECML)

The global style timing strategies developed in this research include a value-momentum rotation strategy and 4 tactical style allocation (TSA) strategies over the out-of-sample period from 1 January 1994 to 31 December 2008. The value-momentum rotation strategy is designed to hold Value SW100 at the beginning of the out-of-sample period, and switch to Mom SW100 if the macroeconomic timing model predicts the value-momentum spread is narrowing, and vice versa. The macroeconomic timing model uses the lagged 3-month growth rate for the industrial production of advanced economies and the lagged 3-month U.S. dollar return relative to the composite currency of advanced economies as model inputs to predict the monthly value-momentum spread over the out-of-sample period. On the other hand, the TSA strategies are trained to predict the best style allocations monthly based on the Sharpe ratio-optimised portfolio compositions in the prior 36-month period using the weighted least squares (WLS) technique. The empirical capital market line (ECML) represents risk-return characteristics for asset mixes between the risk-free proxy (USTB3M) and the market proxy (MSCI World Index) over the out-of-sample period using standard deviation as the measure of risk.

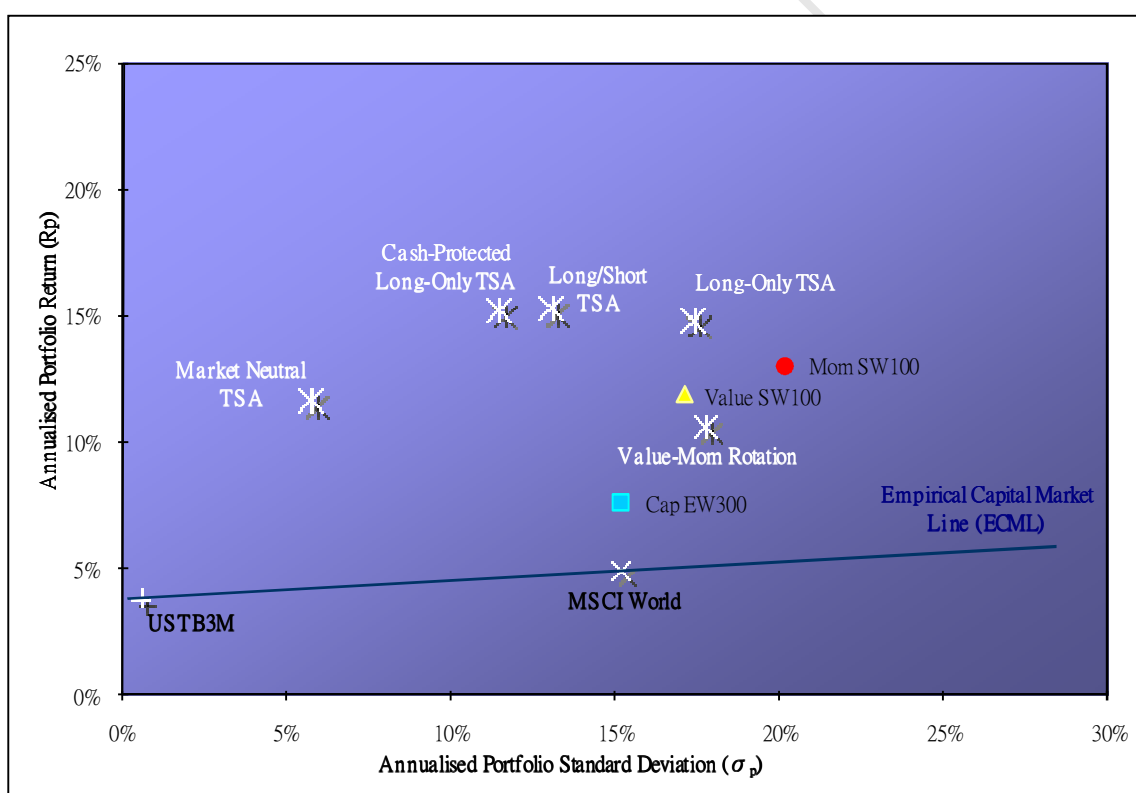


Figure 8.9 Relative Performances of the Global Style Timing Strategies Measured by the Empirical Security Market Line (ESML)

The global style timing strategies developed in this research include a value-momentum rotation strategy and 4 tactical style allocation (TSA) strategies over the out-of-sample period from 1 January 1994 to 31 December 2008. The value-momentum rotation strategy is designed to hold Value SW100 at the beginning of the out-of-sample period, and to switch to Mom SW100 if the macroeconomic timing model predicts the value-momentum spread is narrowing, and vice versa. The macroeconomic timing model uses the lagged 3-month growth rate for the industrial production of advanced economies and the lagged 3-month U.S. dollar return relative to the composite currency of advanced economies as model inputs to predict the monthly value-momentum spread over the out-of-sample period. On the other hand, the TSA strategies are trained to predict the best style allocations monthly based on the Sharpe ratio-optimised portfolio compositions in the prior 36-month period using the weighted least squares (WLS) technique. The empirical capital market line (ECML) represents the risk-return characteristics for asset mixes between the risk-free proxy (USTB3M) and the market proxy (MSCI World Index) over the out-of-sample period using the beta coefficient against the market proxy as the measure of risk.

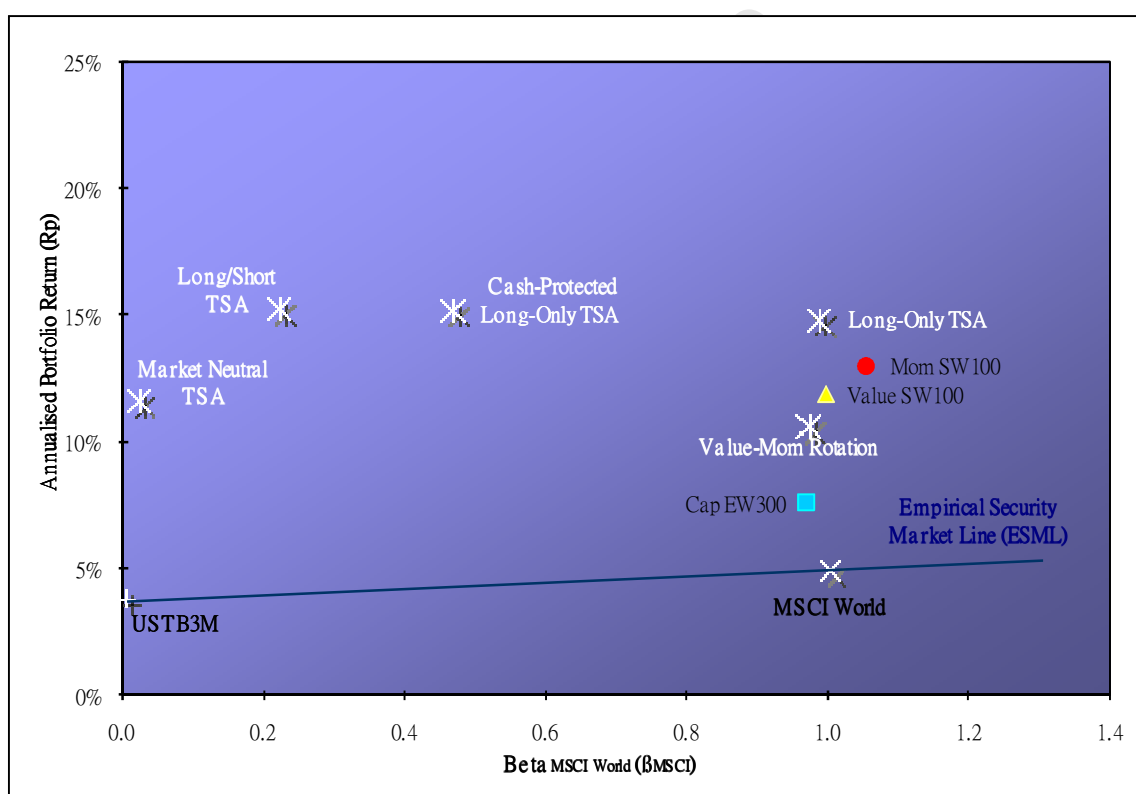
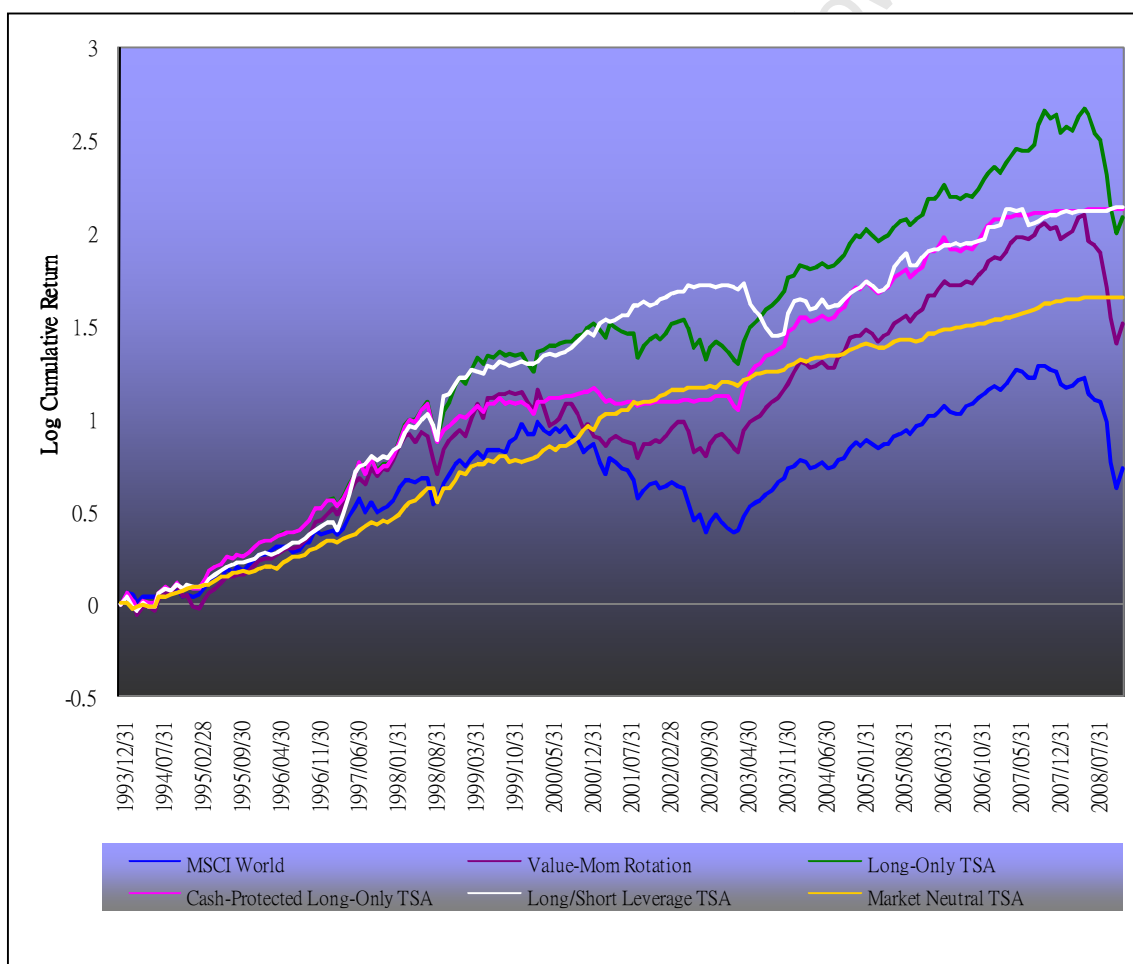


Figure 8.10 depicts the log cumulative performances of the global style timing strategies over the out-of-sample period. The cumulative performance of the MSCI World Index is also illustrated in the form of the blue trend line. The long-only TSA strategy (refer to the green trend line) and the global value-momentum rotation strategy (refer to the purple trend line) are pure long-only strategies with no cash protections. As a result, these two strategies suffer severely from the impacts of the global downturns in the early 2000s and 2008. By contrast, the cash-protected, long-only TSA strategy (refer to the pink trend line) successfully levels off during the economic downturns by switching its equity investments to cash holdings during turbulent times. On the other hand, the values of the long-short TSA strategy (refer to the white trend line) and the market neutral TSA strategy (refer to the orange trend line) continue to incline during economic downturns through the permission of short position in the MSCI World Index.

Overall, the out-of-sample performances of the TSA strategies are in line with their corresponding Sharpe-ratio optimised portfolios developed in Chapter 7, which confirms the robustness of the optimisation procedure in replicating the in-sample Sharpe ratio-optimised portfolios.

Figure 8.10 Performances of the Global Style Timing Strategies

The global style timing strategies implement their respective style allocations in month t based on outputs of the respective style timing models trained using information available from $t-36$ to $t-1$. The first in-sample (training) period is from 1 January 1991 to 31 December 1993 to predict the style allocations for 1 January 1994. The training process is updated monthly thereafter until the style allocations for 1 January 2008 are estimated. Thus, the out-of-sample period in this research is from 1 January 1994 to 31 December 2008 (a total of 180 months). The global style timing strategies include a value-momentum rotation strategy and four tactical style allocation (TSA) strategies. The value-momentum rotation strategy is designed to hold Value SW100 at the beginning of the out-of-sample period, and to switch to Mom SW100 if the macroeconomic timing model predicts the value-momentum spread is narrowing, and vice versa. The macroeconomic timing model uses the lagged 3-month growth rate for the industrial production of advanced economies and the lagged 3-month U.S. dollar return relative to the composite currency of advanced economies as model inputs to predict the monthly value-momentum spread over the out-of-sample period. On the other hand, the TSA strategies are trained to predict the best style allocations monthly based on the Sharpe ratio-optimised portfolio compositions in the prior 36-month period using the weighted least squares (WLS) technique.



8.4 Conclusion

There are five global style timing strategies developed and examined in this chapter, which includes a value-momentum rotation strategy and four tactical style allocation (TSA) strategies. The value-momentum rotation strategy that frequently switches between the two investment styles, based on the predictions of specific style timing from macroeconomic variables, is proven to be unsuccessful in generating positive abnormal returns. A possible reason for the low predictive power of the macroeconomic timing model could be due to the complex international parity relations in the global capital market. In addition, the value-momentum spread only exhibits significant movements around the major turning points of the economic cycle. In fact, the long-only TSA strategies only invest in the global momentum proxy prior to the market peaks. As a result, the global value proxy is regarded as a more mean-variance efficient investment choice compared to the global momentum proxy.

The fact that the MSCI World Index and the global size proxy do not have active roles in the long-only optimisation procedure serves as evidence that these two indices are less mean-variance efficient relative to the global momentum and value proxies. However, when the short positions and leverage are permitted in the optimisation procedure, the combinations of the long position in the global size proxy and the short position in the MSCI World Index serve as partial substitutes for the holdings in the risk-free proxy initiated by the long-only TSA strategy during economic downturns. This observation implies that the synthetic cash position created by holding the global size proxy and simultaneously selling short the MSCI World Index has the potential to beat the risk-free rate of return in turbulent times.

All of the four TSA strategies are found to outperform their constituent indices on a risk-adjusted return basis. In addition, they manage to generate statistically significant abnormal returns, as measured by Jensen's alpha, in the out-of-sample period. Introducing the risk-free proxy as the constituent in the long-only TSA optimisation procedure provides sufficient cash protection during economic downturns. The relaxation of the long-only and no leverage constraint provide further improvements in the risk-adjusted performances for the hedge fund TSA strategies. The market neutral TSA strategy not only earns competitive returns as the global momentum and value proxies, it also has substantially below-average standard deviation and close-to-zero beta coefficient. Thus, the market neutral TSA strategy is essentially a strategy that generates equity-like return with bond-like risk. With the short position in the MSCI World Index and application of financial leverage, the long-short TSA strategy and the market neutral strategy both manage to accumulate returns during the economic downturns in the early 2000s and 2008 as opposed to simple cash protection initiated by the long-only TSA strategy.

In conclusion, the risk-return characteristics of the TSA strategies are in line with the risk-return characteristics of their corresponding Sharpe ratio-optimised portfolios developed in Chapter 7. This finding confirms that the optimisation procedure using the weighted least squares (WLS) regression technique offers an effective way of replicating the performance of the hypothetical Sharpe-ratio optimised portfolios.

GLOBAL CASH PROTECTION MECHANISMS

9.1 Introduction

The global financial crisis in 2008 impacts on all asset classes, which renders diversification an ineffective mechanism for controlling downside risk. Empirical research conducted by Billio, Getmansky and Pelizzon (2009) indicates that even hedge funds that target at generating absolute returns with low levels of systematic risk have failed to cope with the global financial crisis (refer to Section 3.4). The successful downside protection of the moving average trading mechanism, devised by Faber (2009), motivates this research to develop trend-following models that provide warning signals, which trigger cash protection against expected significant drawdown in turbulent times by creating a synthetic cash position using derivative overlay.

Section 9.2 discusses the methodology of the trend-following models employed to construct cash protection strategies in this research. The cash protection strategies are tested on the global momentum proxy and the global value proxy over the examination period from 1 January 1991 to 31 December 2008. In addition, the cash protection strategies are also tested on the MSCI World Index (the market proxy) since its inception from 1 January 1970 to 31 December 2008. The examination period for the MSCI World Index is divided into two sub-periods: from 1 January 1970 to 31 December 1990; and from 1 January 1991 to 31 December 2008. The second sub-period is in line with the examination period for the two global style proxies for comparison purposes.

Section 9.3 presents the performance of the cash-protected MSCI World Index against the performance of the unprotected MSCI World Index over the two sub-periods and the entire examination period since inception. The results of the cash-protected global momentum proxy and the cash-protected global value proxy are demonstrated and discussed in section 9.4 and section 9.5 respectively.

Successful cash protection strategies should be able to preserve the value of the protected index during significant drawdown without introducing significant drag in its profits when the market rebounds. Section 9.6 summarizes and consolidates the empirical findings of and insights into the cash-protection mechanisms on the pre-specified indices over the examination periods.

9.2 Methodology and Descriptive Statistics

The trend-following models developed in this research include a strategy that applies a filter rule, based on drawdown (DD) and drawup (DU) estimated from the most recent peak and trough, and an exponential moving average (EMA) strategy, based on the crossover of the fast moving average (FMA) and the slow moving average (SMA).

Two cash protection mechanisms are tested on the pre-specified indices for each of the trend-following models: a 100% cash protection mechanism that converts the entire exposure in the index into cash using derivative overlay; and a 50% cash protection mechanism that convert half of the equity exposure into cash when the warning signal is received. The cash protection on the pre-specified indices under each of the cash protection mechanisms are lifted with full equity exposure when the waning signal is released. Thus, four cash protection strategies are developed for each of the pre-specified indices: a 100% cash protection strategy based on DD and DU; a 50% cash protection strategy based on DD and DU; a 100% cash protection strategy based on the crossover of FMA and SMA; and a 50% cash protection strategy based on the crossover of FMA and SMA.

The implementation of the cash protection mechanism is based on the lagged 1-month signal generated by the respective trend-following models. The performances of the cash-protected indices are evaluated based on the annualised geometric return, standard deviation, Sharpe ratio, 5 percent value-at-risk (VaR) and the maximum drawdown over the examination periods.

9.2.1 Trend-Following Model Based on Drawdown and Drawup

The drawdown (DD) of an investment in month t is the investment's return to date (month t) since the most recent peak of the investment's value. On the other hand, the drawup (DU) of an index in month t is defined as the return to date since the most recent market trough. The maximum tolerable drawdown filter for the global momentum proxy represents the threshold that generates the warning signal as the risk for the expected significant drawdown increases. The warning signal triggers full or partial cash protection on the pre-specified indices until the minimum required drawup filter is exceeded.

The drawdown for each of the pre-specified indices is computed monthly in order to determine whether the cash protection is needed for the coming month before significant expected drawdown impacts on the value of the index. When the cash protection is triggered by the warning signal, the drawup for the index is computed monthly in order to remove the cash protection timeously as soon as the minimum required drawup filter is exceeded.

The permutations of the maximum tolerable DD filter that triggers cash protection and the minimum required DU filter that lifts the cash protection are simulated from 0% to 50% at a 5% interval. The permutations of DD and DU that maximise the Sharpe ratios of the respective strategies over the examination periods are extracted with their performances evaluated based on the annualised geometric return, standard deviation, Sharpe ratio, 5 percent value-at-risk (VaR) and maximum drawdown over the examination periods.

9.2.2 Exponential Moving Average Trend-Following Model

The exponential moving average trend-following model generates signals based on the crossover of the fast moving average (FMA) and the slow moving average (SMA) computed from the pre-specified indices. The FMA and SMA are exponential moving average series (EMA) that allocate greater weights to recent observations by reducing the weight for each of the older observation exponentially.

The FMA and SMA of index i in month t are computed using Equation 9.1 and Equation 9.2 respectively:

$$FMA_{i,t} = x\% \times Index_{i,t} + (1 - x\%) \times FMA_{i,t-1} \quad \dots\dots\dots (9.1)$$

$$SMA_{i,t} = y\% \times Index_{i,t} + (1 - Y\%) \times SMA_{i,t-1} \quad \dots\dots\dots (9.2)$$

Where:

- $Index_{i,t}$ is the index value of the unprotected index i in month t ;
- $x\%$ represents the speed at which the FMA tracks the current value of index i ; and
- $y\%$ represents the speed at which the SMA tracks the current value of index i .

The FMA in month t allocates $x\%$ of the value to the current underlying index value in month t and $(1-x)\%$ of the value to the FMA value in month $t-1$. On the other hand, the SMA in month t is calculated as $y\%$ of the current underlying index value plus $(1-y)\%$ of the SMA value in month $t-1$. Thus, the $x\%$ and $y\%$ represent the speed at which the FMA and SMA track the current value of the underlying index. For the FMA to represent faster moving average series relative to the SMA, the weight

allocation of the FMA to the current underlying index value ($x\%$) has to be greater than the weight allocation of the SMA to the current underlying index value ($y\%$). When the FMA breaks through the SMA from above, the warning signal is generated and the exposure in the underlying index is converted to cash or partial cash in the coming month until the FMA breaks through the SMA from below.

The permutations of the rates at which the FMA and the SMA track the underlying index value are simulated from 0% to 100% at a 10% interval over the examination periods. The best permutations of $x\%$ and $y\%$ for the respective cash protection strategies over the examination periods are extracted with their performances evaluated based on the annualised geometric return, standard deviation, Sharpe ratio, 5 percent VaR and maximum drawdown over the examination periods.

9.3 Results: Cash-Protected MSCI World Index

The complete performance statistics for all permutations of the maximum tolerable DD threshold and the minimum required DU threshold under the 100% cash protection mechanism and the 50% cash protection mechanism for the first sub-period from 1970 to 1990 are demonstrated in Appendix H.1 and Appendix H.2 respectively. On the other hand, Appendix I.1 and Appendix I.2 demonstrate the results for all of the permutations of the rates at which the FMA and SMA track the MSCI World Index under the respective 100% cash protection mechanism and the 50% cash protection mechanism, over the first sub-period. Table 1 through Table 7 in each appendix present the heat map regarding the annualised geometric return, standard deviation, 5 percent VaR, Sharpe ratio, percentage of months in partial cash, maximum drawdown and number of signals generated for each permutation in the table. The optimal historical permutation that maximises the Sharpe ratio for the strategy presented in each appendix is highlighted in the thick box border in each table of the appendix.

Examining the heat maps for the filter rule strategy over the first sub-period presented in Appendix H.1 and H.2 reveals that the Sharpe ratios under the 100% and 50% cash protection mechanisms are maximised when the maximum tolerable DD is set at -5% with the minimum required DU is set at 5%. This permutation optimises the Sharpe ratios at 38.26% and 32.70% for the 100% and 50% cash protection mechanisms respectively. The low thresholds for the maximum tolerable DD and the minimum required DU result in approximately 24.10% of months in cash, with cash protection being triggered 13 times in the first sub-period, which is just slightly lower than 15 times (the highest frequency) triggered when the maximum tolerable DD and the minimum required DU are set at -5% and 0% respectively. Similar phenomenon is

observed in the heat maps for the EMA strategy over the first sub-period in that the Sharpe ratio is optimised with cash protection triggered 47 times in the period, which is the second highest frequency among all permutations for the EMA strategy (refer to Appendix H.3 and Appendix H.4). The sensitive in- and out-of-cash signals are due to the fact that the Sharpe ratio-optimised permutation requires the FMA (100%) and SMA (80%) to track each other closely at all times.

The high frequency of cash protection required for the first sub-period is not robust in the second sub-period from 1991 to 2008. The results for the second sub-period are demonstrated in Appendix I. The heat maps in Appendix I.1 and Appendix I.2 indicate that the Sharpe ratios for the 100% and 50% cash-protection mechanisms are maximised when -15% maximum tolerable DD and 10% minimum required DU are used. On the other hand, the heat maps in Appendix I.3 and Appendix I.4 indicate that the Sharpe ratios for the 100% and 50% cash-protection mechanisms are maximised when FMA and SMA are set at 30% and 20% respectively. The cash protections based on these permutations are triggered only twice and 5 times for the filter rule strategy and the EMA strategy respectively.

When the permutations of the optimal DD (-5%) and DU (5%) for the filter rule strategy in the first sub-period are applied to the second sub-period, the Sharpe ratios actually turn negative for both the 100% and 50% cash protection mechanisms. Similarly, when the FMA and SMA are set at 100% and 80% for the second sub-period, the Sharpe ratios for the 100% and 50% cash protection mechanisms are coloured in green in the respective heat maps, yielding one of the worst Sharpe ratios amongst the permutations. On the contrary, when the best permutations of the filter rule strategy and the best EMA strategy in the second sub-period are applied to the

first sub-period, the Sharpe ratios are highlighted in orange and not far from the best permutations in the first sub-period. These observations suggest that the best permutations for both the filter rule strategy and the EMA strategy extracted from the second sub-period are more robust compared to the best permutations extracted from the first sub-period. In addition, the heat maps in Appendix H (first sub-period) are more scattered compared to the heat maps in Appendix I (second sub-period), which suggests that the results obtained from the second sub-period are more reliable relative to the results obtained from the first sub-period. These findings are confirmed by the consolidated results over the entire examination period from 1970 to 2008 displayed in Appendix J, where the best permutations extracted from the second sub-period for both the filter rule strategy and the EMA strategy maximise the Sharpe ratios for the respective strategies.

The summarised performance statistics for the cash protection strategies based on the best permutations are presented in Table 9.1. Panel (a) and Panel (b) of the table display the results for the first and second sub-periods respectively. The result of the entire examination period is displayed in Panel (c). No significant improvements in the performances of the optimal cash protection strategies are detected in the first sub-period (refer to Panel (a)). By contrast, the Sharpe ratios for the cash protection strategies are more than double the Sharpe ratio for the unprotected MSCI World Index in the second sub-period (refer to Panel (b)). The low-frequency, high-performance of the cash protection strategies in the second sub-period, in contrast to the high-frequency, low-performance of the cash protection strategies in the first sub-period, suggests that the trend-following models developed in this research are more efficient in protecting the value of MSCI World Index over the first sub-period compared to the second sub-period. Nevertheless, the downside risk of the

cash protection strategies in terms of the standard deviation, 5 percent VaR and maximum drawdown are effectively reduced over the two sub-periods (refer to Panel (a) and Panel (b) and the entire examination period (refer to Panel (c)).

Table 9.1 Performance Statistics of the Cash-Protected MSCI World Index (1970 to 2008)

Two cash protection strategies are tested on the MSCI World Index: a filter rule strategy that creates a synthetic cash/partial position based on the maximum tolerable drawdown (DD) and minimum drawup (DU) requirement (calculated as the return since the most recent trough); and an exponential moving average (EMA) strategy that creates a synthetic cash/partial cash position, based on the crossover of the fast moving average (FMA) and the slow moving average (SMA) of the MSCI World Index. Two cash protection mechanisms are implemented for each of the strategies: a 100% cash protection mechanism that converts the entire fund exposure to cash using derivative overlay; and a 50% cash protection mechanism that converts half of the equity exposure into cash when the warning signal is received. The permutations of the maximum tolerable DD that triggers cash protection and the minimum DU requirement that removes the protection are simulated from 0% to 50% at a 5% interval. On the other hand, the permutations of the rates at which the respective FMA and SMA track the underlying index are simulated from 0% to 100% at a 10% interval over the examination period. The best simulated results for the two cash protection strategies over the two sub-periods from 1 January 1970 to 31 December 1990 and from 1 January 1991 to 31 December 2008 are demonstrated in Panel (a) and Panel (b) of the table. The best simulated results for the overall examination period from 1 January 1970 to 31 December 2008 is demonstrated in Panel (c) of the table.

Panel (a) Cash-Protected MSCI World Index (1970 ~ 1990)

	Benchmark (No Protection)	Cash Protection Based on Filter Rule Strategy		Cash Protection Based on Exponential Moving Average	
	Unprotected Mom SW100	MSCI World -5% DD 5% DU 100% Cash	MSCI World -5% DD 5% DU 50% Cash	MSCI World 100% FMA 80% SMA 100% Cash	MSCI World 100% FMA 80% SMA 50% Cash
Geometric Return	11.62%	12.78%	12.30%	12.57%	12.26%
Standard Deviation	15.08%	12.60%	13.26%	10.77%	12.00%
Sharpe Ratio	24.30%	38.26%	32.70%	42.84%	35.86%
5% VaR	-5.99%	-4.33%	-4.52%	-3.36%	-4.31%
Percentage of Months in Cash/ Partial Cash	0.00%	24.07%	24.07%	35.19%	35.19%
Maximum Drawdown	-40.12%	-24.30%	-24.02%	-16.27%	-27.24%
Number of Signals	0 Times	13 Times	13 Times	47 Times	47 Times

Table 9.1 Performance Statistics of the Cash-Protected MSCI World Index (1970 to 2008) - Continued

Panel (b) Cash-Protected MSCI World Index (1991 ~ 2008)

	Benchmark (No Protection)	Cash Protection Based on Filter Rule Strategy		Cash Protection Based on Exponential Moving Average	
	Unprotected Mom SW100	MSCI World -15% DD 10% DU 100% Cash	MSCI World -15% DD 10% DU 50% Cash	MSCI World 30% FMA 20% SMA 100% Cash	MSCI World 30% FMA 20% SMA 50% Cash
Geometric Return	6.10%	10.69%	8.49%	10.71%	8.53%
Standard Deviation	14.69%	11.31%	12.30%	10.57%	11.79%
Sharpe Ratio	15.00%	60.10%	37.39%	64.53%	39.28%
5% VaR	-6.53%	-4.73%	-5.35%	-4.30%	-5.02%
Percentage of Months in Cash/ Partial Cash	0.00%	13.43%	13.43%	21.30%	21.30%
Maximum Drawdown	-48.20%	-18.81%	-33.47%	-13.45%	-31.17%
Number of Signals	0 Times	2 Times	2 Times	5 Times	5 Times

Panel (c) Cash-Protected MSCI World Index (1970 ~ 2008)

	Benchmark (No Protection)	Cash Protection Based on Filter Rule Strategy		Cash Protection Based on Exponential Moving Average	
	Unprotected Mom SW100	MSCI World -15% DD 10% DU 100% Cash	MSCI World -15% DD 10% DU 50% Cash	MSCI World 30% FMA 20% SMA 100% Cash	MSCI World 30% FMA 20% SMA 50% Cash
Geometric Return	9.04%	10.80%	10.01%	11.17%	10.22%
Standard Deviation	14.90%	12.31%	13.02%	11.68%	12.58%
Sharpe Ratio	19.95%	38.51%	30.34%	43.69%	33.00%
5% VaR	-6.26%	-5.15%	-5.46%	-4.33%	-4.96%
Percentage of Months in Cash/ Partial Cash	0.00%	12.50%	12.50%	14.35%	14.35%
Maximum Drawdown	-48.20%	-22.66%	-33.47%	-22.40%	-31.17%
Number of Signals	0 Times	9 Times	9 Times	11 Times	11 Times

Figure 9.1 and Figure 9.2 illustrate the performances of the 100% cash-protected MSCI World Index and the 50% cash-protected MSCI World Index relative to the performance of the unprotected MSCI World Index, over the examination period from 1970 to 2008 based on the best permutation of DD (-15%) and DU (10%). Chart (a) in the respective figures depict the log cumulative return of the cash-protected index (refer to the green trend line) relative to the unprotected index (refer to the red trend line). The relative strength ratio of the protected index level over the unprotected index level is represented by the purple trend line in the chart. The grey-shaded areas indicate the periods during which cash protection is activated. The relative strength ratio only inclines during the market downturn in 1994, the early 2000s and 2008. Other protected-periods are relatively short and the timing of kicking in- and out-of-cash seems to lag the actual events. However, the benefits of cash protection during major global downturns significantly outweigh the temporary inaccurate short-term timing over the prolonged examination period. This finding indicates that moderate thresholds for the maximum tolerable DD and the minimum required DU applied in the second sub-period are more appropriate than small thresholds that provide sensitive signals in the first sub-period in protecting the portfolio value. Similar results are obtained for the EMA strategy demonstrated in Figure 9.3 and 9.4, where additional benefits for cash protection are achieved during 1992.

The time-series drawdown for the protected and the unprotected indices are displayed in Chart (b) of Figure 9.1 through Figure 9.4. The drawdown of the 100% cash-protected indices is much less than the drawdown of the 50% cash-protected indices, which is in turn less than that of the unprotected MSCI World Index.

Figure 9.1 Performance of the 100% Cash-Protected MSCI World Index Based on the Filter Rule Strategy (1970 to 2008)

The 100% cash protection mechanism based on the filter rule is applied to the MSCI World Index over the period from 1 January 1970 to 31 December 2008. The strategy converts 100% of the exposure in the MSCI World Index to synthetic cash when the maximum tolerable drawdown (DD) is exceeded until the minimum drawup (DU) requirement from the most recent trough is exceeded. The best permutation for the filter rule strategy (-15% DD and 10% DU) is illustrated in this figure. Chart (a) depicts the time-series cash holding, the log cumulative returns for MSCI World Index, with and without cash protection, and the performance of the cash-protected MSCI World Index relative to the performance of the unprotected MSCI World Index. Chart (b) depicts the time-series drawdown for the MSCI World Index, with and without cash protection, over the examination period.

Chart (a) Relative Strength of the Cash-Protected MSCI World Index

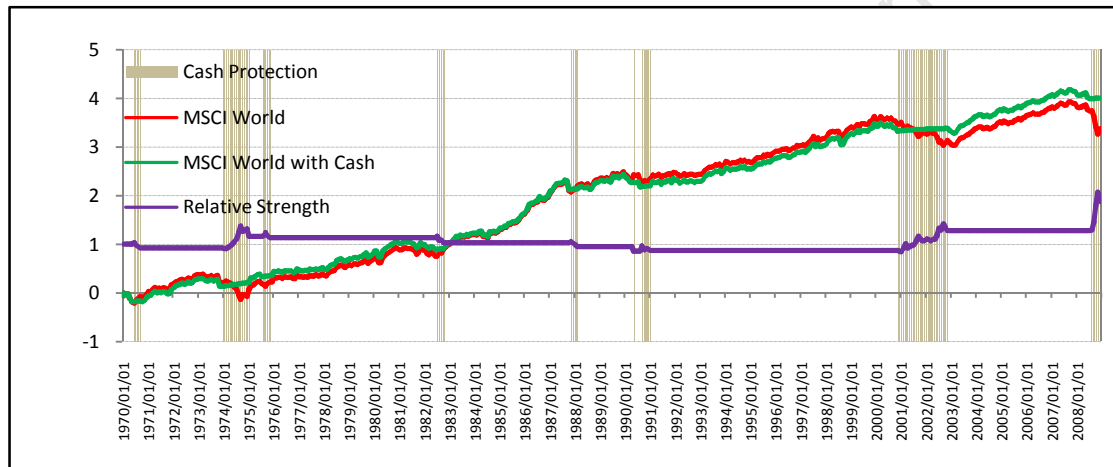


Chart (b) Time-Series Drawdown of the Cash-Protected MSCI World Index

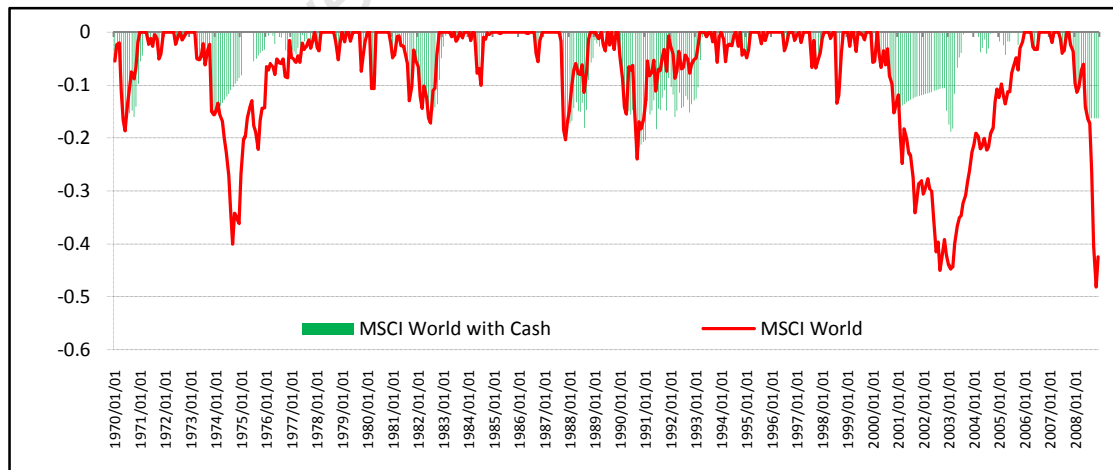


Figure 9.2 Performance of the 50% Cash-Protected MSCI World Index Based on the Filter Rule Strategy (1970 to 2008)

The 50% cash protection mechanism based on the filter rule is applied to the MSCI World Index over the period from 1 January 1970 to 31 December 2008. The strategy converts 50% of the exposure in the MSCI World Index to synthetic cash when the maximum tolerable drawdown (DD) is exceeded until the minimum drawup (DU) requirement from the most recent trough is exceeded. The best permutation for the filter rule strategy (-15% DD and 10% DU) is illustrated in this figure. Chart (a) depicts the time-series cash holding, the log cumulative returns for MSCI World Index with and without cash protection and the performance of the cash-protected MSCI World Index relative to the performance of the unprotected MSCI World Index. Chart (b) depicts the time-series drawdown for the MSCI World Index, with and without cash protection, over the examination period.

Chart (a) Relative Strength of the Cash-Protected MSCI World Index

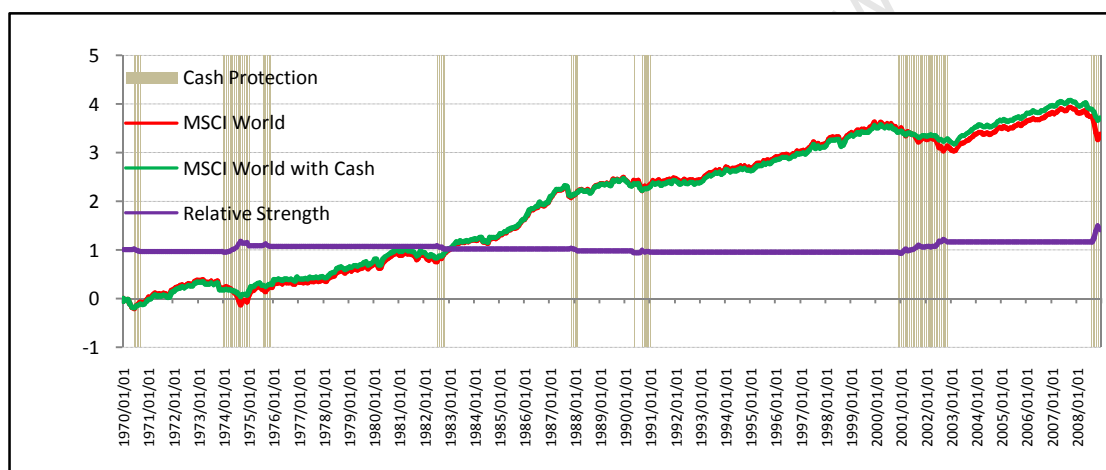


Chart (b) Time-Series Drawdown of the Cash-Protected MSCI World Index

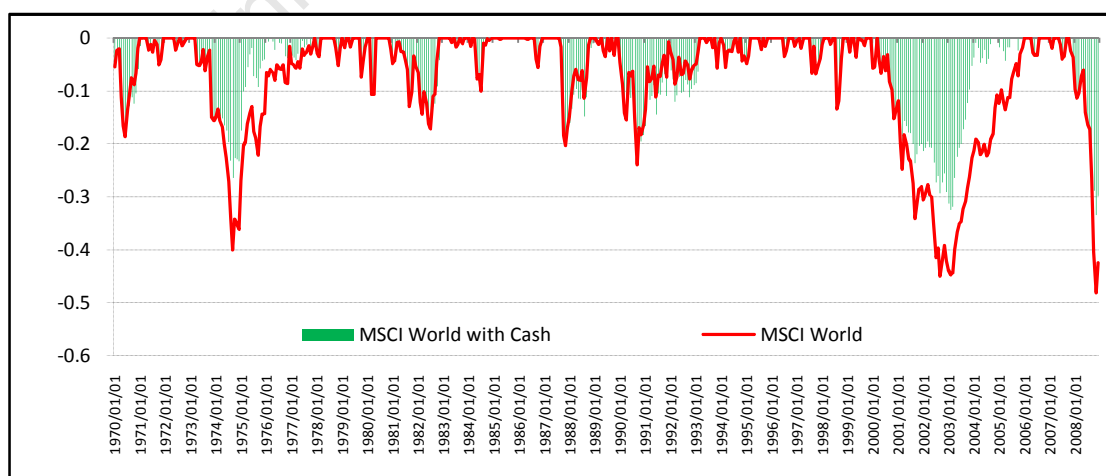


Figure 9.3 Performance of the 100% Cash-Protected MSCI World Index Based on the Exponential Moving Average (EMA) Strategy (1970 to 2008)

The 100% cash protection mechanism is applied to the MSCI World Index over the period from 1 January 1970 to 31 December 2008. The strategy converts the entire exposure in the MSCI World Index to synthetic cash when the fast moving average (FMA) breaks through the slow moving average (SMA) of the MSCI World Index from above until the SMA breaks through the FMA from below. The best permutation over the examination period (30% FMA and 20% SMA) is illustrated in this figure. Chart (a) depicts the time-series cash holding, the log cumulative returns for the MSCI World Index, with and without cash protection, and the relative performance between the MSCI World Index, with and without cash protection. Chart (b) depicts the time-series drawdown for the MSCI World Index, with and without cash protection, over the examination period.

Chart (a) Relative Strength of the Cash-Protected Global MSCI World Index

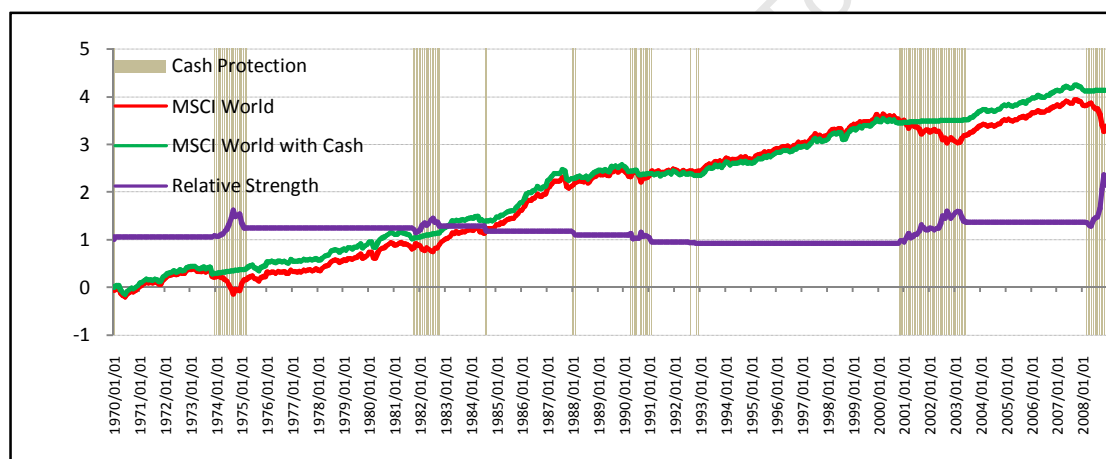


Chart (b) Time-Series Drawdown of the Cash-Protected MSCI World Index

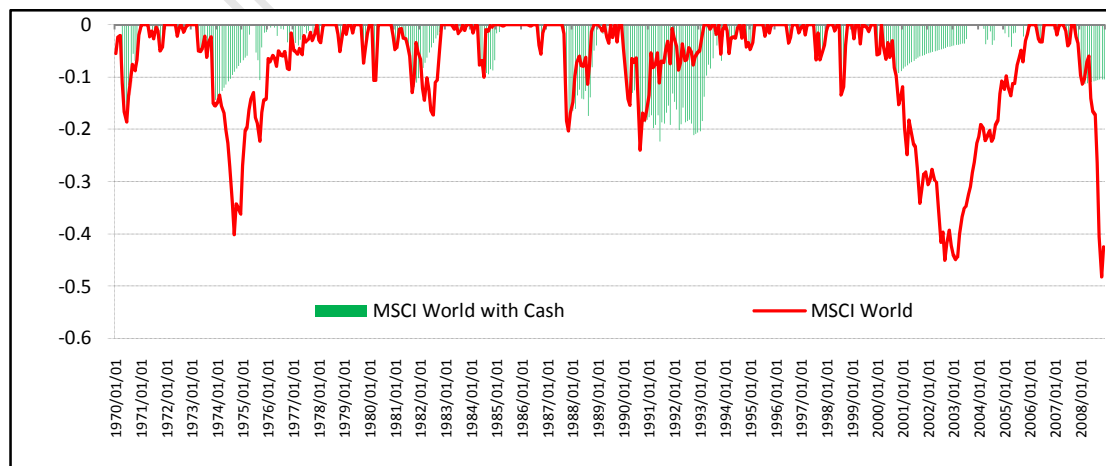


Figure 9.4 Performance of the 50% Cash-Protected MSCI World Index Based on the Exponential Moving Average (EMA) Strategy (1970 to 2008)

The 50% cash protection mechanism is applied to the MSCI World Index over the period from 1 January 1970 to 31 December 2008. The strategy converts 50% of the exposure in the MSCI World Index to synthetic cash when the fast moving average (FMA) breaks through the slow moving average (SMA) of the MSCI World Index from above until the SMA breaks through the FMA from below. The best permutation over the examination period (30% FMA and 20% SMA) is illustrated in this figure. Chart (a) depicts the time-series cash holding, the log cumulative returns for the MSCI World Index, with and without cash protection, and the relative performance between the MSCI World Index, with and without cash protection. Chart (b) depicts the time-series drawdown for the MSCI World Index, with and without cash protection, over the examination period.

Chart (a) Relative Strength of the Cash-Protected MSCI World Index

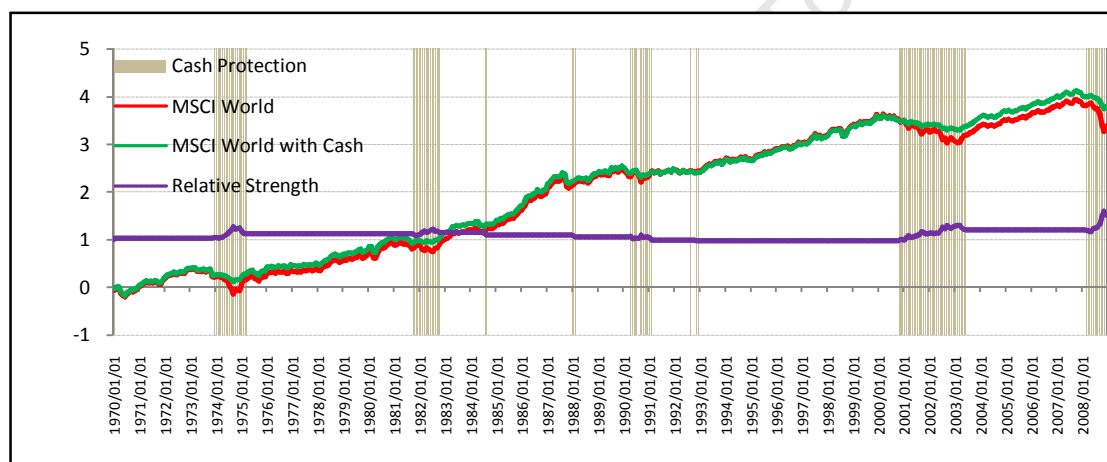
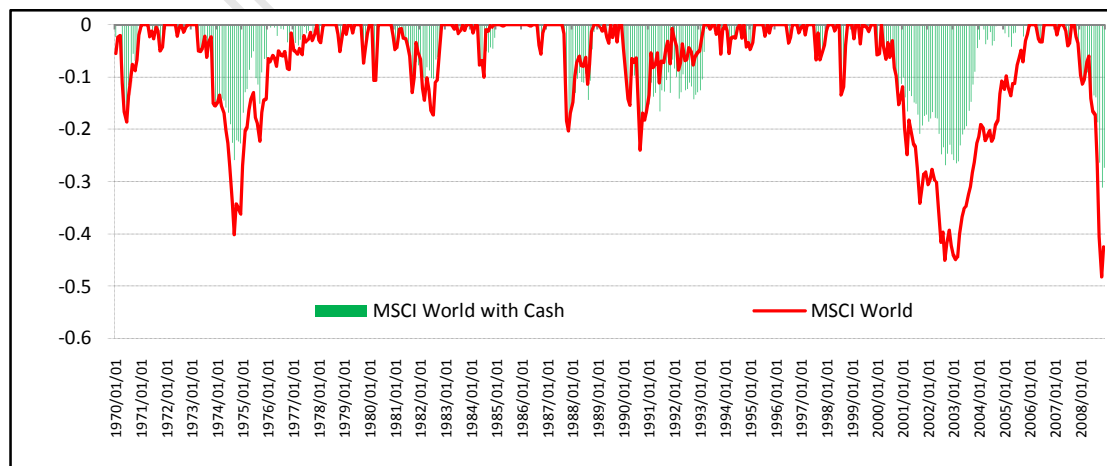


Chart (b) Time-Series Drawdown of the Cash-Protected MSCI World Index



9.4 Results: Cash-Protected Global Momentum Proxy

The performance statistics for the 100% and 50% cash-protected global momentum proxy based on the filter rule strategy are presented in Appendix K.1 and Appendix K.2 respectively. In line with the performance results of the cash-protected MSCI World Index, the best permutations for the filter rule strategy that maximise the Sharpe ratio over the period from 1991 to 2008 is when the maximum tolerable DD and the minimum required DU are set at -15% and 10% respectively. This permutation triggers cash protection 5 times, which results in 33.80% of the months in synthetic cash. Examining the heat map for the 100% and 50% cash protection mechanism in Appendix K.1 and Appendix K.2 indicates that the annualised Sharpe ratio of the global momentum proxy can be improved by keeping the maximum tolerable DD between -10% and -30% and the minimum required DU below 30%. If the objective is to improve the annualised Sharpe ratio with higher annualised geometric return, the maximum tolerable DD has to be narrowed down to be in between -15% and -30% with the minimum required DU kept below 15%.

The results for the 100% and 50% cash-protected global momentum proxy based on the EMA strategy are demonstrated by Appendix K.3 and K.4 respectively. Compared to the best permutation for the cash-protected EMA strategy on the MSCI World Index that sets the FMA 1.5 times of the SMA (30% FMA and 20% SMA), the Sharpe ratio for the cash-protected global momentum proxy is maximised when the FMA is set 4 times of the SMA (80% FMA and 20%). This permutation triggers cash protection 9 times over the examination period. Examining the heat maps in Appendix K.3 and K.4 indicates that the annualised Sharpe ratio can be improved for almost all permutations of FMA and SMA. However, if the objective is to earn higher

annualised geometric returns, the FMA has to be kept above 40% with their corresponding SMA lower than 60%.

With regard to downside risk management, as long as there is some sort of cash protection, the portfolio standard deviation, 5 percent VaR and the maximum drawdown are reduced over the examination period. However, in order to protect downside risk without sacrificing the upside return potential, the range of maximum tolerable DD and the minimum required DU based on the filter rule strategy, and the range of FMA and SMA based on the EMA trend-following model, have to be maintained in the desired optimal range discussed above.

The performance statistics of the cash-protected momentum strategies based on the best permutations of the maximum tolerable DD and the minimum required DU based on the filter rule strategy, and the best permutation of the FMA and SMA based on the EMA strategy, over the examination period are displayed in Table 9.1. As shown in the table, the best permutation for the filter rule strategy is represented by -10% maximum tolerable DD and 15% minimum required DU, and the best permutation for the EMA strategy is represented by 80% FMA and 20% SMA respectively. With 33.80% of the months in cash/partial cash, the annualised geometric return, standard deviation and maximum drawdown for the filter rule strategy are lower than they are for the EMA strategy with 21.76% of the months in cash/partial cash. However, the cash protection for the filter rule strategy is only triggered 5 times compared to 9 times warning signals generated for the EMA strategy. This observation serves as an indication that the best filter rule strategy over the examination period is less sensitive in kicking in- and out-of-cash than the best EMA strategy.

The 100% cash protection mechanism is better than the 50% cash protection mechanism in terms of the risk, return and risk-adjusted return for both the filter rule strategy and the EMA strategy. The performances of the cash-protected global momentum indices constructed by the filter rule and the EMA strategies are comparable, and they outperform the MSCI World Index and the unprotected global momentum proxy in terms of the risk, return and risk-adjusted return.

Table 9.2 Performance Statistics of the Cash-Protected Global Momentum Proxy (1991 to 2008)

Two cash protection strategies are tested on the global momentum proxy (Mom SW100) over the period from 1 January 1991 to 31 December 2008: a filter rule strategy that creates a synthetic cash/partial position based on the maximum tolerable drawdown (DD) and minimum drawup (DU) requirement (calculated as the return since the most recent trough); and an exponential moving average (EMA) strategy that creates a synthetic cash/partial cash position based on the crossover of the fast moving average (FMA) and the slow moving average (SMA) of Mom SW100. Two cash protection mechanisms are implemented for each of the strategies: a 100% cash protection mechanism that converts the entire fund exposure to cash using derivative overlay; and a 50% cash protection mechanism that converts half of the equity exposure into cash when the warning signal is received. The permutations of the maximum tolerable DD that triggers cash protection and the minimum DU requirement that removes the protection are simulated from 0% to 50% at a 5% interval. On the other hand, the permutations of the rates at which the respective FMA and SMA track the underlying index are simulated from 0% to 100% at a 10% interval over the examination period. The best simulated results for the two cash protection strategies are demonstrated in this table.

	Benchmarks (No Protection)		Cash Protection Based on Filter Rule Strategy		Cash Protection Based on Exponential Moving Average	
	MSCI World	Unprotected Mom SW100	Mom SW100 -10% DD 15% DU 100% Cash	Mom SW100 -10% DD 15% DU 50% Cash	Mom SW100 80% FMA 20% SMA 100% Cash	Mom SW100 80% FMA 20% SMA 50% Cash
Geometric Return	6.10%	14.77%	17.64%	16.39%	18.35%	16.70%
Standard Deviation	14.69%	18.96%	15.06%	16.16%	15.84%	16.73%
Sharpe Ratio	15.00%	57.35%	91.28%	77.35%	91.24%	76.58%
5% VaR	-6.53%	-8.10%	-5.59%	-6.61%	-6.24%	-6.90%
Percentage of Months in Cash/ Partial Cash	0.00%	0.00%	33.80%	33.80%	21.76%	21.76%
Maximum Drawdown	-48.20%	-48.76%	-18.37%	-30.84%	-19.59%	-32.25%
Number of Signals	0 Times	0 Times	5 Times	5 Times	9 Times	9 Times

Figure 9.5 and Figure 9.6 illustrate the performances of the 100% cash-protected global momentum index and the 50% cash-protected global momentum index, relative to the performance of the unprotected global momentum global proxy over the examination period. The cash-protected global momentum indices are constructed from the best permutation of the maximum tolerable DD (15%) and the minimum required DU (10%) over the examination period. The cash-protected momentum indices in Figure 9.5 and Figure 9.6 kick into cash from 1994 to 1995, late 1998, early 2000s, 2005 and 2008. However, the relative strength ratio represented by the green trend line indicates that the cash protection mechanism only successfully enhances the value of the protected index relative to the value of the unprotected index during the major global downturn in the early 2000s and during the global financial crisis in 2008. Similar to the findings from the cash-protected MSCI Index, the timing of triggering and lifting cash protection seems to be inaccurate during relatively shorter periods of uncertainty. Overall, the protection of the index value during major financial market turmoil overrides the cost of small timing errors.

The time-series drawdown for the protected and the unprotected indices and the MSCI World Index are demonstrated in Chart (b) of Figure 9.1 and Figure 9.2. The drawdown of the 100% cash-protected strategy is much less than the drawdown of the 50% cash-protected strategy, which is, in turn, less than the unprotected global momentum proxy and the MSCI World Index.

Figure 9.5 Performance of the 100% Cash-Protected Global Momentum Proxy Based on the Filter Rule Strategy (1991 to 2008)

The 100% cash protection mechanism based on the filter rule is applied to the global momentum proxy (Mom SW100) over the period from 1 January 1991 to 31 December 2008. The strategy converts the entire exposure in Mom SW100 to synthetic cash when the maximum tolerable drawdown (DD) is exceeded until the minimum drawup (DU) requirement from the most recent trough is exceeded. The best permutation for the filter rule strategy (-10% DD and 15% DU) is illustrated in this figure. Chart (a) depicts the time-series cash holding, the log cumulative returns for Mom SW100, with and without cash protection and the performance of the cash-protected Mom SW100 relative to the performance of the unprotected Mom SW100. Chart (b) depicts the time-series drawdown for Mom SW100, with and without cash protection and the MSCI World Index over the examination period.

Chart (a) Relative Strength of the Cash-Protected Global Momentum Proxy

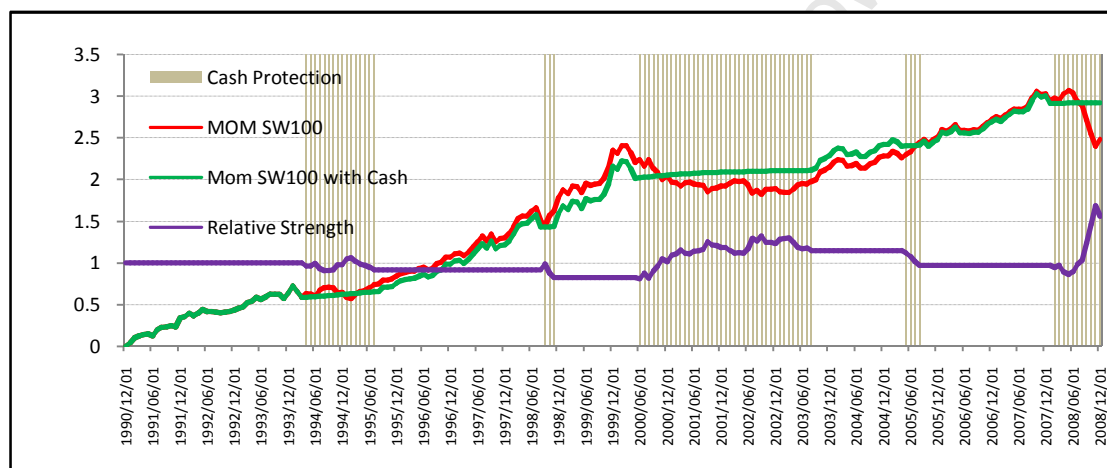


Chart (b) Time-Series Drawdown of the Cash-Protected Global Momentum Proxy

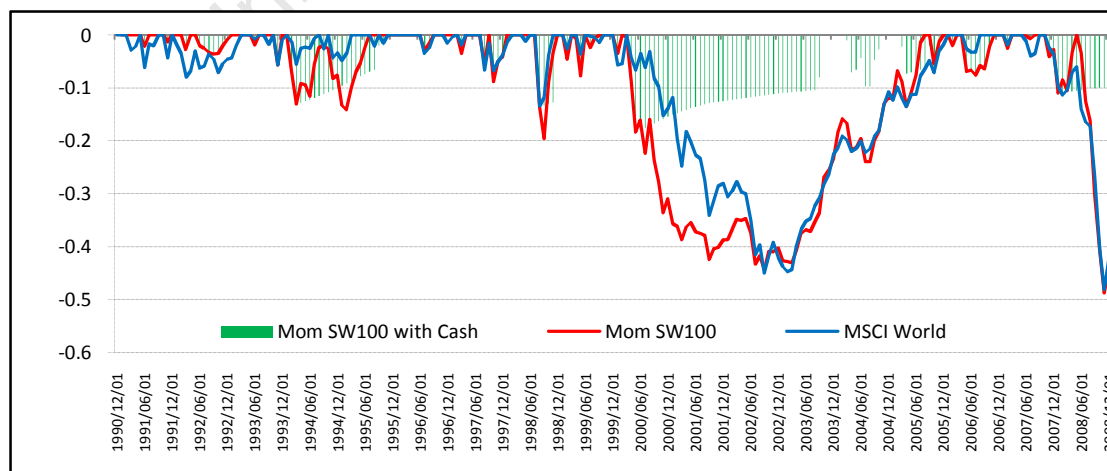


Figure 9.6 Performance of the 50% Cash-Protected Global Momentum Proxy Based on the Filter Rule Strategy (1991 to 2008)

The 50% cash protection mechanism based on the filter rule is applied to the global momentum proxy (Mom SW100) over the period from 1 January 1991 to 31 December 2008. The strategy converts 50% of the exposure in Mom SW100 to synthetic cash when the maximum tolerable drawdown (DD) is exceeded until the minimum drawup (DU) requirement from the most recent trough is exceeded. The best permutation for the filter rule strategy (-10% DD and 15% DU) is illustrated in this figure. Chart (a) depicts the time-series cash holding, the log cumulative returns for Mom SW100, with and without cash protection and the performance of the cash-protected Mom SW100 relative to the performance of the unprotected Mom SW100. Chart (b) depicts the time-series drawdown for Mom SW100, with and without cash protection and the MSCI World Index over the examination period.

Chart (a) Relative Strength of the Cash-Protected Global Momentum Proxy

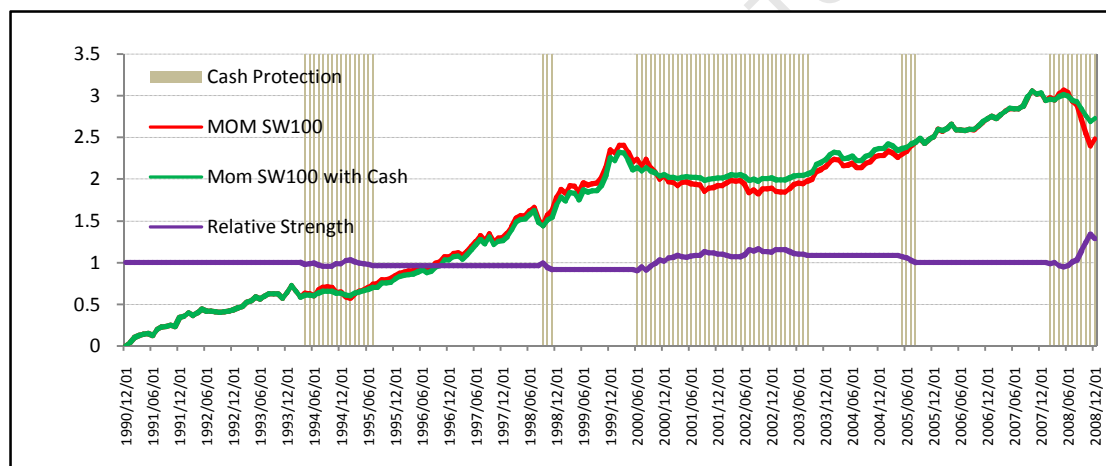


Chart (b) Time-Series Drawdown of the Cash-Protected Global Momentum Proxy

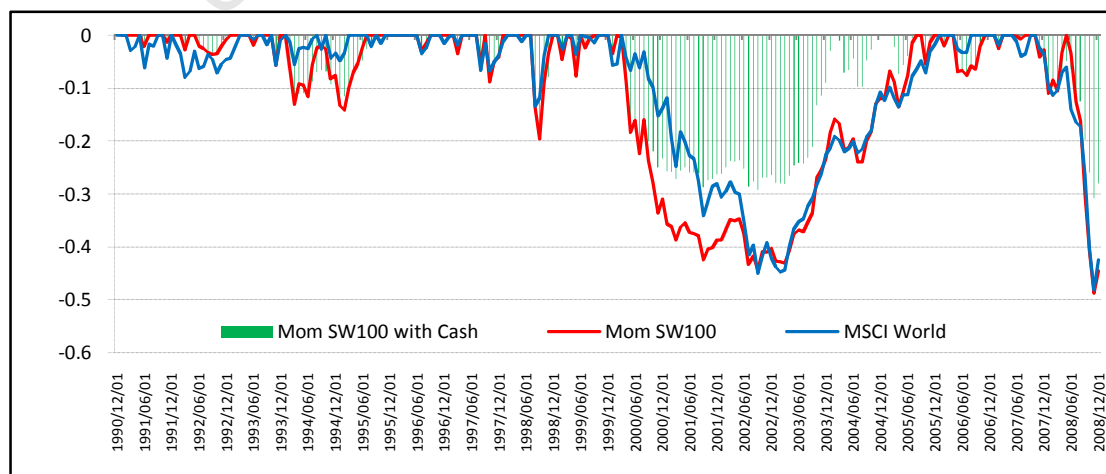


Figure 9.7 and Figure 9.8 illustrates the performance of the 100% cash-protected global momentum index and the 50% cash-protected global momentum index relative to the performance of the unprotected global momentum proxy over the examination period. The cash-protected global momentum indices are constructed from the best permutation of the rates at which the FMA (80%) and the SMA (20%) track the index value of the unprotected global momentum proxy.

As can be seen from the shaded area in Chart (A) of Figure 9.7 and Figure 9.8, the cash protection mechanism for the best EMA permutation is more sensitive than the cash protection mechanism for the filter rule strategy demonstrated in Figure 9.5 and Figure 9.6. Similar to the findings for the filter rule strategy, the cash protection for the EMA strategy is only effective during early 2000s and 2008. As can be seen in Chart (b) of Figure 9.7 and Figure 9.8, the inaccurate timing of cash protection from 1994 to 1995 and 1998 actually result in relatively greater drawdown for the cash-protected global momentum index. However, the major lifts of the relative strength ratio during major global downturn more than offset the negligible performance drag through periodic incorrect timing of the cash protection.

Figure 9.7 Performance of the 100% Cash-Protected Global Momentum Proxy Based on the Exponential Moving Average (EMA) Strategy (1991 to 2008)

The 100% cash protection mechanism is applied to the global momentum proxy (Mom SW100) over the period from 1 January 1991 to 31 December 2008. The strategy converts the entire exposure in Mom SW100 to synthetic cash when the fast moving average (FMA) breaks through the slow moving average (SMA) of Mom SW100 from above until the SMA breaks through the FMA from below. The best permutation over the examination period (30% FMA and 20% SMA) is illustrated in this figure. Chart (a) depicts the time-series cash holding, the log cumulative returns for Mom SW100, with and without cash protection and the relative performance between the Mom SW100, with and without cash protection. Chart (b) depicts the time-series drawdown for Mom SW100, with and without cash protection and the MSCI World Index over the examination period.

Chart (a) Relative Strength of the Cash-Protected Global Momentum Proxy

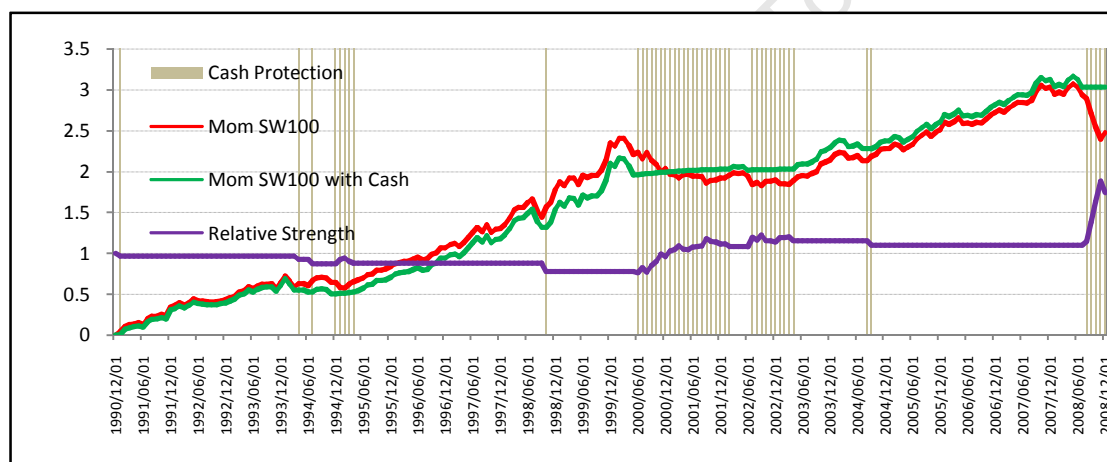


Chart (b) Time-Series Drawdown of the Cash-Protected Global Momentum Proxy

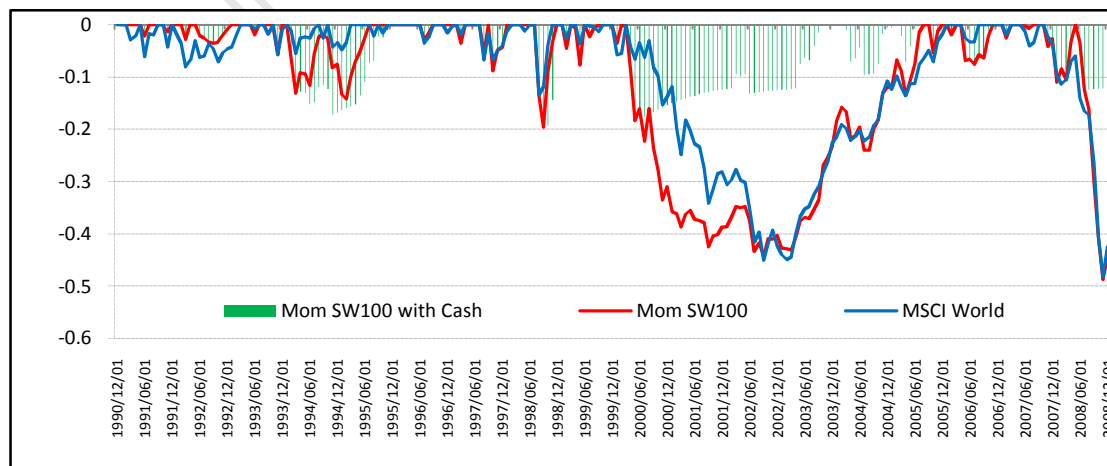


Figure 9.8 Performance of the 50% Cash-Protected Global Momentum Proxy Based on the Exponential Moving Average (EMA) Strategy (1991 to 2008)

The 50% cash protection mechanism is applied to the global momentum proxy (Mom SW100) over the period from 1 January 1991 to 31 December 2008. The strategy converts 50% of the exposure in Mom SW100 to synthetic cash when the fast moving average (FMA) breaks through the slow moving average (SMA) of Mom SW100 from above until the SMA breaks through the FMA from below. The best permutation over the examination period (30% FMA and 20% SMA) is illustrated in this figure. Chart (a) depicts the time-series cash holding, the log cumulative returns for Mom SW100, with and without cash protection and the relative performance between the Mom SW100, with and without cash protection. Chart (b) depicts the time-series drawdown for Mom SW100, with and without cash protection and the MSCI World Index over the examination period.

Chart (a) Relative Strength of the Cash-Protected Global Momentum Proxy

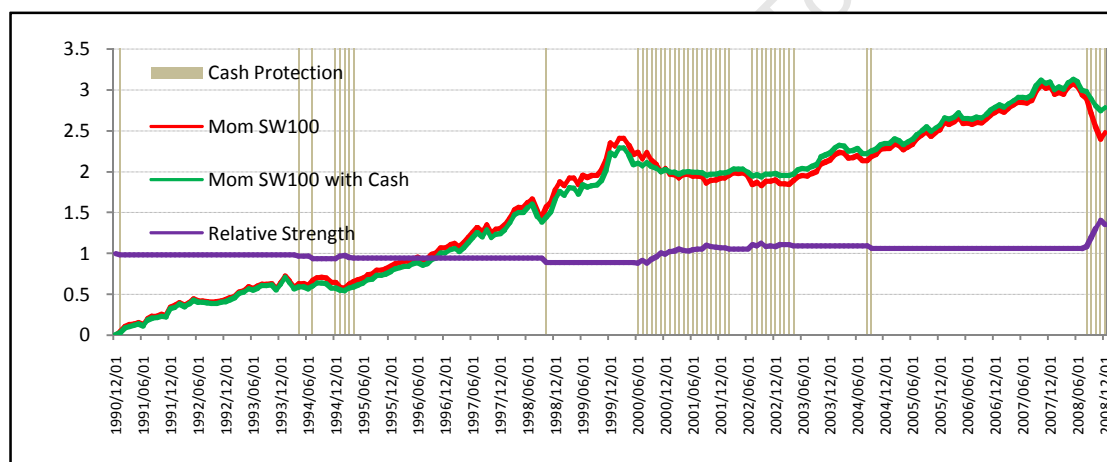
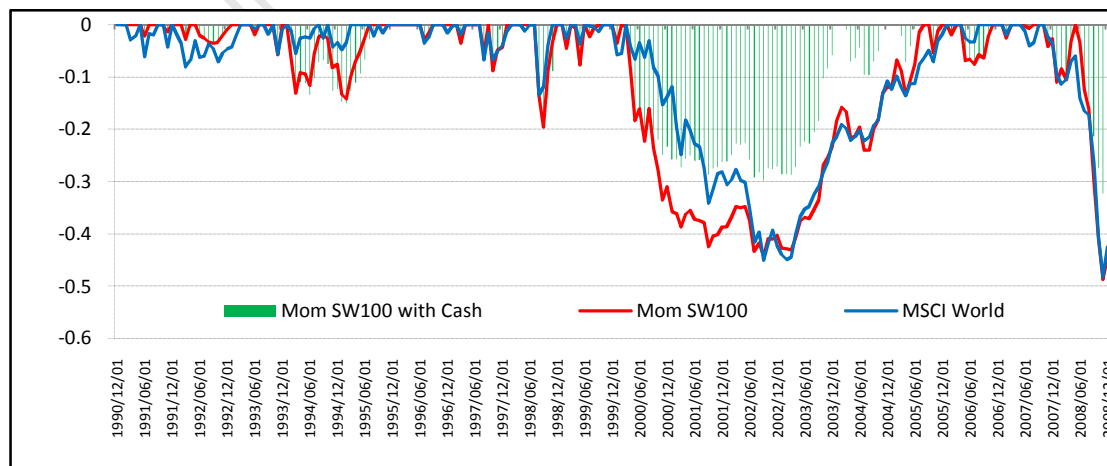


Chart (b) Time-Series Drawdown of the Cash-Protected Global Momentum Proxy



9.5 Results: Cash-Protected Global Value Proxy

The performance statistics for the 100% and 50% cash-protected global value proxy constructed under the filter rule strategy are demonstrated in Appendix L.1 and Appendix L.2 respectively. The Sharpe ratio for the filter rule strategy is maximised when the maximum tolerable DD and the minimum required DU are set at -10% and 30% respectively. This permutation results in 26.85% of the months in synthetic cash, and triggers cash protection only 3 times in the examination period. The heat maps indicate that the risk, return and Sharpe ratios can be improved for most of the permutations that trigger cash protection from 1 to 3 times.

Appendix L.3 and Appendix L.4 demonstrate the results for all of the permutations of the rates at which the FMA and SMA track the unprotected global value proxy for the 100% cash protection mechanism and the 50% cash protection mechanism respectively. The Sharpe ratio for the EMA strategy is maximised when the FMA and SMA are set at 100% and 50% respectively. Compared to only 3 times of cash protection triggered under the filter rule strategy, the best permutation of the EMA strategy triggers cash protection 29 times in the examination period with more or less the same percentage of the months in synthetic cash (27.78%). The heat maps in Appendix L.3 and Appendix L.4 indicate that the closer the FMA and SMA track each other with high frequency of cash protection, the greater the risk reduction in terms of standard deviation, 5 percent VaR and maximum drawdown. However, the heat maps for the upside return potential is scattered, with no clear indication of how the return of the cash-protected global value proxy can be improved.

The summarised performance statistics are presented in Table 9.3. Examining the performance of the cash-protected global value proxy indicates that the drastic enhancements in the Sharpe ratios are achieved through risk reduction, rather than improvements in the geometric returns for the cash-protected global value proxy. In addition, the cash-protected indices have significantly lower maximum drawdown compared to the unprotected global value proxy over the examination period.

Table 9.3 Performance Statistics of the Cash-Protected Global Value Proxy (1991 to 2008)

Two cash protection strategies are tested on the global value proxy (Value SW100) over the period from 1 January 1991 to 31 December 2008: a filter rule strategy that creates a synthetic cash/partial position based on the maximum tolerable drawdown (DD) and minimum drawup (DU) requirement (calculated as the return since the most recent trough); and an exponential moving average (EMA) strategy that creates a synthetic cash/partial cash position based on the crossover of the fast moving average (FMA) and the slow moving average (SMA) of Value SW100. Two cash protection mechanisms are implemented for each of the strategies: a 100% cash protection mechanism that converts the entire fund exposure to cash using derivative overlay; and a 50% cash protection mechanism that converts half of the equity exposure into cash when the warning signal is received. The permutations of the maximum tolerable DD that triggers cash protection and the minimum DU requirement that removes the protection are simulated from 0% to 50% at a 5% interval. On the other hand, the permutations of the rates at which the respective FMA and SMA track the underlying index are simulated from 0% to 100% at a 10% interval over the examination period. The best simulated results for the two cash protection strategies are demonstrated in this table.

	Benchmarks (No Protection)		Cash Protection Based on Filter Rule Strategy		Cash Protection Based on Exponential Moving Average	
	MSCI World	Unprotected Value SW100	Value SW100 -10% DD 30% DU 100% Cash	Value SW100 -10% DD 30% DU 50% Cash	Value SW100 100% FMA 50% SMA 100% Cash	Value SW100 100% FMA 50% SMA 50% Cash
Geometric Return	6.10%	13.27%	14.10%	13.92%	14.14%	13.95%
Standard Deviation	14.69%	16.52%	10.73%	12.45%	10.21%	12.11%
Sharpe Ratio	15.00%	56.73%	95.13%	80.57%	100.41%	83.05%
5% VaR	-6.53%	-5.58%	-3.59%	-5.08%	-3.33%	-4.75%
Percentage of Months in Cash/ Partial Cash	0.00%	0.00%	26.85%	26.85%	27.78%	27.78%
Maximum Drawdown	-48.20%	-54.58%	-14.85%	-35.01%	-14.87%	-36.76%
Number of Signals	0 Times	0 Times	3 Times	3 Times	29 Times	29 Times

Figure 9.9 and Figure 9.10 illustrate the time-series performances of the cash-protected global value proxy for the filter rule strategy constructed under the best permutations of the maximum tolerable DD (-10%) and the minimum required DU (30%). On the other hand, the time-series performances of the cash-protected global value proxy for the best permutation of the FMA (100%) and SMA (50%) are illustrated in Figure 9.11 and Figure 9.12 respectively.

Examining the relative strength of the cash-protected global value proxy versus the unprotected global value proxy in Chart (a) of each figure indicates that the only effective cash protection is during the market crash in 2008 under both of the filter rule strategy in Figure 9.9 and Figure 9.10 and the EMA strategy in Figure 9.11 and Figure 9.12. Chart (b) in each Figure shows that global value stocks are less prone to significant drawdown compared to the MSCI World Index over the examination period, with the exception of the significant drawdown during the market crash in 2008. The global value proxy is also less affected during the burst of the I.T. bubble in the early 2000s. Thus, although cash protections for the global value proxy, under various cash-protection mechanisms, drag down the upside return potential prior to the global financial crisis in 2008, the benefits derived from the successful protection of the systemic risk in 2008 that impacts on all asset classes, outweigh the costs incurred in all prior mis-measurements.

**Figure 9.9 Performance of the 100% Cash-Protected Global Value Proxy
Proxy Based on the Filter Rule Strategy (1991 to 2008)**

The 100% cash protection mechanism based on the filter rule is applied to the global value proxy (Value SW100) over the period from 1 January 1991 to 31 December 2008. The strategy converts the entire exposure in Value SW100 to synthetic cash when the maximum tolerable drawdown (DD) is exceeded until the minimum drawup (DU) requirement from the most recent trough is exceeded. The best permutation for the filter rule strategy (-10% DD and 30% DU) is illustrated in Figure 9.9. Chart (a) depicts the time-series cash holding, the log cumulative returns for Value SW100, with and without cash protection and the performance of the cash-protected Value SW100 relative to the performance of the unprotected Value SW100. Chart (b) depicts the time-series drawdown for Value SW100, with and without cash protection and the MSCI World Index over the examination period.

Chart (a) Relative Strength of the Cash-Protected Global Value Proxy

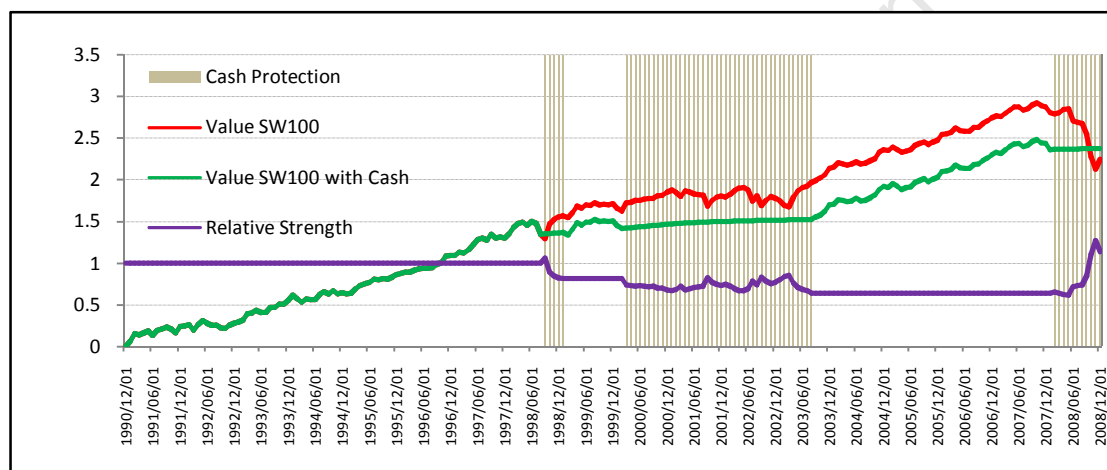


Chart (b) Time-Series Drawdown of the Cash-Protected Global Value Proxy

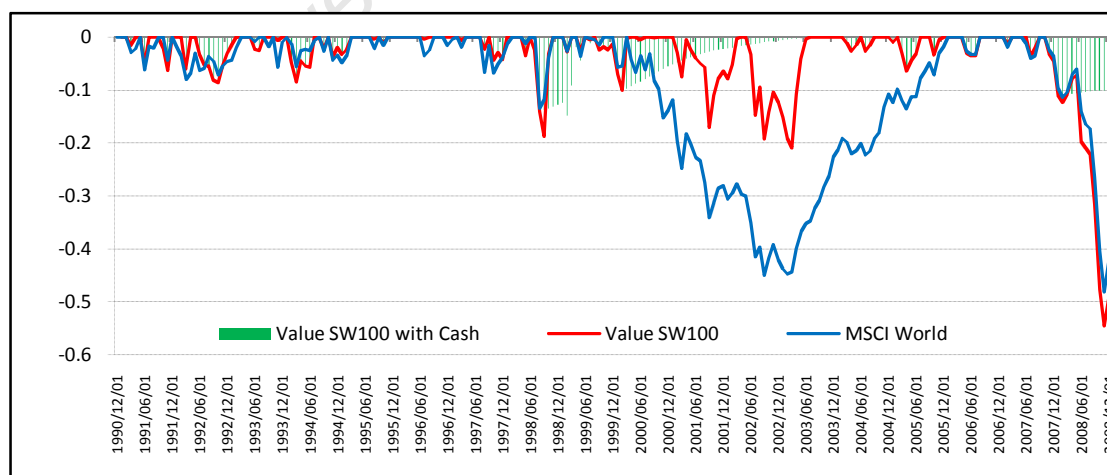


Figure 9.10 Performance of the 50% Cash-Protected Global Value Proxy Based on the Filter Rule Strategy (1991 to 2008)

The 50% cash protection mechanism based on the filter rule is applied to the global value proxy (Value SW100) over the period from 1 January 1991 to 31 December 2008. The strategy converts 50% of the exposure in Value SW100 to synthetic cash when the maximum tolerable drawdown (DD) is exceeded until the minimum drawup (DU) requirement from the most recent trough is exceeded. The best permutation for the filter rule strategy (-10% DD and 30% DU) is illustrated in Figure 9.10. Chart (a) depicts the time-series cash holding, the log cumulative returns for Value SW100, with and without cash protection and the performance of the cash-protected Value SW100 relative to the performance of the unprotected Value SW100. Chart (b) depicts the time-series drawdown for Value SW100, with and without cash protection and the MSCI World Index over the examination period.

Chart (a) Relative Strength of the Cash-Protected Global Value Proxy

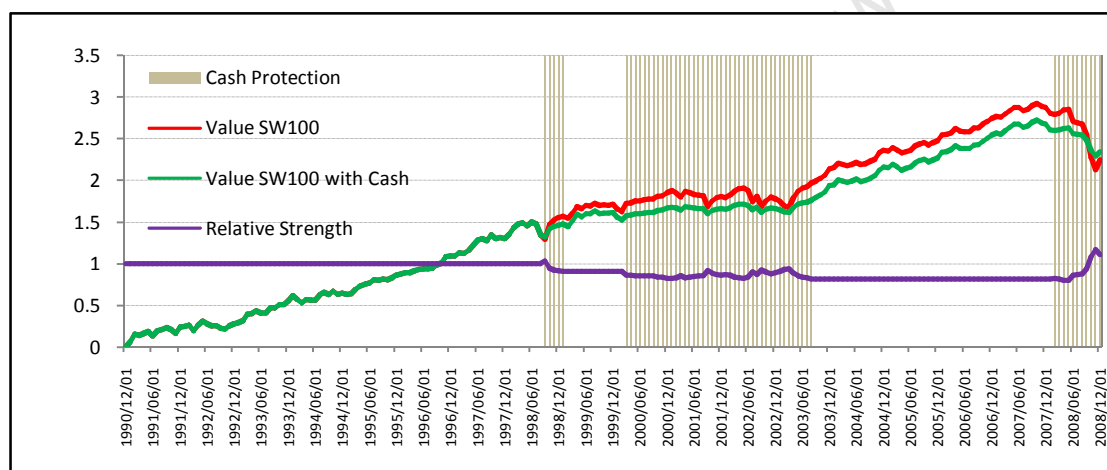


Chart (b) Time-Series Drawdown of the Cash-Protected Global Value Proxy

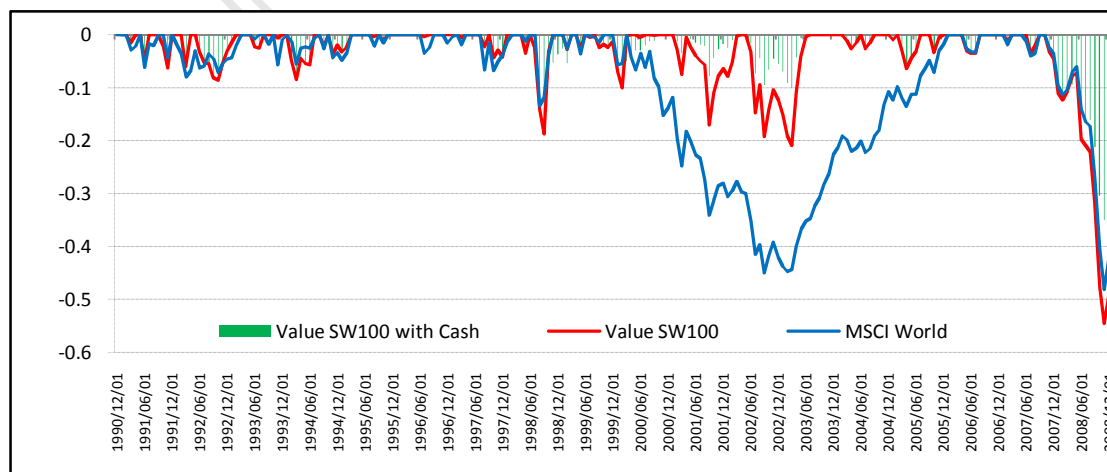


Figure 9.11 Performance of the 100% Cash-Protected Global Value Proxy Based on the Exponential Moving Average (EMA) Strategy (1991 to 2008)

The 100% cash protection mechanism is applied to the global value proxy (Value SW100) over the period from 1 January 1991 to 31 December 2008. The strategy converts the entire exposure in Value SW100 to synthetic cash when the fast moving average (FMA) breaks through the slow moving average (SMA) of Value SW100 from above until the SMA breaks through the FMA from below. The best permutation over the examination period (100% FMA and 50% SMA) is illustrated in this figure. Chart (a) depicts the time-series cash holding, the log cumulative returns for Value SW100 with and without cash protection and the relative performance between the Value SW100, with and without cash protection. Chart (b) depicts the time-series drawdown for Value SW100, with and without cash protection and the MSCI World Index over the examination period.

Chart (a) Relative Strength of the Cash-Protected Global Value Proxy

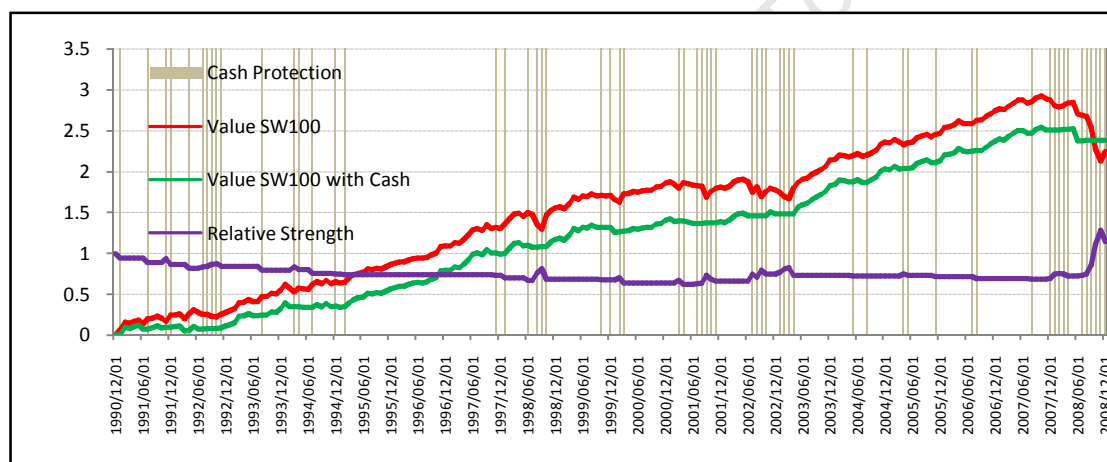


Chart (b) Time-Series Drawdown of the Cash-Protected Global Value Proxy

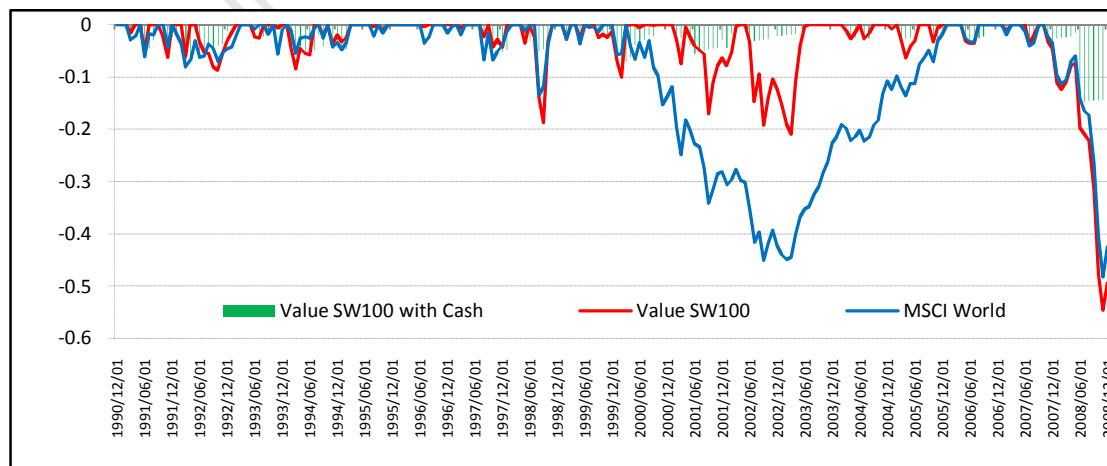


Figure 9.12 Performance of the 50% Cash-Protected Global Value Proxy Based on the Exponential Moving Average (EMA) Strategy (1991 to 2008)

The 50% cash protection mechanism is applied to the global value proxy (Value SW100) over the period from 1 January 1991 to 31 December 2008. The strategy converts 50% of the exposure in Value SW100 to synthetic cash when the fast moving average (FMA) breaks through the slow moving average (SMA) of Value SW100 from above until the SMA breaks through the FMA from below. The best permutation over the examination period (100% FMA and 50% SMA) is illustrated in this figure. Chart (a) depicts the time-series cash holding, the log cumulative returns for Value SW100, with and without cash protection and the relative performance between the Value SW100, with and without cash protection. Chart (b) depicts the time-series drawdown for Value SW100, with and without cash protection and the MSCI World Index over the examination period.

Chart (a) Relative Strength of the Cash-Protected Global Value Proxy

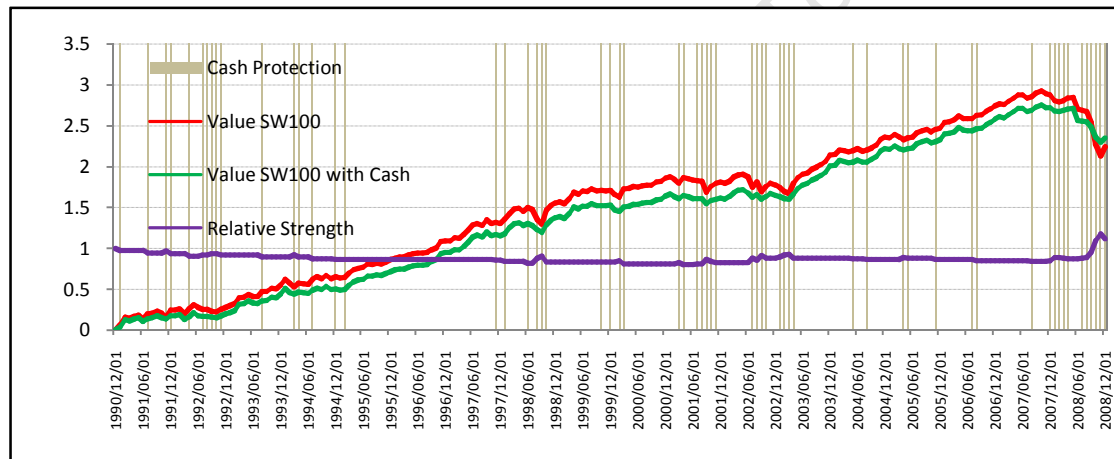
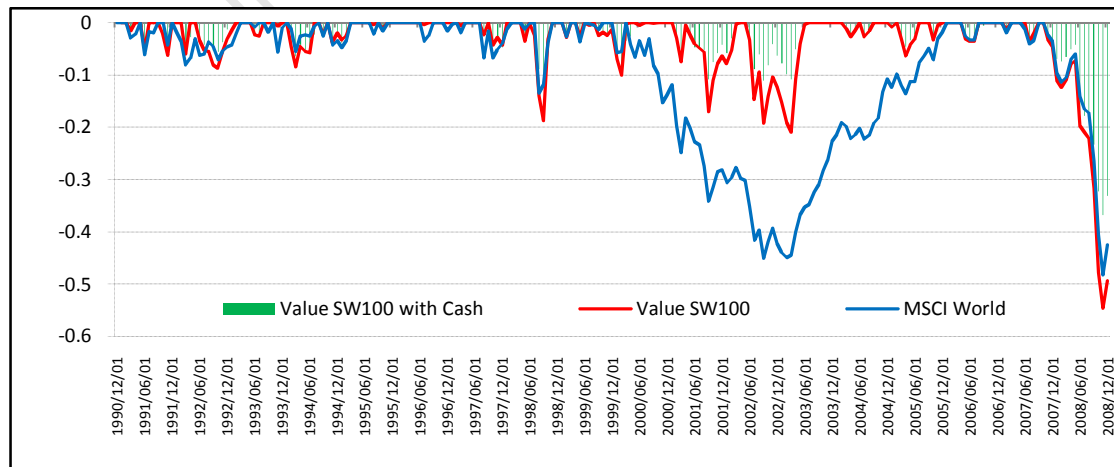


Chart (b) Time-Series Drawdown of the Cash-Protected Global Value Proxy



9.6 Conclusion

There are four cash protection strategies developed for each of the MSCI World Index, the global momentum proxy and the global value proxy in this chapter, two of which are 100% and 50% cash-protected strategies based on the filter rule, the other two are 100% and 50% cash-protected strategies developed from the exponential moving average (EMA) model.

The results for both the filter rule strategy and the EMA strategy over the examination periods are impressive in that most of the permutations improve the Sharpe ratio and the return of the unprotected indices. In addition, as long as there is some sort of cash protection, the portfolio standard deviation, 5 percent VaR and the maximum drawdown are reduced over the examination period. However, when the cash-protected MSCI World Index is examined over two sub-periods from 1970 to 1990 and from 1991 to 2008, it is found that the best permutations for both of the filter rule strategy and the EMA strategy in the first sub-period are not robust in the second sub-period. This is because the expected drawdown detected in the first sub-period are relatively short, which results in inaccurate timing for kicking in- and out-of-cash.

In general cash protection mechanisms based on trend-following models lag the actual events slightly, and hence work better for relatively longer periods of drawdown. As a result, the optimised permutations of the cash protection strategies are the ones that provide timely protections in 1974, the early 2000s and 2008. Although the global value proxy is less prone to significant drawdown compared to the MSCI World Index and the global momentum proxy, it does not escape the systemic impact of the global

financial crisis in 2008. Overall, the cash-protected style indices outperform the MSCI World Index and the unprotected indices on a risk-adjusted basis, and the value protected during major economic downturn overrides the cost incurred through random timing errors.

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CONCLUSION

Theories and asset pricing models such as the modern portfolio theory (MPT), the separation theorem, the capital asset pricing model (CAPM) and the arbitrage pricing theory (APT) provide solutions to asset allocation problems in efficient capital markets where investors are rational in making investment decisions. Behavioural finance, on the other hand, argues that investors are irrational and influenced by psychological biases in making investment decisions. The major development of behavioural finance stems from prospect theory of Kahneman and Tversky (1979), and behavioural biases are regarded as outcomes of the prospect theory. The cognitive errors highlighted by prospect theory include loss aversion, the disposition effect, the certainty effect, the reflection effect, mental accounting and heuristic simplification. These biases lead investors to violate the assumptions of traditional finance and drift their decisions away from the basis of the mean, variance and covariance of asset returns. As a result, asset prices contain errors and do not reflect their long-term intrinsic values as suggested by the efficient market hypothesis (EMH).

Market anomalies documented in empirical research include long-term price reversals, short-term return momentum, the value effect, the size effect and the underperformance of cap-weighted indices. These anomalies can be explained from the perspective of behavioural finance based on investor irrationality. The systematic overshooting of stock prices lead glamour stocks and large caps to be overpriced, and value stocks and small caps to be underpriced before market corrections. The argument of Hirshleifer (2001) that investors all share the same heuristics raises the

question as to whether the impacts of cognitive errors on asset pricing are temporary and diversifiable in an irrational capital market. On the other hand, it can be argued that the documented market anomalies are products of methodological biases in conducting empirical research rather than due to market inefficiencies. In addition, size and value effects can also be interpreted as missing risk factors in the CAPM, and investors demand adequate premium for holding value stocks and small caps. When the proxies of value and size effects are employed as risk factors in addition to the market risk premium, Fama and French (1993) find that the 3-factor model is capable of capturing most of the empirical anomalies with the exception of the momentum anomaly. This result suggests that return momentum could be included as the fourth factor in the model.

The presence of the size, value and momentum effects in the global equity market motivates this research to construct global style indices to represent major investment styles in the investment universe. Allocating assets according to investment styles rather than holding the market portfolio has the potential to outperform the market by exploiting the observed CAPM anomalies. There are in total 80 global size indices, 80 global momentum indices, 360 global value indices, 80 global loser indices and 360 global glamour indices developed and examined over the period from 1991 to 2008 in this research. The first half of the examination period (1991 to 1999) is more bullish than the second half of the examination period (2000 to 2008). With regard to global size indices, the price-sensitive cap-weighted indices are the worst performers during the market downturn due to the inherent capitalisation drag. On the other hand, large equally-weighted indices and fundamental indices are found to be a good hedge against global market downturn. It is also found that fundamental indices share the same risk and return characteristics with the value indices that produce outstanding

performances when the market sentiment is bearish. This observation suggests that the value bias might be embedded in the fundamental indices. The top 300 equally-weighted large cap index is chosen to represent the global size proxy for further tests in this research.

Constructing value indices based on the undervalued (negative) residuals of cross-sectional regressions rather than financial ratios represents an effective method of developing unbiased value attributes from multiple fundamental attributes. The majority of the value indices developed from financial ratios such as book value-to-price or earnings yield underperform their corresponding undervalued residual indices in the univariate test. In addition, the cross-sectional regression approach has an advantage of developing unbiased value attributes from multiple fundamental attributes, compared to financial ratios. The most representative global value proxy identified for further tests in this research is the top 100 style-weighted undervalued residual index constructed from all five fundamental values (book value, net earnings, dividends, net cash flow and sales).

The global momentum (winner) and loser indices are developed based on the mean-adjusted returns of the sample shares. Grouping stocks based on their cross-sectional mean-adjusted returns is a more effective mechanism in classifying prior winners and losers than taking equal number of stocks from the two ends of the cross-sectional returns. This innovative approach makes it possible for constructing style-weighted winner and loser indices even when the constituent shares have negative returns. This method successfully avoids drastic rebalancing during the market crash in 2008, during which the majority of the sample shares have negative returns. Global momentum (winner) indices formed by 6- to 12-month past returns achieve excellent

returns during the bullish first sub-period through substantially higher standard deviation, above average beta coefficient, high portfolio concentration and aggressive rebalancing. By contrast, significant reversals are exhibited by momentum indices formed by 1-month prior returns. By removing the most recent month return from the computation of prior 12-month returns, the lagged 11-month momentum indices earn significant positive alpha over the examination period. The top 100 style-weighted lagged 11-month momentum index is used to represent the global momentum proxy in this research.

The global size, momentum and value proxies identified by this research outperform the MSCI World Index, which in turn outperforms the respective global counterpart proxies (the top 300 cap-weighted index, the top 100 style-weighted lagged 11-month loser index and the top 100 style-weighted glamour index) on a risk-adjusted return basis over the examination period. The global value proxy that is characterised by outstanding risk-adjusted return, average beta, average standard deviation and average portfolio turnover among the global style proxies offers the most consistent performance throughout the examination period. When the rebalancing frequency is changed from monthly to semi-annually, the global value proxy retains its Sharpe ratio above 50% over the examination period.

Although the global momentum proxy is the best performer during the bullish first sub-period, its performance in the bearish second sub-period is adversely affected by its aggressive rebalancing strategy and volatile returns. The Sharpe ratio of the global momentum proxy also deteriorates drastically when the rebalancing frequency is reduced from monthly to semi-annually. The examination of the log cumulative returns of the global style proxies reveal that the global momentum proxy has

significant upward drift prior to the Asian financial crisis in 1998, the crash of the Information Technology (I.T.) bubble in 2000 and the global financial crisis in 2008. Due to the fact that momentum stocks tend to exhibit significant drift at the market peak, they appear to be most vulnerable to financial crises relative to stocks in other investment style categories. The significant drawdown of the global momentum proxy during market crash hampers its profits gained at the market peak, which increases the volatility of the global momentum proxy substantially. When the cash protection mechanism is applied to the global momentum proxy, the protected global momentum proxy outperforms the unprotected global momentum proxy on a risk-adjusted basis under most of the scenarios for both the filter rule strategy and the EMA strategy. The outperformance of the global momentum proxy is mainly due to the synthetic cash protection during the crash of the I.T. bubble in the early 2000s and the global financial crisis in 2008.

When the cash protection mechanism is applied to the global value proxy, the relative strength of the protected global value proxy over the unprotected global value proxy reveals that the protection mechanism is only effective during the global financial crisis of 2008 over the examination period. The systemic nature of the global financial crisis in 2008 impacts on all asset classes and investment styles, which renders diversification an ineffective risk management mechanism, since long positions in any asset class will suffer from significant drawdown during the period. The global value proxy does not suffer significant drawdown during the global market downturn in the early 2000s compared to the global momentum proxy and the MSCI Index.

When the cash protection mechanism is applied to the MSCI World Index over the examination period from 1991 to 2008, the result is similar to that of the global

momentum proxy discussed earlier. When the cash protection mechanism is applied to the MSCI World Index prior to 1991, since its inception in 1970, it is found that the cash protection only uplifts the index value during the significant drawdown in 1974. The optimal permutations of the maximum tolerable drawdown and the minimum required drawup for the filter rule strategy and the optimal rates at which the fast and slow moving average series track the index value for this period are not robust in the following period from 1991 to 2008. This is mainly due to the fact that the significant drawdown detected in the first period are relatively short, which results in inaccurate timing of cash protection being executed. Since cash protection strategies are based on trend-following models that lag major economic events, the strategies in general work better for relatively longer periods of significant drawdown. Overall, the value preserved by the cash protection strategies during significant economic downturn outweighs the costs incurred through temporary timing errors.

Along with the MSCI World Index, the global size, momentum and value proxies developed in this research are found to successfully replicate the underlying investment styles of the selected South African-based and internationally-domiciled global equity funds over the examination period. In general, internationally-domiciled global equity funds demonstrate better ability in outperforming their style benchmarks compared to South African-based global equity funds. With limited contribution from the selection return to the actual fund return, the return of the replicated style portfolio serves as an unbiased estimate of the actual fund returns. This observation supports the results of studies conducted by Sharpe (1992), Ibbotson and Kaplan (2000), Vardharaj and Fabozzi (2007) and Yu (2008). These findings together with the Barron's report in 1997 and the S&P Indices Versus Active (SPIVA) scorecard service report (refer to Section 3.3.2) indicate that tactical stock picking is an

ineffective way of generating active returns beyond what could be achieved by the style benchmarks.

When the global size proxy is removed from the replication procedure, its contribution is replaced by the global value proxy and the MSCI World Index at with no reduction in the regression R -squared. The correlation analysis and the cross-sector analysis also find that there are no distinguishable risk-return characteristics between the global value proxy and the global size proxy. By contrast, the global momentum proxy and the global value proxy, coupled with distinctive differences between their specific style timing, investment risks, rebalancing strategies and sector allocation policies indicate that the momentum and value investment styles represent two distinctive investment segments in the global equity market. Although the country allocation policies are different between the global momentum and value proxies, the country allocation effect does not meaningfully contribute to the return differences between the global momentum and value proxies. This result supports the argument of Vardharag and Fabozzi (2007) that sector and style allocations are interrelated as certain sectors tend to reflect unique investment styles at times.

When the MSCI World Index and the three global style proxies are employed as constituent indices in the mean-variance optimisation procedure and the mean-tracking error optimisation procedure over the entire examination period, the global size proxy is not utilised by any of the Sharpe ratio-optimised portfolios. This finding serves as evidence that the global size proxy is less efficient compared to the global momentum and value proxies. However, when the mean-variance optimisation procedure is conducted from month to month based on the prior 36-month data from 1994 to 2008, it is found that the cash component of the long-short and market neutral

tactical style allocation (TSA) strategies is partially replaced by the combination of long positions in the global size proxy and short positions in the MSCI World Index during the subprime crisis in 2007 and 2008. This is due to the fact that the global size proxy and the MSCI World Index share the common (large cap) investment style. Holding a long position in the equally-weighted global size proxy and simultaneously going short in the MSCI World Index that exhibits capitalisation drag can potentially beat cash returns in turbulent times. However, such synthetic cash position is less pronounced in high interest rate regimes during global downturn in the early 2000s.

In general, the risk-return characteristics of the TSA strategies are consistent with the risk-return characteristics of their corresponding Sharpe ratio-optimised portfolios developed within the static in-sample period. The optimisation procedure using the weighted least squared (WLS) approach is robust in replicating the performances of the hypothetical Sharpe ratio-optimised portfolios. The long only TSA strategy holds the global value proxy for most of the months in the examination period and tactically shifts the investment to the global momentum proxy during market peaks. This observation serves as evidence that value investing is the most mean-variance investment style in the global capital market over the examination period. When the risk-free proxy (cash) is incorporated in the optimisation procedure for the long-only TSA strategy, the significant drawdown during the market crash is effectively protected by cash. The relaxation of the long-only and no leverage constraint further improve the Sharpe ratios of the long-short and market neutral TSA strategies mainly through substantial risk reduction rather than enhancing returns. Overall, all four TSA strategies outperform their constituent indices on the risk-adjusted return basis and generate statistically significant abnormal returns measured by Jensen's alpha over the out-of-sample period.

In conclusion, holding a cap-weighted market index that represents the theoretical ideal market portfolio, in combination with the risk-free proxy, is an impractical and mean-variance inefficient method of asset allocation in the real world. The popular market proxy, the MSCI World Index, significantly underperforms the global style proxies on the risk-adjusted basis over the examination period. As long as the rebalancing frequency of the cap-weighted market proxy is faster than market corrections, the market proxy remains suboptimal through noise trading. Tests conducted in this research suggest that value investing is the most consistent and mean-variance efficient investment style in the global capital market. The global value proxy offers similar return to the global momentum proxy with lower standard deviation and drawdown over the 18-year examination period from 1991 to 2008. The spread between the returns of the global value and momentum proxies remains tight, except for the upward drifts of the momentum proxy return during market peaks, which dissipate subsequently through significant drawdown. Thus, cash protection is an important risk management tool to hedge against systemic risk that cannot be avoided through diversification. An efficient long-only TSA strategy can be developed to tactically allocate investments to momentum stocks during market peaks by replicating the mean-variance efficient portfolio composition in the most recent pre-defined prior period. The drawdown of such strategy can be substantially reduced by either incorporating the risk-free proxy in the optimisation procedure, or applying cash protection mechanisms based on the filter rule or the EMA strategy described in Chapter 9.

While the transaction costs and portfolio turnover are incorporated in the analysis of the performances of style indices in this research, the tax implications on the global style indices have not been explicitly discussed. In addition, security regulations for

short and leverage positions in the fund industry are different from country to country. While single stock futures (SSF) and contract for difference (CFD) are available for short positions in individual stocks and applications of leverage in South Africa and other more developed capital markets, SSF on stocks listed on the Taiwan Stock Exchange (TWSE) are only available on the Taiwan Futures Exchange (TAIFEX) since February 2010. In addition, Chinese regulators have just recently approved the launch of SSF and a trial run of margin trading on stocks listed on the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE). The manner in which short and leverage positions are obtained has considerable implications on the practicality and performances of global style portfolios. These issues demand further attention to aid the development of mean-variance efficient global style portfolios in practice. The other area demands for further research is the sources of the return difference between style indices. This research finds that sector allocation contributes to the return difference between the global value and momentum investment styles. Prior research mainly focuses on investigating whether country allocation or sector allocation is the primary driver of global fund returns. However, it is the explanation of the actual “return difference” between global investment strategies that provides insights into the knowledge of tactical asset allocation decision in the global capital market.

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APPENDIX A

Performances of the Candidate Size Indices

The research sample consists of the largest 300 shares of the Dow Jones Sector Titans Composite Index by market capitalisation in each month of the examination period from 1 January 1991 to 31 December 2008. The candidate size indices are ranked and constructed based on the attributes, including monthly market share price, market capitalisation, current book value, trailing 5-year average net earnings after tax, trailing 5-year average gross dividends, trailing 5-year average gross sales and trailing 5-year average net cash flow of the sample shares. In addition, the synthetic Research Affiliate Fundamental Indices (RAFI) are also developed based on the methodology proposed by the Research Affiliates, based on the arithmetic average of the five fundamental attributes. The Research Affiliates propose the use of the trailing average values to avoid the substantial volatility of the attributes to impact on year-to-year data (Arnott, Hsu and Moore, 2005). The 5 attributes are equally-weighted to provide the consolidated indication of firm size for the sample shares. The non-dividend-paying firms are taken into account by computing their composite fundamental size attributes, based on the average of the remaining 4 fundamental attributes.

The attributes of the sample shares are winsorised monthly to keep the values of the attributes within the 99.5th and 0.5th percentiles of the monthly cross-sectional distribution. The sample shares are ranked by the values of their respective winsorised attributes at the beginning of each month, and are subsequently included in, or excluded from, the equally-weighted (EW) and style-weighted (SW) indices based on the pre-specified target number of constituents in the respective indices. The overall evaluation period of 216 months from 1 January 1991 to 31 December 2008 are subdivided into 2 equal sub-periods of 108 months. The basic statistics and the risk-adjusted performance measures of candidate indices are annualised. The benchmark employed to evaluate the risk-adjusted performance of the candidate indices is the Morgan Stanley Composite International World Index (MSCI World), and the risk-free rate applied is the return on the 3-month U.S. Treasury Bill (USTB3M). The cost-adjusted geometric return under basic statistics is computed by subtracting 2% transaction costs of the monthly percentage portfolio turnover through rebalancing from the monthly index return. The monthly cost-adjusted returns are linked geometrically and annualised to arrive at the annualised cost-adjusted geometric return. The average effective number of index constituents under measure of representativeness is defined as “*the number of equally-weighted shares required to achieve the same share-specific risk as the portfolio.*” (Van Rensburg and Kruger, 2008: 1).

APPENDIX B

Performances of the Candidate Momentum Indices

The research sample consists of the largest 300 shares of the Dow Jones Sector Titans Composite Index by market capitalisation in each month of the examination period from 1 January 1991 to 31 December 2008. The excess cross-sectional mean of the prior 1-month (Mom1), 6-month (Mom6), 12-month (Mom12), 24-month (Mom24), 36-month (Mom36), 48-month (Mom48), 60-month (Mom60) and the 1-month lagged prior 11-month return momentum (Mom12-1) of the sample shares are computed monthly, and the candidate momentum indices are constructed, based on the sample shares with the largest positive excess return momentum. Both of the capital gains and dividend yield are included in the total return index for the computation of the prior return momentum.

The attributes of the sample shares are winsorised monthly to keep the values of the attributes within the 99.5th and 0.5th percentiles of the monthly cross-sectional distribution. The sample shares are ranked by the values of their respective winsorised attributes at the beginning of each month, and are subsequently included in, or excluded from, the equally-weighted (EW) and style-weighted (SW) indices based on the pre-specified target number of constituents in the respective indices. The overall evaluation period of 216 months from 1 January 1991 to 31 December 2008 are subdivided into 2 equal sub-periods of 108 months. The basic statistics and the risk-adjusted performance measures of candidate indices are annualised. The benchmark employed to evaluate the risk-adjusted performance of the candidate indices is the Morgan Stanley Composite International World Index (MSCI World), and the risk-free rate applied is the return on the 3-month U.S. Treasury Bill (USTB3M). The cost-adjusted geometric return under basic statistics is computed by subtracting 2% transaction costs of the monthly percentage portfolio turnover through rebalancing from the monthly index return. The monthly cost-adjusted returns are linked geometrically and annualised to arrive at the annualised cost-adjusted geometric return. The average effective number of index constituents under measure of representativeness is defined as “*the number of equally-weighted shares required to achieve the same share-specific risk as the portfolio.*” (Van Rensburg and Kruger, 2008: 1).

APPENDIX C

Performances of the Candidate Value Indices

The research sample consists of the largest 300 shares of the Dow Jones Sector Titans Composite Index by market capitalisation in each month of the examination period from 1 January 1991 to 31 December 2008. The candidate value indices are constructed from the financial ratios and the cross-sectional undervalued residual proxies. The financial ratios employed to indicate the attractiveness of the sample shares include the book value-to-price ratio (BVTP), earnings yield (EY), dividend yield (DY), sales-to-price ratio (SALESTP) and cash flow-to-price ratio (CFTP). On the other hand, the 31 available combinations of the monthly book value per share (B), earnings per share (EPS), dividends per share (D), sales per share (S) and cash flow per share (C) of the sample shares are employed as the independent variables to explain the monthly cross-sectional log returns of the sample shares using ordinary least squares (OLS) regressions. The sample shares with negative regression residuals at the beginning of each month in the examination period are regarded as the undervalued shares for the month, and the absolute values of their respective regression residuals (U_{res}) are computed and ranked for the construction of the regression-based candidate value indices.

The attributes of the sample shares are winsorised monthly to keep the values of the attributes within the 99.5th and 0.5th percentiles of the monthly cross-sectional distribution. The sample shares are ranked by the values of their respective winsorised attributes at the beginning of each month, and are subsequently included in, or excluded from, the equally-weighted (EW) and style-weighted (SW) indices based on the pre-specified target number of constituents in the respective indices. The overall evaluation period of 216 months from 1 January 1991 to 31 December 2008 are subdivided into 2 equal sub-periods of 108 months. The basic statistics and the risk-adjusted performance measures of candidate indices are annualised. The benchmark employed to evaluate the risk-adjusted performance of the candidate indices is the Morgan Stanley Composite International World Index (MSCI World), and the risk-free rate applied is the return on the 3-month U.S. Treasury Bill (USTB3M). The cost-adjusted geometric return under basic statistics is computed by subtracting 2% transaction costs of the monthly percentage portfolio turnover through rebalancing from the monthly index return. The monthly cost-adjusted returns are linked geometrically and annualised to arrive at the annualised cost-adjusted geometric return. The average effective number of index constituents under measure of representativeness is defined as “*the number of equally-weighted shares required to achieve the same share-specific risk as the portfolio.*” (Van Rensburg and Kruger, 2008: 1).

APPENDIX D

Performances of the Candidate Loser Indices (Counterpart Indices of the Momentum Indices)

The research sample consists of the largest 300 shares of the Dow Jones Sector Titans Composite Index by market capitalisation in each month of the examination period from 1 January 1991 to 31 December 2008. The candidate loser indices serve as the counterpart indices of the candidate momentum indices. The excess cross-sectional mean of the prior 1-month (Mom1), 6-month (Mom6), 12-month (Mom12), 24-month (Mom24), 36-month (Mom36), 48-month (Mom48), 60-month (Mom60) and the 1-month lagged prior 11-month return momentum (Mom12-1) of the sample shares are computed monthly, and the candidate loser indices are constructed, based on the sample shares with the largest absolute values of their negative excess return momentum. Both of the capital gains and dividend yield are included in the total return index for the computation of the prior return momentum.

The attributes of the sample shares are winsorised monthly to keep the values of the attributes within the 99.5th and 0.5th percentiles of the monthly cross-sectional distribution. The sample shares are ranked by the values of their respective winsorised attributes at the beginning of each month, and are subsequently included in, or excluded from, the equally-weighted (EW) and style-weighted (SW) indices based on the pre-specified target number of constituents in the respective indices. The overall evaluation period of 216 months from 1 January 1991 to 31 December 2008 are subdivided into 2 equal sub-periods of 108 months. The basic statistics and the risk-adjusted performance measures of candidate indices are annualised. The benchmark employed to evaluate the risk-adjusted performance of the candidate indices is the Morgan Stanley Composite International World Index (MSCI World), and the risk-free rate applied is the return on the 3-month U.S. Treasury Bill (USTB3M). The cost-adjusted geometric return under basic statistics is computed by subtracting 2% transaction costs of the monthly percentage portfolio turnover through rebalancing from the monthly index return. The monthly cost-adjusted returns are linked geometrically and annualised to arrive at the annualised cost-adjusted geometric return. The average effective number of index constituents under measure of representativeness is defined as “*the number of equally-weighted shares required to achieve the same share-specific risk as the portfolio.*” (Van Rensburg and Kruger, 2008: 1).

APPENDIX E

Performances of the Candidate Glamour Indices (Counterpart Indices of the Value Indices)

The research sample consists of the largest 300 shares of the Dow Jones Sector Titans Composite Index by market capitalisation in each month of the examination period from 1 January 1991 to 31 December 2008. The candidate glamour indices serve as the counterpart indices of the candidate value indices. The candidate glamour indices are constructed from the financial ratios and the cross-sectional undervalued residual proxies. The financial ratios employed to indicate how expensive the sample shares are include the price-to-book value ratio (PTBV), price-to-earnings ratio (P/E), price-to-dividend ratio (P/D), price-to-sales ratio (PTSALES) and price-to-cash flow ratio (PTCF). On the other hand, the 31 available combinations of the monthly book value per share (B), earnings per share (E), dividends per share (D), sales per share (S) and cash flow per share (C) of the sample shares are employed as the independent variables to explain the monthly cross-sectional log returns of the sample shares using ordinary least squares (OLS) regressions. The sample shares with positive regression residuals at the beginning of each month in the examination period are regarded as the overvalued/glamorous shares for the month, and the values of their respective regression residuals (Ores) are computed and ranked for the construction of the regression-based candidate glamour indices.

The attributes of the sample shares are winsorised monthly to keep the values of the attributes within the 99.5th and 0.5th percentiles of the monthly cross-sectional distribution. The sample shares are ranked by the values of their respective winsorised attributes at the beginning of each month, and are subsequently included in, or excluded from, the equally-weighted (EW) and style-weighted (SW) indices based on the pre-specified target number of constituents in the respective indices. The overall evaluation period of 216 months from 1 January 1991 to 31 December 2008 are subdivided into 2 equal sub-periods of 108 months. The basic statistics and the risk-adjusted performance measures of candidate indices are annualised. The benchmark employed to evaluate the risk-adjusted performance of the candidate indices is the Morgan Stanley Composite International World Index (MSCI World), and the risk-free rate applied is the return on the 3-month U.S. Treasury Bill (USTB3M). The cost-adjusted geometric return under basic statistics is computed by subtracting 2% transaction costs of the monthly percentage portfolio turnover through rebalancing from the monthly index return. The monthly cost-adjusted returns are linked geometrically and annualised to arrive at the annualised cost-adjusted geometric return. The average effective number of index constituents under measure of representativeness is defined as “*the number of equally-weighted shares required to achieve the same share-specific risk as the portfolio.*” (Van Rensburg and Kruger, 2008: 1).

APPENDIX F

Performances of the South African-Based Global Equity Funds

The selected South African-based global equity funds include ABSA International Fund of Funds, Allan Gray Orbis Global Equity Fund of Funds, Coronation International Active Fund of Funds, Investec Global Equity Fund of Funds, RMB International Equity Fund of Funds and Sanlam Global Equity Fund.

The appendix contains information regarding the fund description, inception date, market value as at 30 June 2009 and the results of performance attribution analysis for the selected South African-based global equity funds from the database of Bloomberg Limited Partnership. The exposures of the selected funds to movements in the MSCI World index and the size (Size EW300), momentum (Mom SW100) and value (Value SW100) style proxies are estimated using the weighted least squares (WLS) regressions, based on the style-decomposition approach of Sharpe (1992). The style exposures of the fund are to sum up to 100% and no negative exposures are permitted in the regressions. The trailing 36-month style exposures for the selected funds are used to estimate their forward (out-of-sample) 1-month style exposures. Subsequently, the forward 1-month fund style returns are estimated by summing the products of the estimated style exposures and the style index returns. The difference between the actual fund return and the estimated style return is termed the selection return of the fund. The actual fund returns for the selected funds are regressed on the estimated style returns to determine the extent to which the variance of the actual fund returns are explained by their estimated style returns. The style-factor models employed to replicated the performance of the selected funds are the 4 factor model using MSCI World, Size EW300, Mom SW100 and Value SW100 and the 3 factor model that removes Size EW300 from the independent variables. The results obtained from the 4-factor model are displayed in Panel (a), while the results obtained from the 3-factor model are displayed in Panel (b). The estimated monthly style exposures (weights) of the selected funds for the 4-factor model and the 3-factor model are illustrated in Chart (a) and Chart (b) respectively. The decomposed performances of the funds, based on the results of the 4-factor model, are demonstrated in the form of the log cumulative fund return, the log cumulative style return and the log cumulative selection return in Chart (c).

APPENDIX G

Performances of the Internationally-Domiciled Global Equity Funds

The selected internationally-domiciled global equity funds include American Capital World Growth and Income Fund, American EuroPacific Growth Fund, BlackRock International Opportunities Portfolio, C-QUADRAT – ARTS Best Momentum Fund, Federated Prudent Bear Fund, Fidelity Disciplined Equity Fund, Fidelity Diversified International Fund, Fidelity VIP Contrafund, Russell International Developed Markets Fund, SEI International Equity Fund, Skandia Global Equity Fund and Templeton World Fund.

The appendix contains information regarding the fund description, inception date, market value as at 30 June 2009 and the results of performance attribution analysis for the selected internationally-domiciled global equity funds from the database of Bloomberg Limited Partnership. The exposures of the selected funds to the movements in the MSCI World index and the size (Size EW300), momentum (Mom SW100) and value (Value SW100) style proxies are estimated using the weighted least squares (WLS) regressions, based on the style-decomposition approach of Sharpe (1992). The style exposures of the fund are to sum up to 100% and no negative exposures are permitted in the regressions. The trailing 36-month style exposures for the selected funds are used to estimate their forward (out-of-sample) 1-month style exposures. Subsequently, the forward 1-month fund style returns are estimated by summing the products of the estimated style exposures and the style index returns. The difference between the actual fund return and the estimated style return is termed the selection return of the fund. The actual fund returns for the selected funds are regressed on the estimated style returns to determine the extent to which the variance of the actual fund returns are explained by their estimated style returns. The style-factor models employed to replicated the performance of the selected funds are the 4 factor model using MSCI World, Size EW300, Mom SW100 and Value SW100 and the 3 factor model that removes Size EW300 from the independent variables. The results obtained from the 4-factor model are displayed in Panel (a), while the results obtained from the 3-factor model are displayed in Panel (b). The estimated monthly style exposures (weights) of the selected funds for the 4-factor model and the 3-factor model are illustrated in Chart (a) and Chart (b) respectively. The decomposed performances of the selected funds, based on the results of the 4-factor model, are demonstrated in the form of the log cumulative fund return, the log cumulative style return and the log cumulative selection return in Chart (c).

APPENDIX H

Cash Protection on the MSCI World Index (1970 to 1990)

The cash protection model is a style timing model designed to protect the risk of unexpected drawdown by shifting the equity market exposure into cash using overlay hedging. The model is tested on the MSCI World Index since its inception from 1 January 1970 to 31 December 1990. Two trend-following models are devised to detect the timing of protection before significant expected drawdown: a model that applies the filter rule strategy based on drawdown (DD) and drawup (DU) estimated from the most recent peak and trough; and an exponential moving average (EMA) strategy, based on the crossover of the fast moving average (FMA) and the slow moving average (SMA). The filter rule strategy sends signal to trigger cash protection when the maximum tolerable DD is exceeded and remove the protection when the minimum required DU is exceeded. On the other hand, the EMA strategy triggers cash protection when the FMA breaks through the SMA from above and removes protection when the FMA breaks through the SMA from below. Two cash protection mechanisms are examined for each of the cash-protection strategies: a 100% cash protection mechanism the converts the entire equity exposure to synthetic cash when the warning signal is received; and a 50% cash protection mechanism that converts 50% of the equity exposure to synthetic cash when the warning signal is received.

The out-of-sample performances of the 100% and 50% cash-protected indices, based on the filter rule strategy are demonstrated in Appendix H.1 and Appendix H.2 respectively. The maximum tolerable drawdown and the minimum required drawup in the appendices are simulated from 0% to 50% at a 5% interval. On the other hand, the out-of-sample performances of the 100% and 50% cash-protected indices, based on the EMA strategy, are demonstrated in Appendix H.3 and Appendix H.4 respectively. The rates at which the respective FMA and SMA track the underlying index are simulated from 0% to 100% at a 10% interval.

The simulated out-of-sample annualised geometric return, standard deviation, 5 percent value at risk (VaR), Sharpe ratio, percentage of months in partial cash, maximum drawdown and the total number of warning signals are demonstrated in tables 1 through 7 in the respective appendices. The optimal historical permutation that maximises the Sharpe ratio in each appendix is highlighted in the thick box border in each table of the appendix.

APPENDIX I

Cash Protection on the MSCI World Index (1991 to 2008)

The cash protection model is a style timing model designed to protect the risk of unexpected drawdown by shifting the equity market exposure into cash using overlay hedging. The model is tested on the MSCI World Index over the period from 1 January 1991 to 31 December 2008. Two trend-following models are devised to detect the timing of protection before significant expected drawdown: a model that applies the filter rule strategy based on drawdown (DD) and drawup (DU) estimated from the most recent peak and trough; and an exponential moving average (EMA) strategy, based on the crossover of the fast moving average (FMA) and slow moving average (SMA). The filter rule strategy sends signal to trigger cash protection when the maximum tolerable DD is exceeded and remove the protection when the minimum required DU is exceeded. On the other hand, the EMA strategy triggers cash protection when the FMA breaks through the SMA from above and removes protection when the FMA breaks through the SMA from below. Two cash protection mechanisms are examined for each of the cash-protection strategies: a 100% cash protection mechanism the converts the entire equity exposure to synthetic cash when the warning signal is received; and a 50% cash protection mechanism that converts 50% of the equity exposure to synthetic cash when the warning signal is received.

The out-of-sample performances of the 100% and 50% cash-protected indices, based on the filter rule strategy are demonstrated in Appendix I.1 and Appendix I.2 respectively. The maximum tolerable drawdown and the minimum required drawup in the appendices are simulated from 0% to 50% at a 5% interval. On the other hand, the out-of-sample performances of the 100% and 50% cash-protected indices, based on the EMA strategy, are demonstrated in Appendix I.3 and Appendix I.4 respectively. The rates at which the respective FMA and SMA track the underlying index are simulated from 0% to 100% at a 10% interval.

The simulated out-of-sample annualised geometric return, standard deviation, 5 percent value at risk (VaR), Sharpe ratio, percentage of months in partial cash, maximum drawdown and the total number of warning signals are demonstrated in tables 1 through 7 in the respective appendices. The optimal historical permutation that maximises the Sharpe ratio in each appendix is highlighted in the thick box border in each table of the appendix.

APPENDIX J

Cash Protection on the MSCI World Index

(1970 to 2008)

The cash protection model is a style timing model designed to protect the risk of unexpected drawdown by shifting the equity market exposure into cash using overlay hedging. The model is tested on the MSCI World Index over the period from 1 January 1970 to 31 December 2008. Two trend-following models are devised to detect the timing of protection before significant expected drawdown: a model that applies the filter rule strategy based on drawdown (DD) and drawup (DU) estimated from the most recent peak and trough; and an exponential moving average (EMA) strategy, based on the crossover of the fast moving average (FMA) and slow moving average (SMA). The filter rule strategy sends signal to trigger cash protection when the maximum tolerable DD is exceeded and remove the protection when the minimum required DU is exceeded. On the other hand, the EMA strategy triggers cash protection when the FMA breaks through the SMA from above and removes protection when the FMA breaks through the SMA from below. Two cash protection mechanisms are examined for each of the cash-protection strategies: a 100% cash protection mechanism the converts the entire equity exposure to synthetic cash when the warning signal is received; and a 50% cash protection mechanism that converts 50% of the equity exposure to synthetic cash when the warning signal is received.

The out-of-sample performances of the 100% and 50% cash-protected indices, based on the filter rule strategy are demonstrated in Appendix J.1 and Appendix J.2 respectively. The maximum tolerable drawdown and the minimum required drawup in the appendices are simulated from 0% to 50% at a 5% interval. On the other hand, the out-of-sample performances of the 100% and 50% cash-protected indices, based on the EMA strategy, are demonstrated in Appendix J.3 and Appendix J.4 respectively. The rates at which the respective FMA and SMA track the underlying index are simulated from 0% to 100% at a 10% interval.

The simulated out-of-sample annualised geometric return, standard deviation, 5 percent value at risk (VaR), Sharpe ratio, percentage of months in partial cash, maximum drawdown and the total number of warning signals are demonstrated in tables 1 through 7 in the respective appendices. The optimal historical permutation that maximises the Sharpe ratio in each appendix is highlighted in the thick box border in each table of the appendix.

APPENDIX K

Cash Protection on the Global Momentum Proxy

(1991 to 2008)

The cash protection model is a style timing model designed to protect the risk of unexpected drawdown by shifting the equity market exposure into cash using overlay hedging. The model is tested on the global momentum proxy over the period from 1 January 1991 to 31 December 2008. Two trend-following models are devised to detect the timing of protection before significant expected drawdown: a model that applies the filter rule strategy based on drawdown (DD) and drawup (DU) estimated from the most recent peak and trough; and an exponential moving average (EMA) strategy, based on the crossover of the fast moving average (FMA) and slow moving average (SMA). The filter rule strategy sends signal to trigger cash protection when the maximum tolerable DD is exceeded and remove the protection when the minimum required DU is exceeded. On the other hand, the EMA strategy triggers cash protection when the FMA breaks through the SMA from above and removes protection when the FMA breaks through the SMA from below. Two cash protection mechanisms are examined for each of the cash-protection strategies: a 100% cash protection mechanism the converts the entire equity exposure to synthetic cash when the warning signal is received; and a 50% cash protection mechanism that converts 50% of the equity exposure to synthetic cash when the warning signal is received.

The out-of-sample performances of the 100% and 50% cash-protected indices based on the filter rule strategy are demonstrated in Appendix K.1 and Appendix K.2 respectively. The maximum tolerable drawdown and the minimum required drawup in the appendices are simulated from 0% to 50% at a 5% interval. On the other hand, the out-of-sample performances of the 100% and 50% cash-protected indices, based on the EMA strategy, are demonstrated in Appendix K.3 and Appendix K.4 respectively. The rates at which the respective FMA and SMA track the underlying index are simulated from 0% to 100% at a 10% interval.

The simulated out-of-sample annualised geometric return, standard deviation, 5 percent value at risk (VaR), Sharpe ratio, percentage of months in partial cash, maximum drawdown and the total number of warning signals are demonstrated in tables 1 through 7 in the respective appendices. The optimal historical permutation that maximises the Sharpe ratio in each appendix is highlighted in the thick box border in each table of the appendix.

APPENDIX L

Cash Protection on the Global Value Proxy

(1991 to 2008)

The cash protection model is a style timing model designed to protect the risk of unexpected drawdown by shifting the equity market exposure into cash using overlay hedging. The model is tested on the global value proxy over the period from 1 January 1991 to 31 December 2008. Two trend-following models are devised to detect the timing of protection before significant expected drawdown: a model that applies the filter rule strategy based on drawdown (DD) and drawup (DU) estimated from the most recent peak and trough; and an exponential moving average (EMA) strategy, based on the crossover of the fast moving average (FMA) and slow moving average (SMA). The filter rule strategy sends signal to trigger cash protection when the maximum tolerable DD is exceeded and remove the protection when the minimum required DU is exceeded. On the other hand, the EMA strategy triggers cash protection when the FMA breaks through the SMA from above and removes protection when the FMA breaks through the SMA from below. Two cash protection mechanisms are examined for each of the cash-protection strategies: a 100% cash protection mechanism the converts the entire equity exposure to synthetic cash when the warning signal is received; and a 50% cash protection mechanism that converts 50% of the equity exposure to synthetic cash when the warning signal is received.

The out-of-sample performances of the 100% and 50% cash-protected indices, based on the filter rule strategy are demonstrated in Appendix L.1 and Appendix L.2 respectively. The maximum tolerable drawdown and the minimum required drawup in the appendices are simulated from 0% to 50% at a 5% interval. On the other hand, the out-of-sample performances of the 100% and 50% cash-protected indices, based on the EMA strategy, are demonstrated in Appendix L.3 and Appendix L.4 respectively. The rates at which the respective FMA and SMA track the underlying index are simulated from 0% to 100% at a 10% interval.

The simulated out-of-sample annualised geometric return, standard deviation, 5 percent value at risk (VaR), Sharpe ratio, percentage of months in partial cash, maximum drawdown and the total number of warning signals are demonstrated in tables 1 through 7 in the respective appendices. The optimal historical permutation that maximises the Sharpe ratio in each appendix is highlighted in the thick box border in each table of the appendix.

Appendix A.7 Net Cash flow (5-Year Trailing Average) Indices

Performance Evaluation Measures:		Evaluation Periods:		Candidate Style Indices (Weighing Methods; Target No. of Constituents)											
				MSCI World	EW300	EW200	EW100	EW50	EW30	SW300	SW200	SW100	SW50	SW30	
Basic Statistics:															
Geometric Return (Annualised)	(1/91 ~ 12/99)(108m)	15.67%		16.14%	16.34%	16.09%	15.68%	17.31%		17.75%	17.77%	17.78%	17.76%	17.87%	
Geometric Return (Annualised)	(1/00 ~ 12/08)(108m)	-2.69%		2.09%	1.82%	0.74%	1.22%	2.71%		-0.80%	-0.83%	-0.93%	-0.93%	-0.82%	
Geometric Return (Annualised)	(1/91 ~ 12/08)(216m)	6.10%		8.89%	8.84%	8.14%	8.21%	9.77%		8.08%	8.07%	8.02%	8.01%	8.12%	
Cost Adj. Geometric Return (Annualised)	(1/91 ~ 12/99)(108m)	N/A		14.67%	14.91%	14.70%	14.34%	16.02%		15.85%	15.94%	16.06%	16.12%	16.28%	
Cost Adj. Geometric Return (Annualised)	(1/00 ~ 12/08)(108m)	N/A		0.75%	0.49%	-0.56%	-0.04%	1.50%		-2.25%	-2.28%	-2.37%	-2.35%	-2.23%	
Cost Adj. Geometric Return (Annualised)	(1/91 ~ 12/08)(216m)	N/A		7.48%	7.46%	6.80%	6.91%	8.52%		6.42%	6.44%	6.45%	6.48%	6.62%	
Cumulative Return (Growth of US\$1.0)	(1/91 ~ 12/99)(108m)	3.707		3.844	3.906	3.828	3.709	4.209		4.351	4.359	4.362	4.355	4.391	
Cumulative Return (Growth of US\$1.0)	(1/00 ~ 12/08)(108m)	0.782		1.204	1.176	1.068	1.115	1.272		0.930	0.928	0.919	0.919	0.929	
Cumulative Return (Growth of US\$1.0)	(1/91 ~ 12/08)(216m)	2.901		4.630	4.594	4.090	4.137	5.355		4.048	4.043	4.010	4.004	4.078	
Arithmetic Return (Annualised)	(1/91 ~ 12/99)(108m)	16.57%		17.01%	17.24%	16.98%	16.66%	18.41%		18.86%	18.89%	18.91%	18.91%	19.05%	
Arithmetic Return (Annualised)	(1/00 ~ 12/08)(108m)	-1.36%		3.44%	3.23%	2.33%	2.81%	4.41%		0.84%	0.81%	0.73%	0.74%	0.86%	
Arithmetic Return (Annualised)	(1/91 ~ 12/08)(216m)	7.26%		10.03%	10.03%	9.43%	9.54%	11.21%		9.51%	9.51%	9.47%	9.48%	9.61%	
Standard Deviation (Annualised)	(1/91 ~ 12/99)(108m)	12.56%		12.40%	12.60%	12.60%	13.22%	13.91%		13.96%	13.98%	14.07%	14.22%	14.38%	
Standard Deviation (Annualised)	(1/00 ~ 12/08)(108m)	16.25%		16.01%	16.38%	17.53%	17.41%	17.69%		17.59%	17.62%	17.71%	17.76%	17.81%	
Standard Deviation (Annualised)	(1/91 ~ 12/08)(216m)	14.69%		14.40%	14.70%	15.36%	15.53%	15.98%		16.02%	16.05%	16.14%	16.23%	16.33%	
Measure of Representativeness:															
Avg. No. of Constituents	(1/91 ~ 12/99)(108m)	1,500 +/-		270	200	100	50	30		270	200	100	50	30	
Avg. No. of Constituents	(1/00 ~ 12/08)(108m)	1,500 +/-		274	200	100	50	30		274	200	100	50	30	
Avg. No. of Constituents	(1/91 ~ 12/08)(216m)	1,500 +/-		272	200	100	50	30		272	200	100	50	30	
Avg. Effective No. of Constituents	(1/91 ~ 12/99)(108m)	N/A		270	200	100	50	30		20	19	19	18	17	
Avg. Effective No. of Constituents	(1/00 ~ 12/08)(108m)	N/A		274	200	100	50	30		21	21	20	18	17	
Avg. Effective No. of Constituents	(1/91 ~ 12/08)(216m)	N/A		272	200	100	50	30		20	20	19	18	17	
Max. Constituent Holding	(1/91 ~ 12/99)(108m)	N/A		0.38%	0.50%	1.00%	2.04%	3.33%		10.00%	10.00%	10.00%	10.00%	10.00%	
Max. Constituent Holding	(1/00 ~ 12/08)(108m)	N/A		0.38%	0.50%	1.00%	2.04%	3.33%		10.00%	10.00%	10.00%	10.00%	10.00%	
Max. Constituent Holding	(1/91 ~ 12/08)(216m)	N/A		0.38%	0.50%	1.00%	2.04%	3.33%		10.00%	10.00%	10.00%	10.00%	10.00%	
Indication of Transaction Costs: Portfolio Turnover															
Mean Monthly Rebalancing	(1/91 ~ 12/99)(108m)	N/A		5.38%	5.25%	5.06%	4.90%	4.68%		6.86%	6.63%	6.22%	5.91%	5.74%	
Mean Monthly Rebalancing	(1/00 ~ 12/08)(108m)	N/A		5.52%	5.49%	5.41%	5.21%	4.95%		6.13%	6.12%	6.08%	6.03%	5.98%	
Mean Monthly Rebalancing	(1/91 ~ 12/08)(216m)	N/A		5.45%	5.37%	5.23%	5.06%	4.81%		6.50%	6.38%	6.15%	5.97%	5.86%	
Risk-Adjusted Performance Measures (Annualised):															
Sharpe Ratio (Annualised)	(1/91 ~ 12/99)(108m)	0.872		0.920	0.922	0.901	0.828	0.905		0.933	0.933	0.927	0.916	0.914	
Sharpe Ratio (Annualised)	(1/00 ~ 12/08)(108m)	-0.354		-0.061	-0.076	-0.133	-0.106	-0.020		-0.220	-0.221	-0.226	-0.225	-0.218	
Sharpe Ratio (Annualised)	(1/91 ~ 12/08)(216m)	0.150		0.347	0.337	0.277	0.278	0.368		0.261	0.260	0.256	0.254	0.259	
M Squared (Annulised)	(1/91 ~ 12/99)(108m)	0.00%		0.61%	0.63%	0.37%	-0.54%	0.41%		0.77%	0.77%	0.70%	0.56%	0.53%	
M Squared (Annulised)	(1/00 ~ 12/08)(108m)	0.00%		4.76%	4.52%	3.60%	4.03%	5.43%		2.19%	2.16%	2.09%	2.10%	2.21%	
M Squared (Annulised)	(1/91 ~ 12/08)(216m)	0.00%		2.89%	2.74%	1.86%	1.88%	3.20%		1.63%	1.62%	1.55%	1.53%	1.60%	
Information Ratio (Annualised)	(1/91 ~ 12/99)(108m)	0.000		0.095	0.132	0.074	0.001	0.175		0.215	0.217	0.213	0.205	0.210	
Information Ratio (Annualised)	(1/00 ~ 12/08)(108m)	0.000		1.278	1.142	0.765	0.710	0.673		0.241	0.235	0.218	0.211	0.216	
Information Ratio (Annualised)	(1/91 ~ 12/08)(216m)	0.000		0.633	0.599	0.403	0.329	0.421		0.226	0.224	0.214	0.206	0.211	
Treynor Ratio (Annualised)	(1/91 ~ 12/99)(108m)	0.109		0.125	0.126	0.125	0.123	0.151		0.158	0.159	0.159	0.160	0.162	
Treynor Ratio (Annualised)	(1/00 ~ 12/08)(108m)	-0.058		-0.010	-0.013	-0.022	-0.018	-0.004		-0.040	-0.040	-0.041	-0.041	-0.041	
Treynor Ratio (Annualised)	(1/91 ~ 12/08)(216m)	0.022		0.054	0.052	0.043	0.045	0.064		0.046	0.046	0.045	0.045	0.047	
Jensen's Alpha (Annualised)	(1/91 ~ 12/99)(108m)	0.00%		1.50%	1.60%	1.53%	1.40%	3.79%		4.38%	4.42%	4.49%	4.55%	4.74%	
Jensen's Alpha (Annualised)	(1/00 ~ 12/08)(108m)	0.00%		4.61%	4.49%	3.88%	4.24%	5.63%		2.06%	2.03%	1.95%	1.94%	2.03%	
Jensen's Alpha (Annualised)	(1/91 ~ 12/08)(216m)	0.00%		2.99%	2.94%	2.22%	2.41%	4.24%		2.54%	2.53%	2.50%	2.53%	2.68%	
p-value (Alpha)	(1/91 ~ 12/99)(108m)	1.000		0.098	0.116	0.151	0.263	0.877		0.983	0.976	0.956	0.939	0.900	
p-value (Alpha)	(1/00 ~ 12/08)(108m)	1.000		0.167	0.254	0.629	0.534	0.326		0.739	0.732	0.715	0.726	0.765	
p-value (Alpha)	(1/91 ~ 12/08)(216m)	1.000		0.447	0.406	0.163	0.350	0.835		0.582	0.583	0.582	0.608	0.670	
R Squared	(1/91 ~ 12/99)(108m)	100.00%		84.81%	84.11%	81.22%	71.20%	56.90%		54.95%	54.70%	53.42%	51.68%	49.97%	
R Squared	(1/00 ~ 12/08)(108m)	100.00%		94.96%	94.36%	93.73%	90.17%	79.81%		80.51%	80.33%	79.71%	78.32%	76.75%	
R Squared	(1/91 ~ 12/08)(216m)	100.00%		90.95%	90.36%	88.99%	82.84%	70.82%		70.74%	70.54%	69.64%	68.04%	66.36%	
Beta	(1/91 ~ 12/99)(108m)	1.00		0.91	0.92	0.91	0.89	0.84		0.82	0.82	0.82	0.81	0.81	
Beta	(1/00 ~ 12/08)(108m)	1.00		0.96	0.98	1.04	1.02	0.97		0.97	0.97	0.97	0.96	0.96	
Beta	(1/91 ~ 12/08)(216m)	1.00		0.93	0.95	0.98	0.96	0.91		0.91	0.91	0.91	0.91	0.90	
p-value (Beta)	(1/91 ~ 12/99)(108m)	0.00		0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	
p-value (Beta)	(1/00 ~ 12/08)(108m)	0.00		0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	
p-value (Beta)	(1/91 ~ 12/08)(216m)	0.00		0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	

Appendix F.1 ABSA International Fund of Funds

FUND DESCRIPTION: ABSA International Fund of Funds is a unit trust incorporated in South Africa. The Fund will diversify its holdings across global equity markets and sectors as well as global fixed interest markets. The Fund will be aimed at moderate to high risk profile investors that require foreign investment exposure across asset classes according to market movements.

FUND INCEPTION: 2001/09/01
EVALUATION (OUT-OF-SAMPLE) PERIOD: 2006/02/01 to 2008/12/31
FUND MARKET VALUE (US\$): 10.52 Million

Panel (a): 4-Factor (MSCI, Cap EW300, Mom SW100 and Value SW00) Model

<u>Performance Attribution:</u>		<u>t-Statistic</u>	<u>p-Value</u>
Avg. Monthly Fund Return	-1.05%	-1.189	0.243
Monthly Standard Deviation	5.22%		
Monthly Sharpe Ratio	-0.257		
(1) Avg. Monthly Style Return	-0.21%	-0.226	0.822
Monthly Standard Deviation	5.62%		
Monthly Sharpe Ratio	-0.090		
(2) Avg. Monthly Selection Return	-0.83%	-1.792	0.082
Monthly Standard Deviation	2.75%		
Regressing Fund Return on Style Return:			
R Squared	76.30%		
Intercept	-0.009	-2.004	0.053
Slope Coefficient	0.811	10.307	0.000

Panel (b): 3-Factor (MSCI, Mom SW100 and Value SW00) Model

<u>Performance Attribution:</u>		<u>t-Statistic</u>	<u>p-Value</u>
Avg. Monthly Fund Return	-1.05%	-1.189	0.243
Monthly Standard Deviation	5.22%		
Monthly Sharpe Ratio	-0.257		
(1) Avg. Monthly Style Return	-0.21%	-0.226	0.822
Monthly Standard Deviation	5.62%		
Monthly Sharpe Ratio	-0.090		
(2) Avg. Monthly Selection Return	-0.83%	-1.792	0.082
Monthly Standard Deviation	2.75%		
Regressing Fund Return on Style Return:			
R Squared	76.30%		
Intercept	-0.009	-2.004	0.053
Slope Coefficient	0.811	10.307	0.000

Chart (a): 4-Factor Style Composition

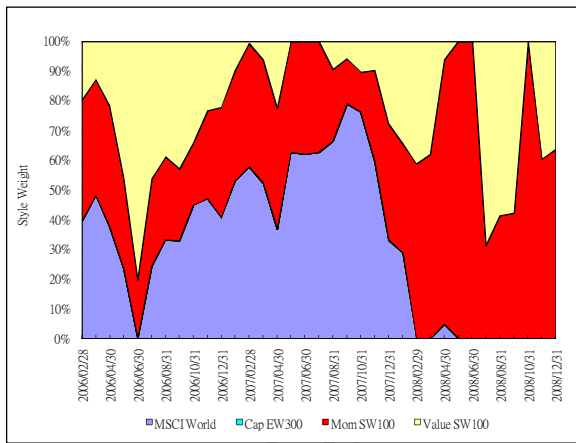


Chart (b): 3-Factor Style Composition

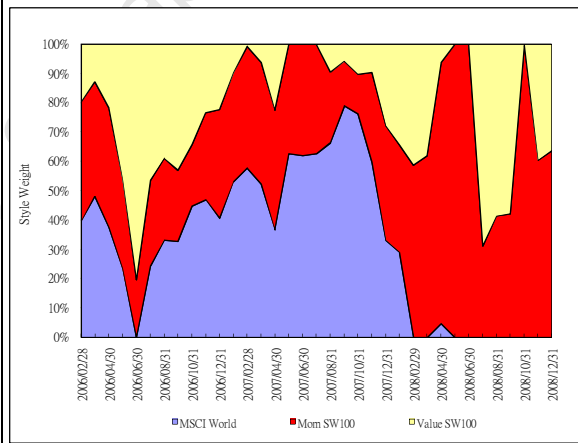
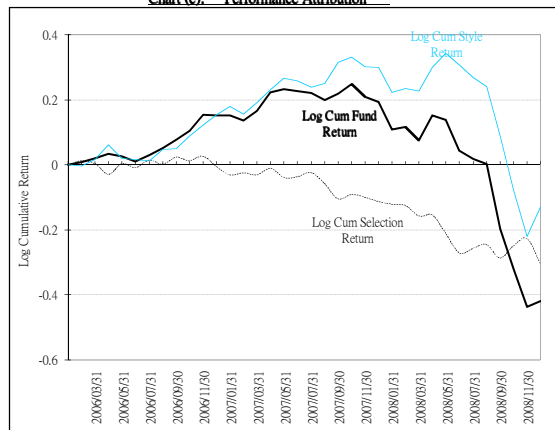


Chart (c): Performance Attribution



Appendix F.2 Allan Gray Orbis Global Equity Fund of Funds

FUND DESCRIPTION: Allan Gray Orbis Global Equity Fund of Funds is an unit trust fund incorporated in South Africa. The Fund's central objective is to provide investors with the opportunity for offshore diversification, a hedge against Rand depreciation and superior returns on a foreign balanced portfolio versus the benchmark, at no greater risk of loss.

FUND INCEPTION: 2001/12/03
EVALUATION (OUT-OF-SAMPLE) PERIOD: 2007/11/01 to 2008/12/31
FUND MARKET VALUE (US\$): 771.40 Million

Panel (a): 4-Factor (MSCI, Cap EW300, Mom SW100 and Value SW00) Model

<u>Performance Attribution:</u>		<u>t-Statistic</u>	<u>p-Value</u>
Avg. Monthly Fund Return	-3.34%	-2.017	0.065
Monthly Standard Deviation	6.19%		
Monthly Sharpe Ratio	-0.561		
(1) Avg. Monthly Style Return	-3.67%	-1.648	0.123
Monthly Standard Deviation	8.34%		
Monthly Sharpe Ratio	-0.457		
(2) Avg. Monthly Selection Return	0.33%	0.377	0.713
Monthly Standard Deviation	3.32%		
<u>Regressing Fund Return on Style Return:</u>			
R Squared	87.98%		
Intercept	-0.008	-1.189	0.258
Slope Coefficient	0.697	9.373	0.000

Panel (b): 3-Factor (MSCI, Mom SW100 and Value SW00) Model

<u>Performance Attribution:</u>		<u>t-Statistic</u>	<u>p-Value</u>
Avg. Monthly Fund Return	-3.34%	-2.017	0.065
Monthly Standard Deviation	6.19%		
Monthly Sharpe Ratio	-0.561		
(1) Avg. Monthly Style Return	-3.67%	-1.648	0.123
Monthly Standard Deviation	8.34%		
Monthly Sharpe Ratio	-0.457		
(2) Avg. Monthly Selection Return	0.33%	0.377	0.713
Monthly Standard Deviation	3.32%		
<u>Regressing Fund Return on Style Return:</u>			
R Squared	87.98%		
Intercept	-0.008	-1.189	0.258
Slope Coefficient	0.697	9.373	0.000

Chart (a): 4-Factor Style Composition

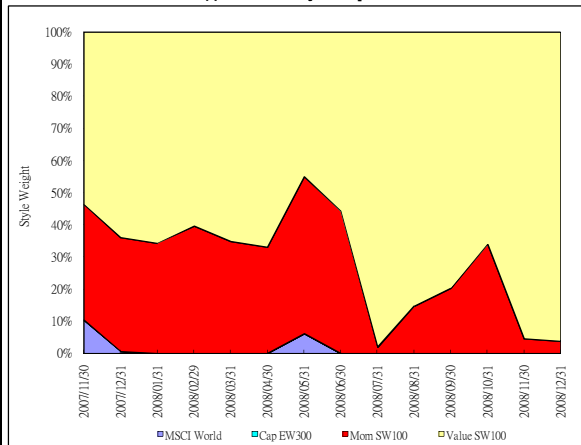


Chart (b): 3-Factor Style Composition

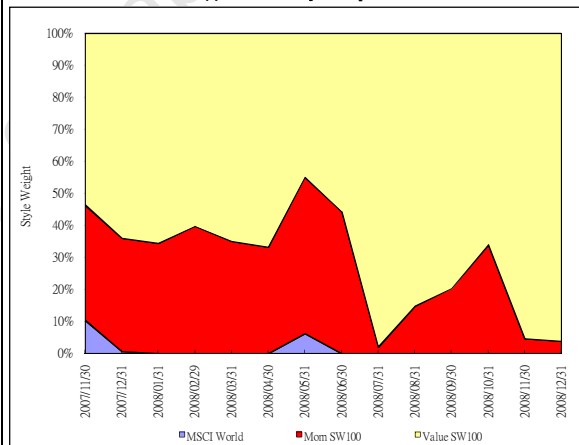
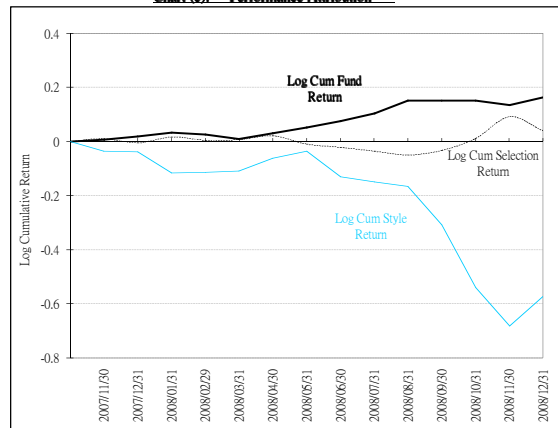


Chart (c): Performance Attribution



Appendix F.3 Coronation International Active Fund of Funds

FUND DESCRIPTION: Coronation International Active Fund of Funds is a unit trust incorporated in South Africa. The objective of the Fund is to achieve long-term US-dollar based capital growth. The Fund invests in shares of international equity collective investment schemes. At least 85% of the Fund's assets will be invested internationally with no more than 20% with any one fund manager.

FUND INCEPTION: 1997/01/08
EVALUATION (OUT-OF-SAMPLE) PERIOD: 2002/05/01 to 2008/12/31
FUND MARKET VALUE (US\$): 105.26 Million

Panel (a): 4-Factor (MSCI, Cap EW300, Mom SW100 and Value SW00) Model

<u>Performance Attribution:</u>		<u>t-Statistic</u>	<u>p-Value</u>
Avg. Monthly Fund Return	1.24%	3.595	0.001
Monthly Standard Deviation	3.09%		
Monthly Sharpe Ratio	0.332		
(1) Avg. Monthly Style Return	0.71%	1.170	0.246
Monthly Standard Deviation	5.42%		
Monthly Sharpe Ratio	0.091		
(2) Avg. Monthly Selection Return	0.53%	1.135	0.260
Monthly Standard Deviation	4.19%		
Regressing Fund Return on Style Return:			
R Squared	40.73%		
Intercept	0.010	3.645	0.000
Slope Coefficient	0.363	7.321	0.000

Panel (b): 3-Factor (MSCI, Mom SW100 and Value SW00) Model

<u>Performance Attribution:</u>		<u>t-Statistic</u>	<u>p-Value</u>
Avg. Monthly Fund Return	1.24%	3.595	0.001
Monthly Standard Deviation	3.09%		
Monthly Sharpe Ratio	0.332		
(1) Avg. Monthly Style Return	0.80%	1.301	0.197
Monthly Standard Deviation	5.50%		
Monthly Sharpe Ratio	0.106		
(2) Avg. Monthly Selection Return	0.44%	0.923	0.359
Monthly Standard Deviation	4.26%		
Regressing Fund Return on Style Return:			
R Squared	40.56%		
Intercept	0.010	3.528	0.001
Slope Coefficient	0.357	7.296	0.000

Chart (a): 4-Factor Style Composition

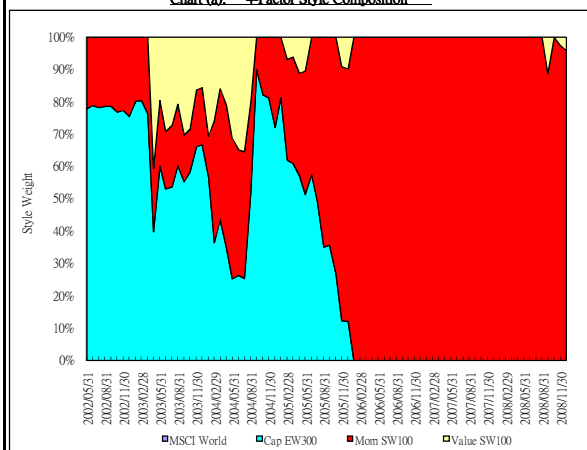


Chart (b): 3-Factor Style Composition

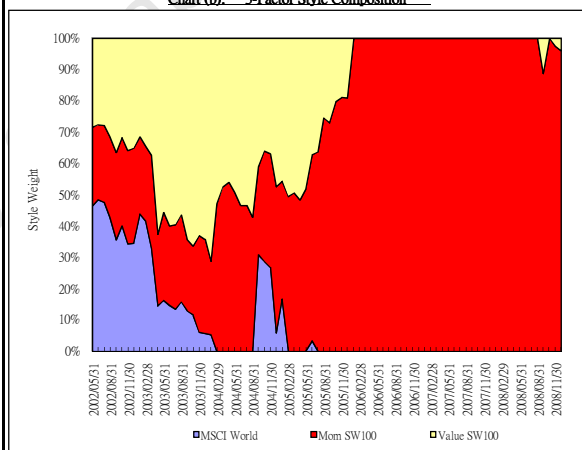
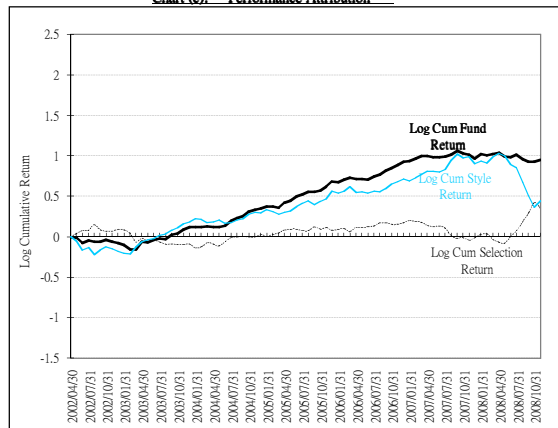


Chart (c): Performance Attribution



Appendix F.4 Investec Global Equity Fund of Funds

FUND DESCRIPTION: Investec Global Equity Fund of Funds is a unit trust incorporated in South Africa. The objective of the Fund is to provide capital growth. The Fund invests primarily in high-quality international equities. The Fund may also invest up to 20% of its assets in other authorized funds.

FUND INCEPTION: 1996/05/01 **FUND MARKET VALUE (US\$):** 144.82 Million
EVALUATION (OUT-OF-SAMPLE) PERIOD: 2002/09/01 to 2008/12/31

Panel (a): 4-Factor (MSCI, Cap EW300, Mom SW100 and Value SW00) Model

<u>Performance Attribution:</u>		<u>t-Statistic</u>	<u>p-Value</u>
Avg. Monthly Fund Return	0.46%	0.836	0.406
Monthly Standard Deviation	4.79%		
Monthly Sharpe Ratio	0.050		
(1) Avg. Monthly Style Return	0.84%	1.372	0.174
Monthly Standard Deviation	5.32%		
Monthly Sharpe Ratio	0.116		
(2) Avg. Monthly Selection Return	-0.38%	-1.653	0.103
Monthly Standard Deviation	2.00%		
<u>Regressing Fund Return on Style Return:</u>		<u>t-Statistic</u>	<u>p-Value</u>
R Squared	86.01%		
Intercept	-0.002	-1.145	0.256
Slope Coefficient	0.835	21.329	0.000

Panel (b): 3-Factor (MSCI, Mom SW100 and Value SW00) Model

<u>Performance Attribution:</u>		<u>t-Statistic</u>	<u>p-Value</u>
Avg. Monthly Fund Return	0.46%	0.836	0.406
Monthly Standard Deviation	4.79%		
Monthly Sharpe Ratio	0.050		
(1) Avg. Monthly Style Return	0.86%	1.410	0.163
Monthly Standard Deviation	5.33%		
Monthly Sharpe Ratio	0.121		
(2) Avg. Monthly Selection Return	-0.40%	-1.760	0.082
Monthly Standard Deviation	2.00%		
<u>Regressing Fund Return on Style Return:</u>		<u>t-Statistic</u>	<u>p-Value</u>
R Squared	86.06%		
Intercept	-0.003	-1.241	0.218
Slope Coefficient	0.834	21.370	0.000

Chart (a): 4-Factor Style Composition

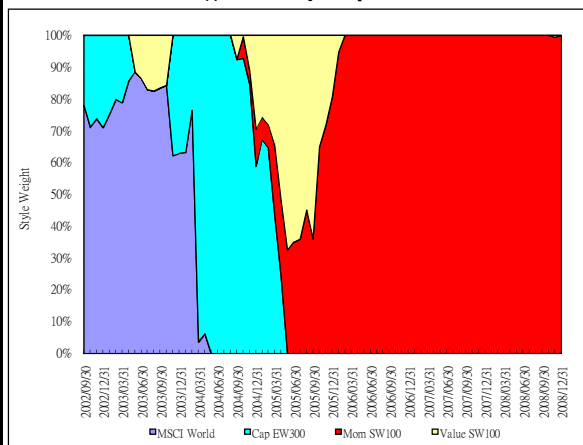


Chart (b): 3-Factor Style Composition

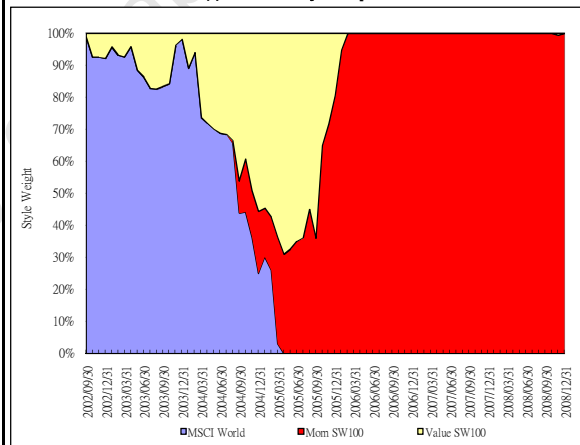
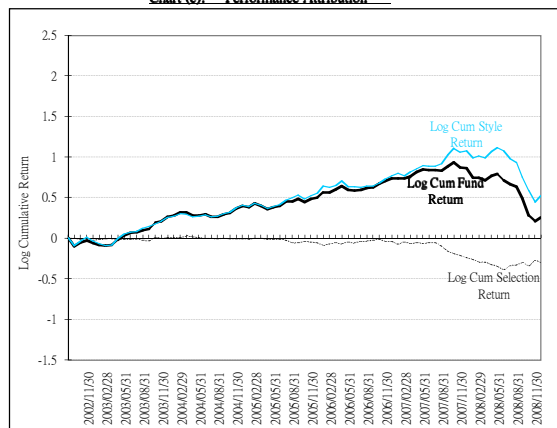


Chart (c): Performance Attribution



Appendix F.5 RMB International Equity Fund of Funds

FUND DESCRIPTION: RMB International Equity Fund of Funds is a unit trust incorporated in South Africa. The aim of the Fund is to provide offshore diversification, a hedge against rand depreciation, and steady capital growth. The Fund invests in offshore unit trusts excluding emerging markets. The Portfolio must hold a minimum of five unit trusts with no more than 20% in a one single investment.

FUND INCEPTION: 1999/04/28 **FUND MARKET VALUE (US\$):** 32.82 Million
EVALUATION (OUT-OF-SAMPLE) PERIOD: 2002/05/01 to 2008/12/31

Panel (a): 4-Factor (MSCI, Cap EW300, Mom SW100 and Value SW00) Model

Performance Attribution:		t-Statistic	p-Value
Avg. Monthly Fund Return	0.14%	0.218	0.828
Monthly Standard Deviation	5.68%		
Monthly Sharpe Ratio	-0.014		
(1) Avg. Monthly Style Return	0.62%	1.031	0.306
Monthly Standard Deviation	5.41%		
Monthly Sharpe Ratio	0.075		
(2) Avg. Monthly Selection Return	-0.49%	-1.257	0.212
Monthly Standard Deviation	3.45%		
Regressing Fund Return on Style Return:		t-Statistic	p-Value
R Squared	65.18%		
Intercept	-0.004	-1.028	0.307
Slope Coefficient	0.848	12.083	0.000

Panel (b): 3-Factor (MSCI, Mom SW100 and Value SW00) Model

Performance Attribution:		t-Statistic	p-Value
Avg. Monthly Fund Return	0.14%	0.218	0.828
Monthly Standard Deviation	5.68%		
Monthly Sharpe Ratio	-0.014		
(1) Avg. Monthly Style Return	0.65%	1.066	0.290
Monthly Standard Deviation	5.42%		
Monthly Sharpe Ratio	0.079		
(2) Avg. Monthly Selection Return	-0.51%	-1.314	0.193
Monthly Standard Deviation	3.45%		
Regressing Fund Return on Style Return:		t-Statistic	p-Value
R Squared	65.19%		
Intercept	-0.004	-1.075	0.286
Slope Coefficient	0.847	12.086	0.000

Chart (a): 4-Factor Style Composition

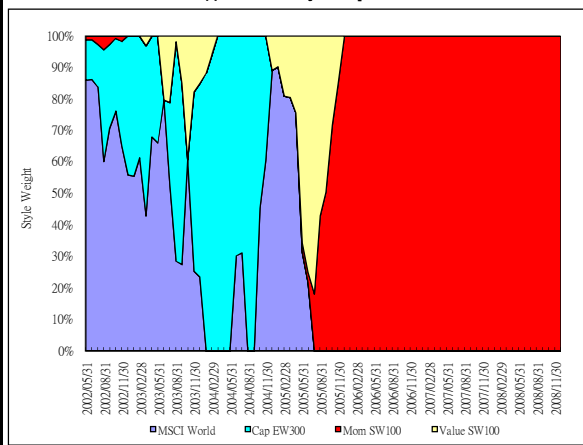


Chart (b): 3-Factor Style Composition

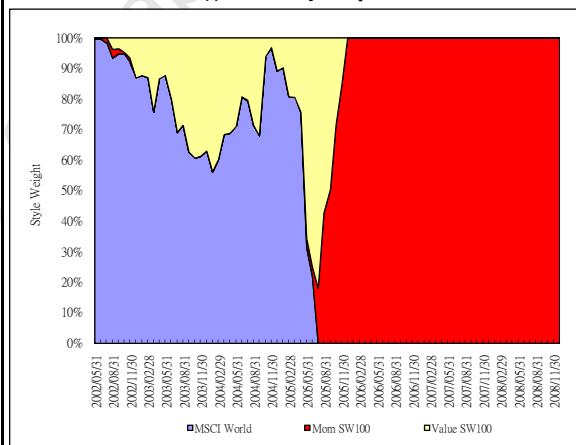
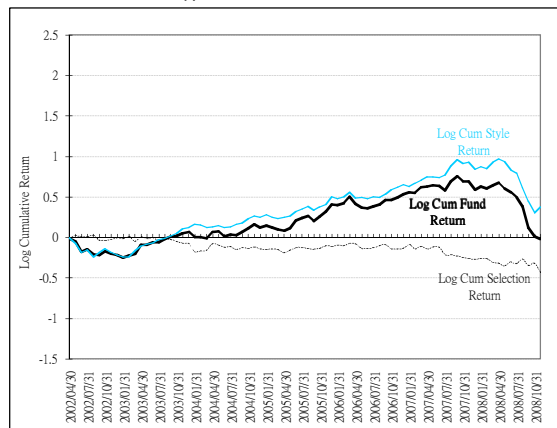


Chart (c): Performance Attribution



Appendix F.6 Sanlam Global Equity Fund

FUND DESCRIPTION: Sanlam Global Equity Fund is a unit trust incorporated in South Africa. The objective of the Fund is to provide superior returns in the medium to long term. The Fund invests in a well spread portfolio of equities across the globe.

FUND INCEPTION: 2002/03/08
EVALUATION (OUT-OF-SAMPLE) PERIOD: 2005/04/01 to 2008/12/31
FUND MARKET VALUE (US\$): 141.88 Million

Panel (a): 4-Factor (MSCI, Cap EW300, Mom SW100 and Value SW00) Model

<u>Performance Attribution:</u>		<u>t-Statistic</u>	<u>p-Value</u>
Avg. Monthly Fund Return	-0.59%	-0.708	0.483
Monthly Standard Deviation	5.59%		
Monthly Sharpe Ratio	-0.158		
(1) Avg. Monthly Style Return	0.41%	0.459	0.649
Monthly Standard Deviation	6.06%		
Monthly Sharpe Ratio	0.020		
(2) Avg. Monthly Selection Return	-1.00%	-2.758	0.008
Monthly Standard Deviation	2.44%		
<u>Regressing Fund Return on Style Return:</u>			
R Squared	83.72%		
Intercept	-0.009	-2.758	0.009
Slope Coefficient	0.845	14.872	0.000

Panel (b): 3-Factor (MSCI, Mom SW100 and Value SW00) Model

<u>Performance Attribution:</u>		<u>t-Statistic</u>	<u>p-Value</u>
Avg. Monthly Fund Return	-0.59%	-0.708	0.483
Monthly Standard Deviation	5.59%		
Monthly Sharpe Ratio	-0.158		
(1) Avg. Monthly Style Return	0.42%	0.467	0.643
Monthly Standard Deviation	6.07%		
Monthly Sharpe Ratio	0.021		
(2) Avg. Monthly Selection Return	-1.01%	-2.774	0.008
Monthly Standard Deviation	2.45%		
<u>Regressing Fund Return on Style Return:</u>			
R Squared	83.70%		
Intercept	-0.009	-2.774	0.008
Slope Coefficient	0.844	14.858	0.000

Chart (a): 4-Factor Style Composition

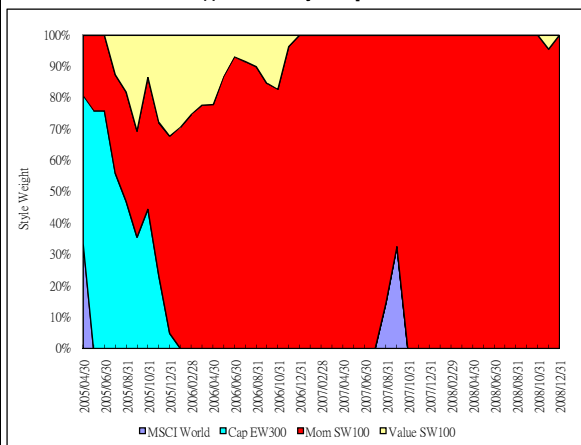


Chart (b): 3-Factor Style Composition

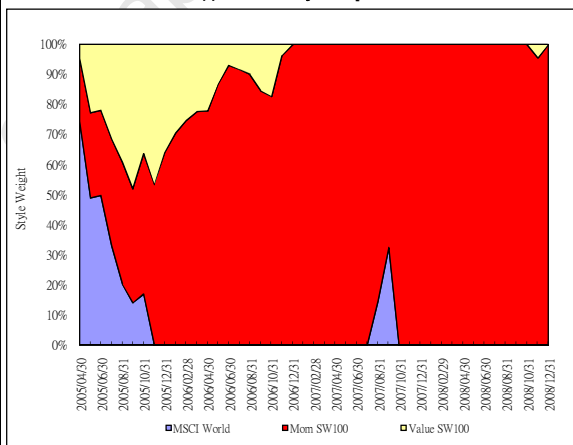
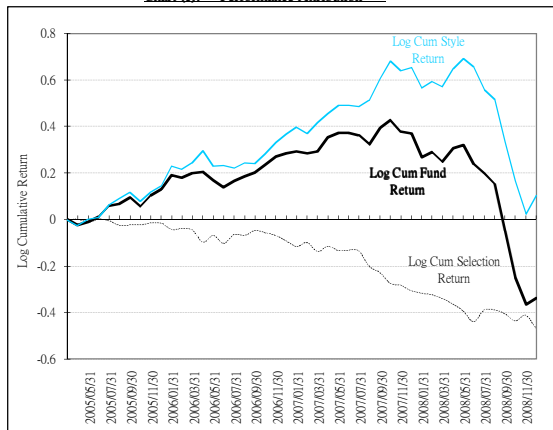


Chart (c): Performance Attribution



Appendix G.1 American Capital World Growth and Income Fund

FUND DESCRIPTION: American Funds - Capital World Growth and Income Fund is an open-end fund incorporated in the USA. The Fund's objective is long-term capital growth while providing current income. The Fund invests primarily in stocks of well-established companies located around the world. The Fund tends to invest in stocks that are believed to be relatively resilient to market declines.

FUND INCEPTION: 1993/03/26 **FUND MARKET VALUE (US\$):** 75.60 Billion
EVALUATION (OUT-OF-SAMPLE) PERIOD: 2002/09/01 to 2008/12/31

Panel (a): 4-Factor (MSCI, Cap EW300, Mom SW100 and Value SW00) Model

Performance Attribution:		t-Statistic	p-Value
Avg. Monthly Fund Return	1.60%	1.963	0.053
Monthly Standard Deviation	7.09%		
Monthly Sharpe Ratio	0.194		
(1) Avg. Monthly Style Return	0.97%	1.642	0.105
Monthly Standard Deviation	5.17%		
Monthly Sharpe Ratio	0.146		
(2) Avg. Monthly Selection Return	0.62%	1.215	0.228
Monthly Standard Deviation	4.47%		
Regressing Fund Return on Style Return:			
R Squared	60.46%		
Intercept	0.006	1.065	0.290
Slope Coefficient	1.067	10.637	0.000

Panel (b): 3-Factor (MSCI, Mom SW100 and Value SW00) Model

Performance Attribution:		t-Statistic	p-Value
Avg. Monthly Fund Return	1.60%	1.963	0.053
Monthly Standard Deviation	7.09%		
Monthly Sharpe Ratio	0.194		
(1) Avg. Monthly Style Return	1.01%	1.683	0.097
Monthly Standard Deviation	5.24%		
Monthly Sharpe Ratio	0.151		
(2) Avg. Monthly Selection Return	0.58%	1.130	0.262
Monthly Standard Deviation	4.51%		
Regressing Fund Return on Style Return:			
R Squared	59.57%		
Intercept	0.005	1.018	0.312
Slope Coefficient	1.045	10.441	0.000

Chart (a): 4-Factor Style Composition

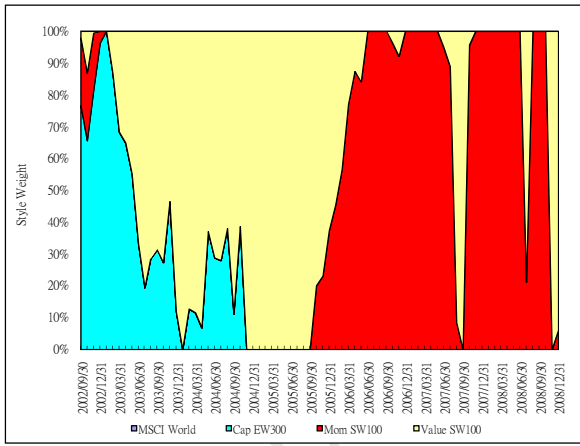


Chart (b): 3-Factor Style Composition

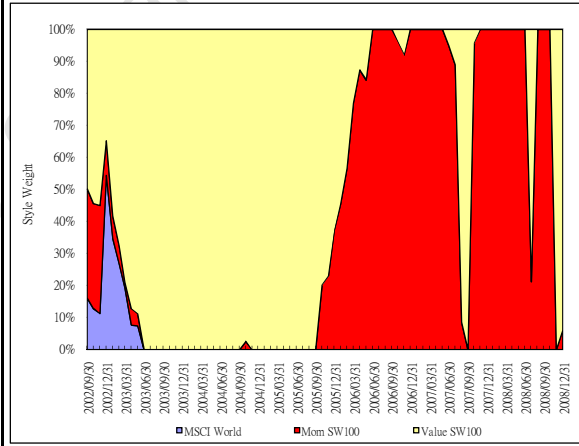
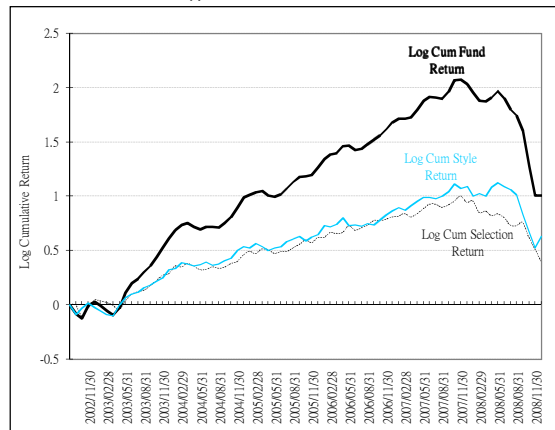


Chart (c): Performance Attribution



Appendix G.2 American EuroPacific Growth Fund

FUND DESCRIPTION: American EuroPacific Growth Fund is an open-end fund incorporated in the USA. The Fund's objective is long-term growth of capital. The Fund invests at least 80% of its assets in securities of issuers located in Europe and the Pacific Basin. The Fund may also hold cash, money market instruments and fixed income securities depending on market conditions

FUND INCEPTION: 1984/04/16
EVALUATION (OUT-OF-SAMPLE) PERIOD: 2002/09/01 to 2008/12/31

FUND MARKET VALUE (US\$): 86.64 Billion

Panel (a): 4-Factor (MSCI, Cap EW300, Mom SW100 and Value SW00) Model

Performance Attribution:	t-Statistic	p-Value
Avg. Monthly Fund Return	1.51%	1.733
Monthly Standard Deviation	7.59%	
Monthly Sharpe Ratio	0.170	
(1) Avg. Monthly Style Return	1.03%	1.730
Monthly Standard Deviation	5.18%	
Monthly Sharpe Ratio	0.156	
(2) Avg. Monthly Selection Return	0.48%	0.875
Monthly Standard Deviation	4.79%	
Regressing Fund Return on Style Return:		
R Squared	61.16%	
Intercept	0.003	0.594
Slope Coefficient	1.146	10.795

Panel (b): 3-Factor (MSCI, Mom SW100 and Value SW00) Model

Performance Attribution:	t-Statistic	p-Value
Avg. Monthly Fund Return	1.51%	1.733
Monthly Standard Deviation	7.59%	
Monthly Sharpe Ratio	0.170	
(1) Avg. Monthly Style Return	1.08%	1.791
Monthly Standard Deviation	5.25%	
Monthly Sharpe Ratio	0.164	
(2) Avg. Monthly Selection Return	0.43%	0.781
Monthly Standard Deviation	4.81%	
Regressing Fund Return on Style Return:		
R Squared	60.61%	
Intercept	0.003	0.525
Slope Coefficient	1.126	10.672

Chart (a): 4-Factor Style Composition

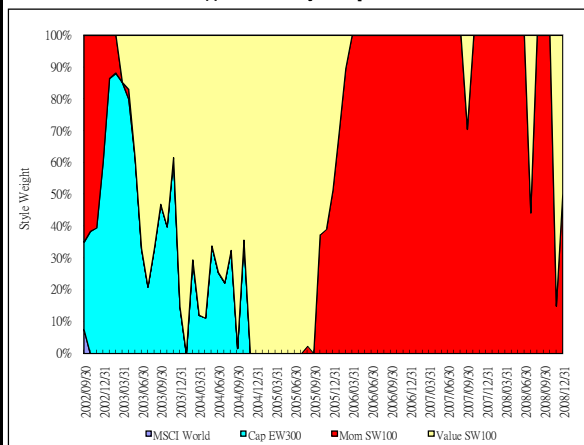


Chart (b): 3-Factor Style Composition

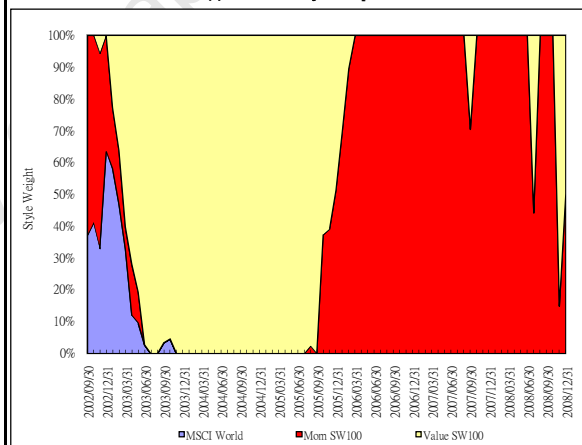
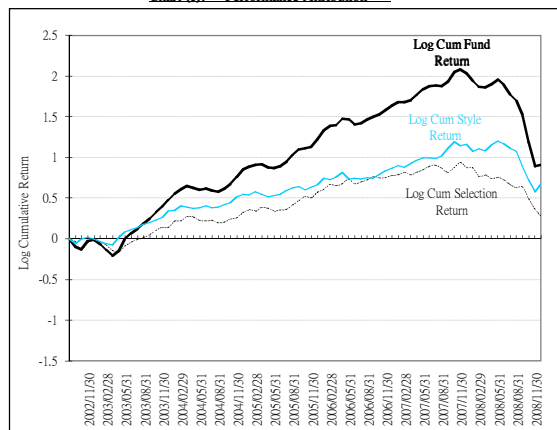


Chart (c): Performance Attribution



Appendix G.3 BlackRock International Opportunities Portfolio

FUND DESCRIPTION: BlackRock International Opportunities Portfolio is an open-end fund incorporated in the USA. The Fund's objective seeks long-term capital appreciation. The Fund invests at least 80% of net assets in equity securities issued by international emerging capitalisation companies. The Fund may invest up to 25% of its net assets in stocks of issuers in emerging market countries.

FUND INCEPTION: 1997/09/26
EVALUATION (OUT-OF-SAMPLE) PERIOD: 2003/02/01 to 2008/12/31
FUND MARKET VALUE (US\$): 1.54 Billion

Panel (a): 4-Factor (MSCI, Cap EW300, Mom SW100 and Value SW00) Model

Performance Attribution:	t-Statistic	p-Value
Avg. Monthly Fund Return	0.55%	0.937
Monthly Standard Deviation	4.91%	
Monthly Sharpe Ratio	0.065	
(1) Avg. Monthly Style Return		
Monthly Standard Deviation	5.22%	
Monthly Sharpe Ratio	0.143	0.120
(2) Avg. Monthly Selection Return		
Monthly Standard Deviation	2.20%	
t-Statistic	-1.640	0.106
Regressing Fund Return on Style Return:	t-Statistic	p-Value
R Squared	82.27%	
Intercept	-0.003	-1.138
Slope Coefficient	0.854	17.894

Panel (b): 3-Factor (MSCI, Mom SW100 and Value SW00) Model

Performance Attribution:	t-Statistic	p-Value
Avg. Monthly Fund Return	0.55%	0.937
Monthly Standard Deviation	4.91%	
Monthly Sharpe Ratio	0.065	
(1) Avg. Monthly Style Return		
Monthly Standard Deviation	5.22%	
Monthly Sharpe Ratio	0.144	0.119
(2) Avg. Monthly Selection Return		
Monthly Standard Deviation	2.20%	
t-Statistic	-1.647	0.104
Regressing Fund Return on Style Return:	t-Statistic	p-Value
R Squared	82.27%	
Intercept	-0.003	-1.145
Slope Coefficient	0.854	17.896

Chart (a): 4-Factor Style Composition

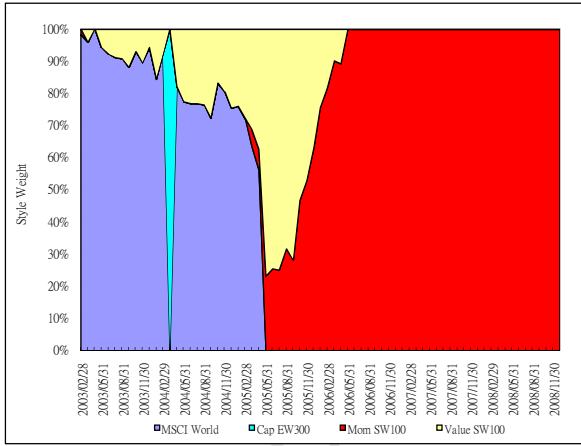


Chart (b): 3-Factor Style Composition

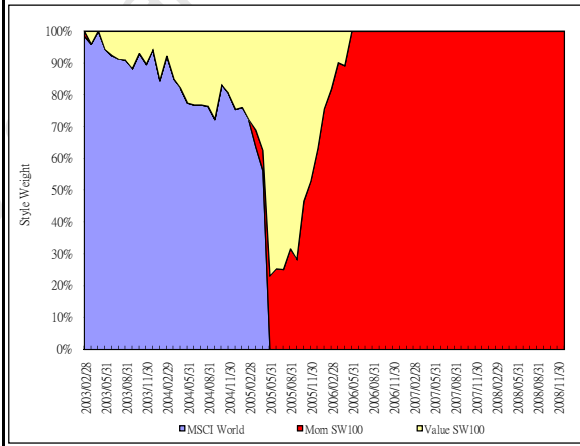
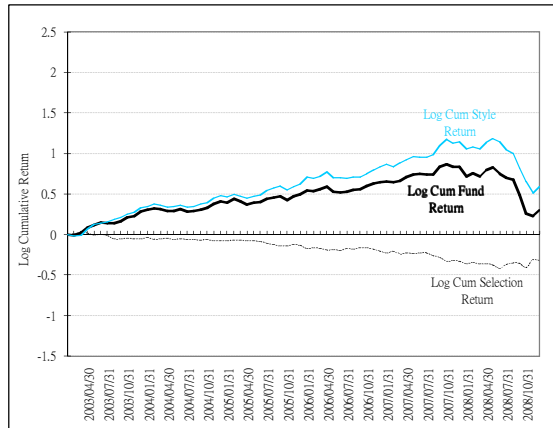


Chart (c): Performance Attribution



Appendix G.4 C-QUADRAT - ARTS Best Momentum Fund

FUND DESCRIPTION: C-QUADRAT - ARTS Best Momentum is an open-end investment fund incorporated in Austria. The investment goal of C-QUADRAT ARTS Best Momentum is long-term capital growth with a higher degree of risk. Investment decisions are generated by a computer-based trend-following trading programme. Fund selection is based on short and medium term momentum of price movements.

FUND INCEPTION: 1999/01/04 **FUND MARKET VALUE (US\$):** 46.63 Million
EVALUATION (OUT-OF-SAMPLE) PERIOD: 2002/09/01 to 2008/12/31

Panel (a): 4-Factor (MSCI, Cap EW300, Mom SW100 and Value SW00) Model

<u>Performance Attribution:</u>		<u>t-Statistic</u>	<u>p-Value</u>
Avg. Monthly Fund Return	2.11%	2.299	0.024
Monthly Standard Deviation	7.99%		
Monthly Sharpe Ratio	0.236		
(1) Avg. Monthly Style Return			
Monthly Standard Deviation	0.88%	1.457	0.149
Monthly Sharpe Ratio	5.28%		
	0.126		
(2) Avg. Monthly Selection Return			
Monthly Standard Deviation	1.22%	1.704	0.092
	6.26%		
<u>Regressing Fund Return on Style Return:</u>		<u>t-Statistic</u>	<u>p-Value</u>
R Squared	38.74%		
Intercept	0.013	1.742	0.086
Slope Coefficient	0.941	6.841	0.000

Panel (b): 3-Factor (MSCI, Mom SW100 and Value SW00) Model

<u>Performance Attribution:</u>		<u>t-Statistic</u>	<u>p-Value</u>
Avg. Monthly Fund Return	2.11%	2.299	0.024
Monthly Standard Deviation	7.99%		
Monthly Sharpe Ratio	0.236		
(1) Avg. Monthly Style Return			
Monthly Standard Deviation	0.92%	1.501	0.138
Monthly Sharpe Ratio	5.32%		
	0.131		
(2) Avg. Monthly Selection Return			
Monthly Standard Deviation	1.19%	1.658	0.102
	6.26%		
<u>Regressing Fund Return on Style Return:</u>		<u>t-Statistic</u>	<u>p-Value</u>
R Squared	38.78%		
Intercept	0.013	1.707	0.092
Slope Coefficient	0.935	6.846	0.000

Chart (a): 4-Factor Style Composition

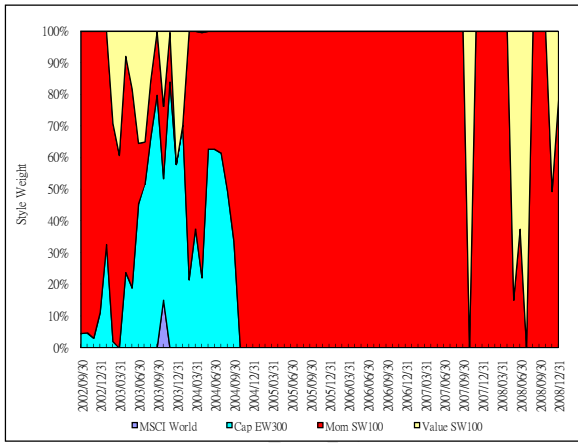


Chart (b): 3-Factor Style Composition

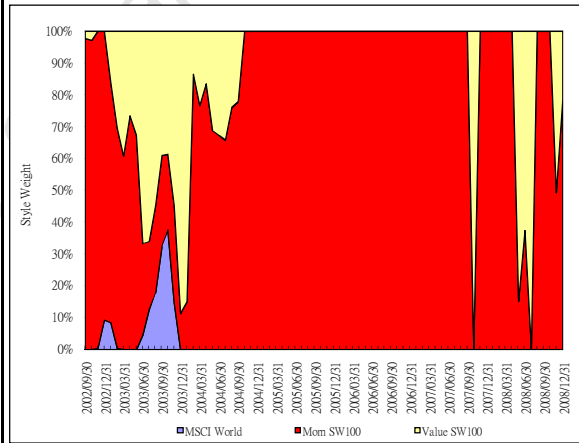
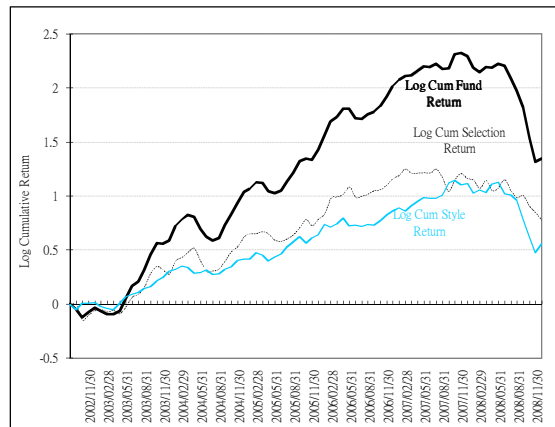


Chart (c): Performance Attribution



Appendix G.5 Federated Prudent Bear Fund

FUND DESCRIPTION: Federated Prudent Bear Fund is an open-end fund incorporated in the USA. The Fund's objective is capital appreciation. The Fund invests primarily through short sales of equity securities when overall market valuations are high and through long positions in value-oriented equity securities when overall market valuations are low.

FUND INCEPTION: 1995/12/28
EVALUATION (OUT-OF-SAMPLE) PERIOD: 2002/09/01 to 2008/12/31
FUND MARKET VALUE (US\$): 1.15 Billion

Panel (a): 4-Factor (MSCI, Cap EW300, Mom SW100 and Value SW00) Model

Performance Attribution:		t-Statistic	p-Value
Avg. Monthly Fund Return	0.88%	1.243	0.218
Monthly Standard Deviation	6.14%		
Monthly Sharpe Ratio	0.107		
(1) Avg. Monthly Style Return	0.53%	0.885	0.379
Monthly Standard Deviation	5.20%		
Monthly Sharpe Ratio	0.059		
(2) Avg. Monthly Selection Return	0.35%	0.295	0.769
Monthly Standard Deviation	10.25%		
Regressing Fund Return on Style Return:			
R Squared	39.99%		
Intercept	0.013	1.829	0.024
Slope Coefficient	-0.747	-7.022	0.000

Panel (b): 3-Factor (MSCI, Mom SW100 and Value SW00) Model

Performance Attribution:		t-Statistic	p-Value
Avg. Monthly Fund Return	0.88%	1.243	0.218
Monthly Standard Deviation	6.14%		
Monthly Sharpe Ratio	0.107		
(1) Avg. Monthly Style Return	0.52%	0.871	0.387
Monthly Standard Deviation	5.19%		
Monthly Sharpe Ratio	0.058		
(2) Avg. Monthly Selection Return	0.36%	0.303	0.763
Monthly Standard Deviation	10.24%		
Regressing Fund Return on Style Return:			
R Squared	39.93%		
Intercept	0.013	1.826	0.025
Slope Coefficient	-0.747	-7.013	0.000

Chart (a): 4-Factor Style Composition

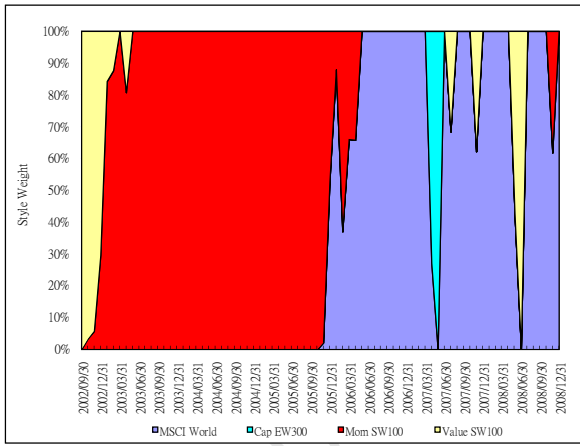


Chart (b): 3-Factor Style Composition

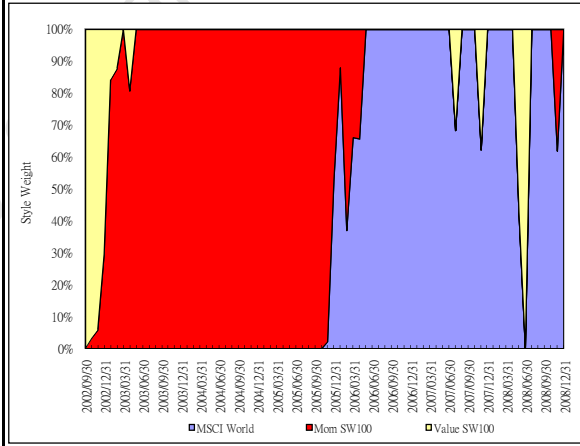
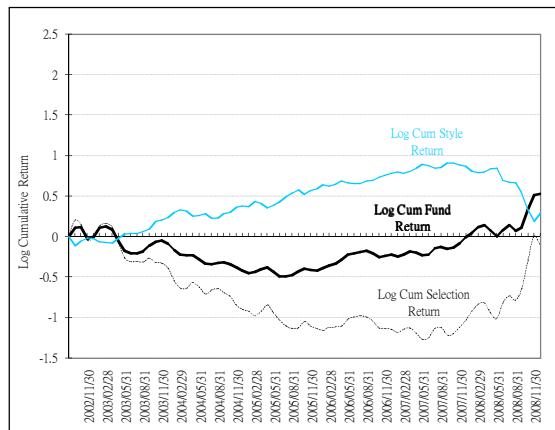


Chart (c): Performance Attribution



Appendix G.6 Fidelity Disciplined Equity Fund

FUND DESCRIPTION: Fidelity Disciplined Equity Fund is an open-end fund incorporated in the USA. The Fund's objective is capital growth. The Fund normally invests at least 80% of assets in equity securities. The Fund seeks to reduce the impact of industry weightings on the performance of the fund relative to the S&P 500 Index. The Fund invests in domestic and foreign issuers.

FUND INCEPTION: 1988/12/28
EVALUATION (OUT-OF-SAMPLE) PERIOD: 2002/09/01 to 2008/12/31
FUND MARKET VALUE (US\$): 10.32 Billion

Panel (a): 4-Factor (MSCI, Cap EW300, Mom SW100 and Value SW00) Model

Performance Attribution:		t-Statistic	p-Value
Avg. Monthly Fund Return	0.55%	0.736	0.464
Monthly Standard Deviation	6.48%		
Monthly Sharpe Ratio	0.050		
(1) Avg. Monthly Style Return	0.75%	1.289	0.202
Monthly Standard Deviation	5.10%		
Monthly Sharpe Ratio	0.105		
(2) Avg. Monthly Selection Return	-0.21%	-0.412	0.682
Monthly Standard Deviation	4.38%		
Regressing Fund Return on Style Return:			
R Squared	54.60%		
Intercept	-0.002	-0.315	0.753
Slope Coefficient	0.939	9.433	0.000

Panel (b): 3-Factor (MSCI, Mom SW100 and Value SW00) Model

Performance Attribution:		t-Statistic	p-Value
Avg. Monthly Fund Return	0.55%	0.736	0.464
Monthly Standard Deviation	6.48%		
Monthly Sharpe Ratio	0.050		
(1) Avg. Monthly Style Return	0.79%	1.350	0.181
Monthly Standard Deviation	5.12%		
Monthly Sharpe Ratio	0.112		
(2) Avg. Monthly Selection Return	-0.25%	-0.490	0.625
Monthly Standard Deviation	4.39%		
Regressing Fund Return on Style Return:			
R Squared	54.29%		
Intercept	-0.002	-0.376	0.708
Slope Coefficient	0.931	9.375	0.000

Chart (a): 4-Factor Style Composition

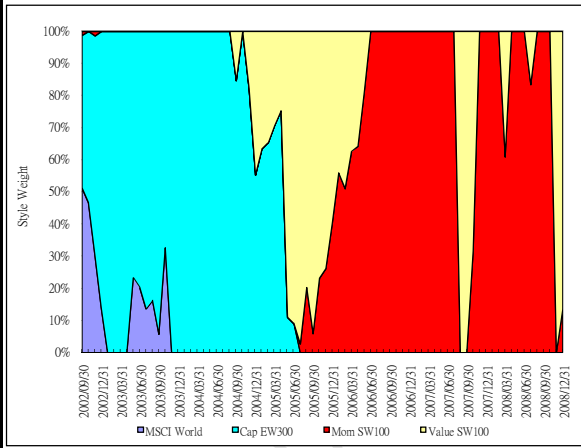


Chart (b): 3-Factor Style Composition

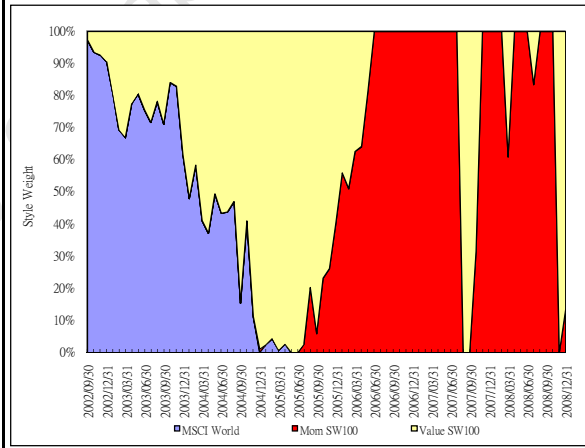
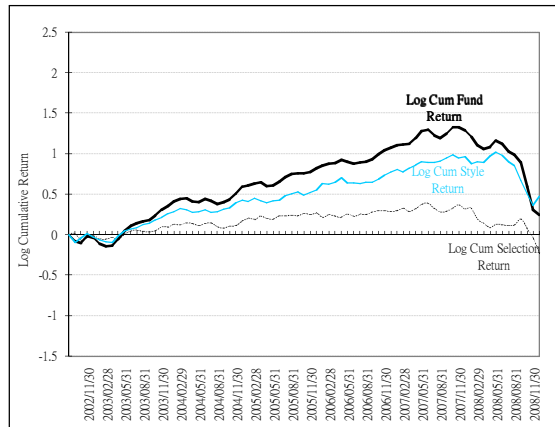


Chart (c): Performance Attribution



Appendix G.7 Fidelity Diversified International Fund

FUND DESCRIPTION: Fidelity Diversified International Fund is an open-end fund incorporated in the USA. The Fund's objective is capital growth. The Fund normally invests primarily in common stocks of non-U.S. issuers. The Fund allocates its investments across countries and regions considering the size of the market in each country and region relative to the size of the international market.

FUND INCEPTION: 1991/12/27
EVALUATION (OUT-OF-SAMPLE) PERIOD: 2002/09/01 to 2008/12/31
FUND MARKET VALUE (US\$): 33.53 Billion

Panel (a): 4-Factor (MSCI, Cap EW300, Mom SW100 and Value SW00) Model

<u>Performance Attribution:</u>		<u>t-Statistic</u>	<u>p-Value</u>
Avg. Monthly Fund Return	1.36%	1.447	0.152
Monthly Standard Deviation	8.22%		
Monthly Sharpe Ratio	0.139		
(1) Avg. Monthly Style Return	0.97%	1.618	0.110
Monthly Standard Deviation	5.20%		
Monthly Sharpe Ratio	0.143		
(2) Avg. Monthly Selection Return	0.40%	0.670	0.505
Monthly Standard Deviation	5.18%		
<u>Regressing Fund Return on Style Return:</u>			
R Squared	62.72%		
Intercept	0.002	0.266	0.791
Slope Coefficient	1.250	11.158	0.000

Panel (b): 3-Factor (MSCI, Mom SW100 and Value SW00) Model

<u>Performance Attribution:</u>		<u>t-Statistic</u>	<u>p-Value</u>
Avg. Monthly Fund Return	1.36%	1.447	0.152
Monthly Standard Deviation	8.22%		
Monthly Sharpe Ratio	0.139		
(1) Avg. Monthly Style Return	1.00%	1.652	0.103
Monthly Standard Deviation	5.27%		
Monthly Sharpe Ratio	0.148		
(2) Avg. Monthly Selection Return	0.37%	0.615	0.540
Monthly Standard Deviation	5.18%		
<u>Regressing Fund Return on Style Return:</u>			
R Squared	62.41%		
Intercept	0.001	0.226	0.822
Slope Coefficient	1.232	11.083	0.000

Chart (a): 4-Factor Style Composition

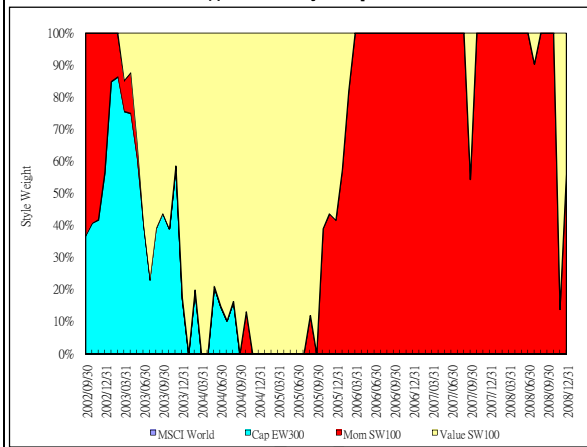


Chart (b): 3-Factor Style Composition

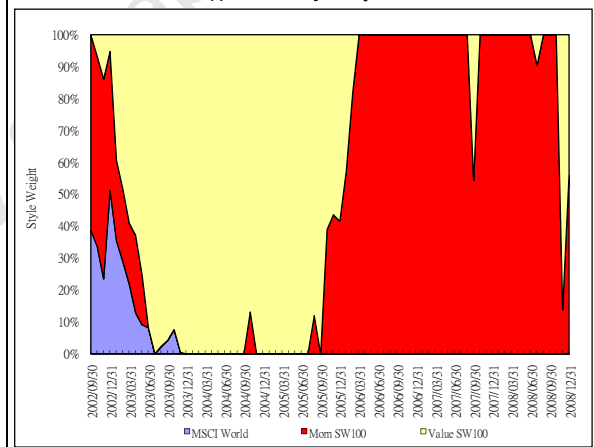
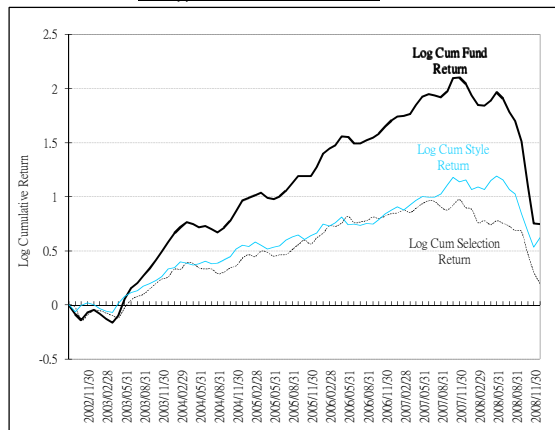


Chart (c): Performance Attribution



Appendix G.8 Fidelity VIP Contrafund

FUND DESCRIPTION: Fidelity VIP Contrafund is a Variable Annuity product in the USA. The Fund's objective is capital appreciation. The Fund invests primarily in the common stock of domestic and foreign companies whose value is not fully recognized by the public. The Fund invests in either "growth" stocks or "value" stocks or both.

FUND INCEPTION: 1995/01/03 **FUND MARKET VALUE (US\$):** 15.56 Billion
EVALUATION (OUT-OF-SAMPLE) PERIOD: 2002/09/01 to 2008/12/31

Panel (a): 4-Factor (MSCI, Cap EW300, Mom SW100 and Value SW00) Model

<u>Performance Attribution:</u>		<u>t-Statistic</u>	<u>p-Value</u>
Avg. Monthly Fund Return	0.82%	1.087	0.281
Monthly Standard Deviation	6.60%		
Monthly Sharpe Ratio	0.091		
(1) Avg. Monthly Style Return			
Monthly Standard Deviation	0.93%	1.539	0.128
Monthly Sharpe Ratio	5.25%		
	0.135		
(2) Avg. Monthly Selection Return			
Monthly Standard Deviation	-0.10%	-0.215	0.830
	4.24%		
<u>Regressing Fund Return on Style Return:</u>		<u>t-Statistic</u>	<u>p-Value</u>
R Squared	58.81%		
Intercept	-0.001	-0.143	0.887
Slope Coefficient	0.964	10.280	0.000

Panel (b): 3-Factor (MSCI, Mom SW100 and Value SW00) Model

<u>Performance Attribution:</u>		<u>t-Statistic</u>	<u>p-Value</u>
Avg. Monthly Fund Return	0.82%	1.087	0.281
Monthly Standard Deviation	6.60%		
Monthly Sharpe Ratio	0.091		
(1) Avg. Monthly Style Return			
Monthly Standard Deviation	0.95%	1.572	0.120
Monthly Sharpe Ratio	5.29%		
	0.139		
(2) Avg. Monthly Selection Return			
Monthly Standard Deviation	-0.13%	-0.269	0.789
	4.24%		
<u>Regressing Fund Return on Style Return:</u>		<u>t-Statistic</u>	<u>p-Value</u>
R Squared	58.81%		
Intercept	-0.001	-0.181	0.857
Slope Coefficient	0.957	10.278	0.000

Chart (a): 4-Factor Style Composition

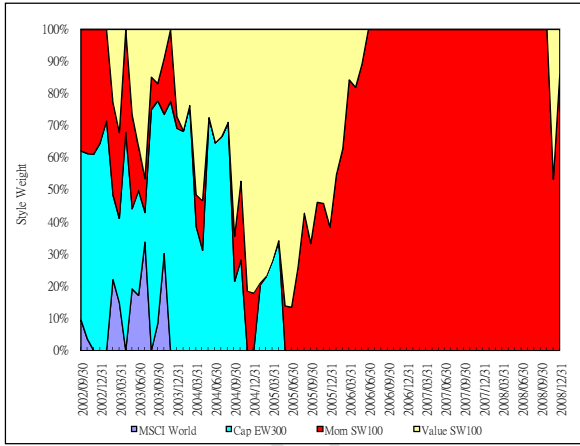


Chart (b): 3-Factor Style Composition

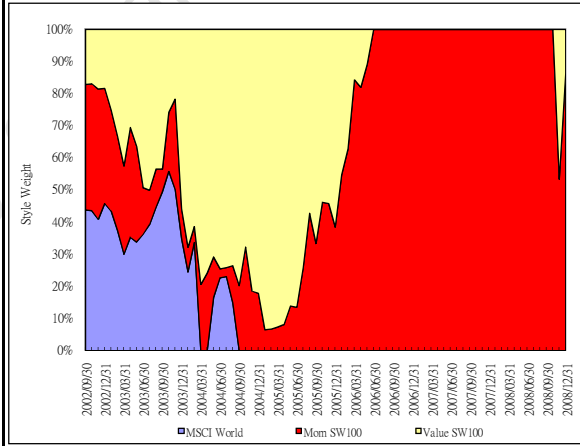
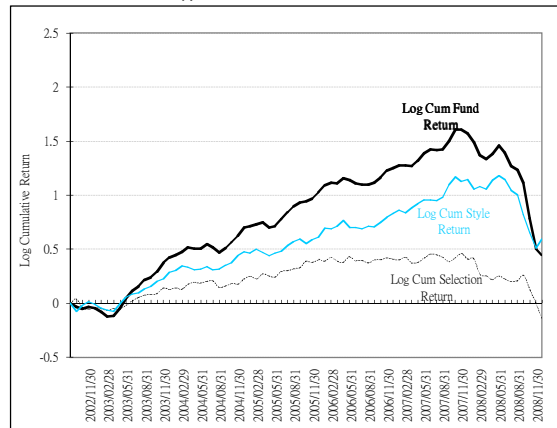


Chart (c): Performance Attribution



Appendix G.9 Russell International Developed Markets Fund

FUND DESCRIPTION: Russell International Developed Markets Fund is an open-end fund incorporated in the USA. The Fund's objective is to provide long-term capital growth. The Fund invests primarily in equity securities issued by companies domiciled outside the US and in depository receipts, which represent ownership of securities of non-US companies.

FUND INCEPTION: 1983/01/31 **FUND MARKET VALUE (US\$):** 146.80 Million
EVALUATION (OUT-OF-SAMPLE) PERIOD: 2002/09/01 to 2008/12/31

Panel (a): 4-Factor (MSCI, Cap EW300, Mom SW100 and Value SW00) Model

<u>Performance Attribution:</u>		<u>t-Statistic</u>	<u>p-Value</u>
Avg. Monthly Fund Return	1.12%	1.206	0.232
Monthly Standard Deviation	8.11%		
Monthly Sharpe Ratio	0.111		
(1) Avg. Monthly Style Return			
Monthly Standard Deviation	0.95%	1.628	0.108
Monthly Sharpe Ratio	5.11%		
	0.144		
(2) Avg. Monthly Selection Return			
Monthly Standard Deviation	0.17%	0.283	0.778
	5.12%		
<u>Regressing Fund Return on Style Return:</u>		<u>t-Statistic</u>	<u>p-Value</u>
R Squared	62.64%		
Intercept	-0.001	-0.132	0.895
Slope Coefficient	1.255	11.138	0.000

Panel (b): 3-Factor (MSCI, Mom SW100 and Value SW00) Model

<u>Performance Attribution:</u>		<u>t-Statistic</u>	<u>p-Value</u>
Avg. Monthly Fund Return	1.12%	1.206	0.232
Monthly Standard Deviation	8.11%		
Monthly Sharpe Ratio	0.111		
(1) Avg. Monthly Style Return			
Monthly Standard Deviation	0.98%	1.642	0.105
Monthly Sharpe Ratio	5.19%		
	0.146		
(2) Avg. Monthly Selection Return			
Monthly Standard Deviation	0.14%	0.242	0.809
	5.15%		
<u>Regressing Fund Return on Style Return:</u>		<u>t-Statistic</u>	<u>p-Value</u>
R Squared	61.78%		
Intercept	-0.001	-0.134	0.893
Slope Coefficient	1.227	10.937	0.000

Chart (a): 4-Factor Style Composition

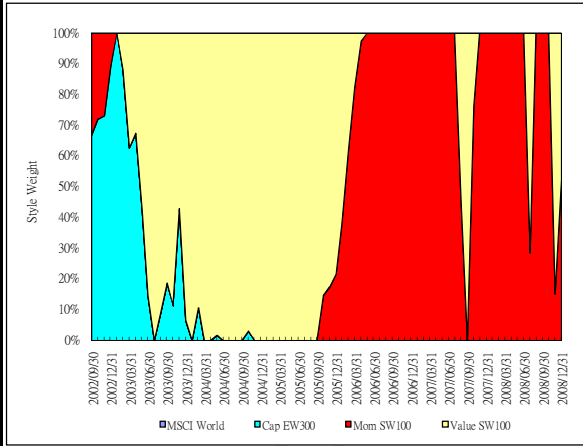


Chart (b): 3-Factor Style Composition

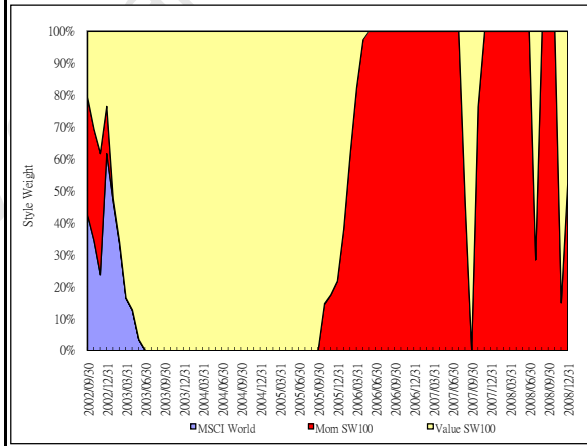
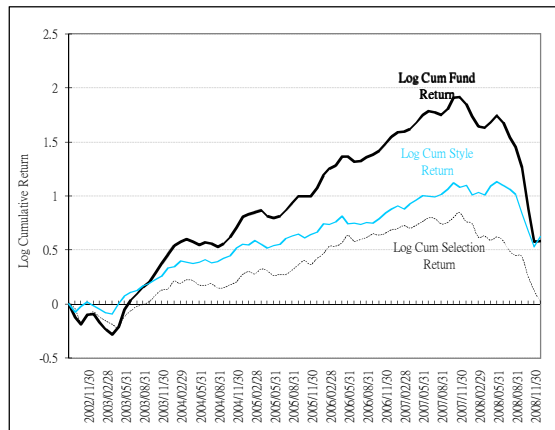


Chart (c): Performance Attribution



Appendix G.10 SEI International Equity Fund

FUND DESCRIPTION: SEI International Equity Fund is an open-end fund incorporated in the USA. The Fund's objective is long-term capital appreciation. The Fund invests at least 80% of its net assets in common stocks and other equity securities of issuers located in at least three countries other than the United States.

FUND INCEPTION: 1989/12/20
EVALUATION (OUT-OF-SAMPLE) PERIOD: 2002/09/01 to 2008/12/31
FUND MARKET VALUE (US\$): 2.06 Billion

Panel (a): 4-Factor (MSCI, Cap EW300, Mom SW100 and Value SW00) Model

<u>Performance Attribution:</u>		<u>t-Statistic</u>	<u>p-Value</u>
Avg. Monthly Fund Return	0.63%	0.632	0.529
Monthly Standard Deviation	8.72%		
Monthly Sharpe Ratio	0.047		
(1) Avg. Monthly Style Return	0.94%	1.636	0.106
Monthly Standard Deviation	5.03%		
Monthly Sharpe Ratio	0.144		
(2) Avg. Monthly Selection Return	-0.31%	-0.472	0.638
Monthly Standard Deviation	5.75%		
<u>Regressing Fund Return on Style Return:</u>		<u>t-Statistic</u>	<u>p-Value</u>
R Squared	60.66%		
Intercept	-0.006	-1.000	0.321
Slope Coefficient	1.352	10.681	0.000

Panel (b): 3-Factor (MSCI, Mom SW100 and Value SW00) Model

<u>Performance Attribution:</u>		<u>t-Statistic</u>	<u>p-Value</u>
Avg. Monthly Fund Return	0.63%	0.632	0.529
Monthly Standard Deviation	8.72%		
Monthly Sharpe Ratio	0.047		
(1) Avg. Monthly Style Return	0.98%	1.664	0.100
Monthly Standard Deviation	5.12%		
Monthly Sharpe Ratio	0.148		
(2) Avg. Monthly Selection Return	-0.34%	-0.520	0.604
Monthly Standard Deviation	5.77%		
<u>Regressing Fund Return on Style Return:</u>		<u>t-Statistic</u>	<u>p-Value</u>
R Squared	59.65%		
Intercept	-0.007	-1.003	0.319
Slope Coefficient	1.316	10.459	0.000

Chart (a): 4-Factor Style Composition

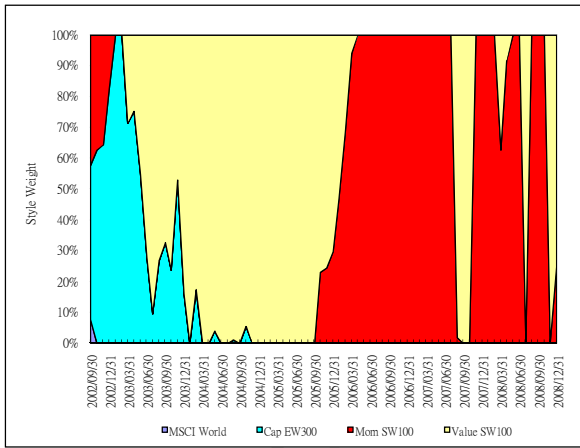


Chart (b): 3-Factor Style Composition

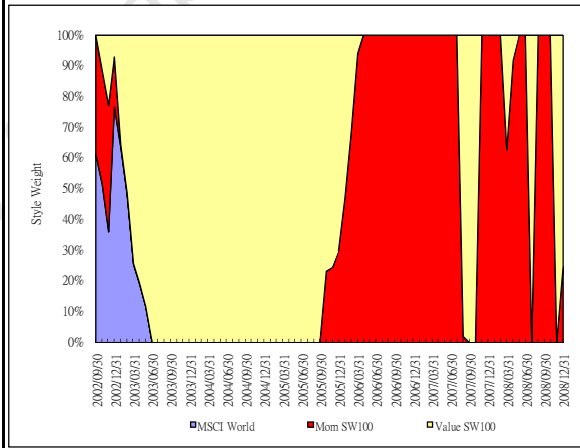
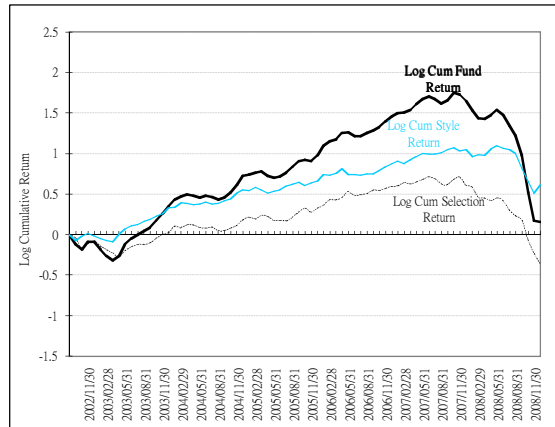


Chart (c): Performance Attribution



Appendix G.11 Skandia Global Equity Fund

FUND DESCRIPTION: Skandia Global Equity Fund is a UCITS certified open-end fund incorporated in Ireland. The objective is capital growth. The Fund will invest primarily in a well diversified portfolio of equity and equity-related securities of issuers worldwide that are listed or traded on Recognised Exchanges.

FUND INCEPTION: 2000/09/13
EVALUATION (OUT-OF-SAMPLE) PERIOD: 2003/10/01 to 2008/12/31
FUND MARKET VALUE (US\$): 262.61 Million

Panel (a): 4-Factor (MSCI, Cap EW300, Mom SW100 and Value SW00) Model

Performance Attribution:		t-Statistic	p-Value
Avg. Monthly Fund Return	0.21%	0.357	0.722
Monthly Standard Deviation	4.73%		
Monthly Sharpe Ratio	-0.007		
(1) Avg. Monthly Style Return			
Monthly Standard Deviation	0.74%	1.082	0.283
Monthly Sharpe Ratio	5.40%		
	0.091		
(2) Avg. Monthly Selection Return			
Monthly Standard Deviation	-0.52%	-1.671	0.100
	2.49%		
Regressing Fund Return on Style Return:			
R Squared		78.80%	
Intercept	-0.004	-1.288	0.203
Slope Coefficient	0.777	15.060	0.000

Panel (b): 3-Factor (MSCI, Mom SW100 and Value SW00) Model

Performance Attribution:		t-Statistic	p-Value
Avg. Monthly Fund Return	0.21%	0.357	0.722
Monthly Standard Deviation	4.73%		
Monthly Sharpe Ratio	-0.007		
(1) Avg. Monthly Style Return			
Monthly Standard Deviation	0.74%	1.081	0.284
Monthly Sharpe Ratio	5.41%		
	0.091		
(2) Avg. Monthly Selection Return			
Monthly Standard Deviation	-0.52%	-1.664	0.101
	2.50%		
Regressing Fund Return on Style Return:			
R Squared		78.70%	
Intercept	-0.004	-1.281	0.205
Slope Coefficient	0.776	15.012	0.000

Chart (a): 4-Factor Style Composition

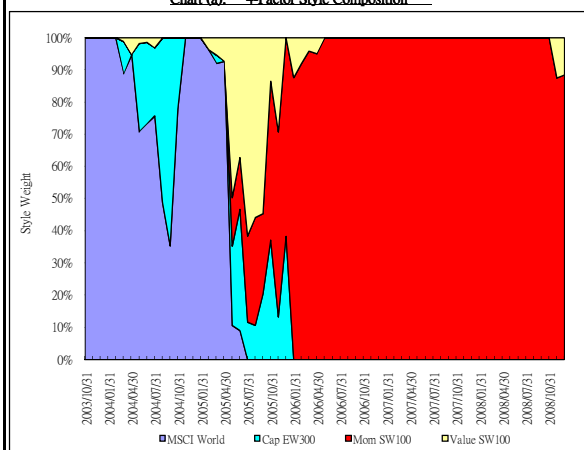


Chart (b): 3-Factor Style Composition

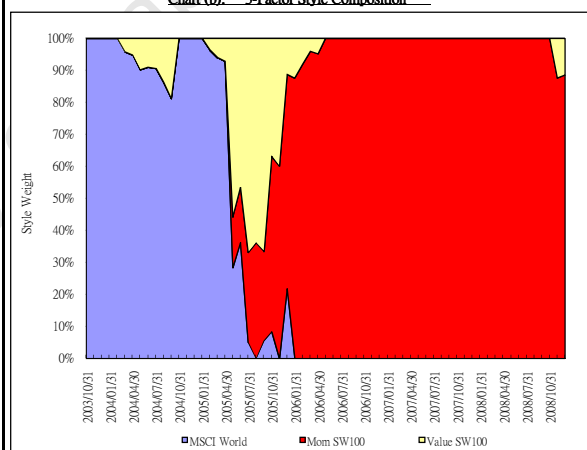
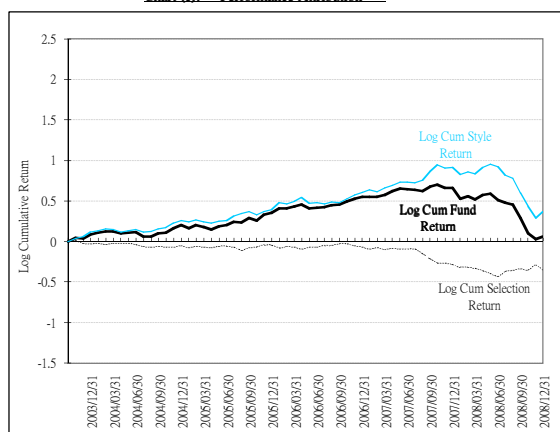


Chart (c): Performance Attribution



Appendix G.12 Templeton World Fund

FUND DESCRIPTION: Templeton World Fund is an open-end fund incorporated in the USA. The Fund's objective is long-term capital growth. The Fund invests mainly in the equity securities of companies located anywhere in the world, including emerging markets. The Funds total assets will be invested in issuers located in at least three different countries including the U.S.

FUND INCEPTION: 1978/01/17
EVALUATION (OUT-OF-SAMPLE) PERIOD: 2002/09/01 to 2008/12/31

FUND MARKET VALUE (US\$): 5.85 Billion

Panel (a): 4-Factor (MSCI, Cap EW300, Mom SW100 and Value SW00) Model

<u>Performance Attribution:</u>		<u>t-Statistic</u>	<u>p-Value</u>
Avg. Monthly Fund Return	0.46%	0.877	0.383
Monthly Standard Deviation	4.57%		
Monthly Sharpe Ratio	0.053		
(1) Avg. Monthly Style Return	1.03%	1.730	0.088
Monthly Standard Deviation	5.18%		
Monthly Sharpe Ratio	0.156		
(2) Avg. Monthly Selection Return	-0.57%	-2.047	0.044
Monthly Standard Deviation	2.42%		
Regressing Fund Return on Style Return:			
R Squared	78.22%		
Intercept	-0.003	-1.362	0.177
Slope Coefficient	0.781	16.301	0.000

Panel (b): 3-Factor (MSCI, Mom SW100 and Value SW00) Model

<u>Performance Attribution:</u>		<u>t-Statistic</u>	<u>p-Value</u>
Avg. Monthly Fund Return	0.46%	0.877	0.383
Monthly Standard Deviation	4.57%		
Monthly Sharpe Ratio	0.053		
(1) Avg. Monthly Style Return	1.05%	1.690	0.095
Monthly Standard Deviation	5.42%		
Monthly Sharpe Ratio	0.153		
(2) Avg. Monthly Selection Return	-0.59%	-2.040	0.045
Monthly Standard Deviation	2.52%		
Regressing Fund Return on Style Return:			
R Squared	78.52%		
Intercept	-0.003	-1.304	0.196
Slope Coefficient	0.748	16.447	0.000

Chart (a): 4-Factor Style Composition

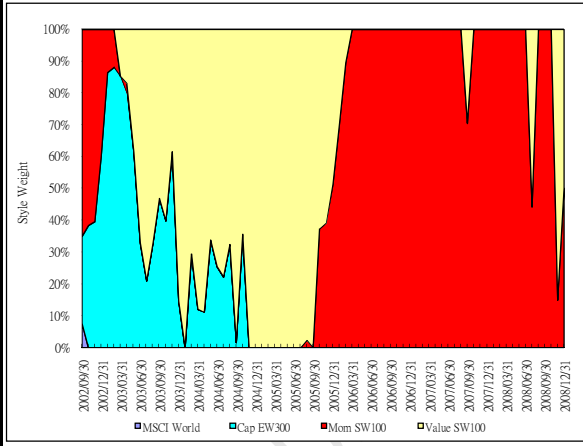


Chart (b): 3-Factor Style Composition

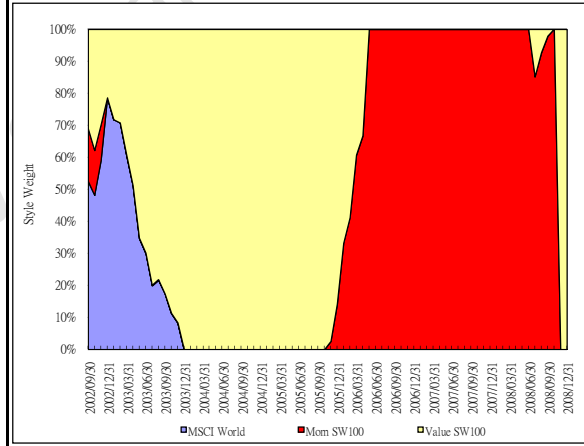


Chart (c): Performance Attribution

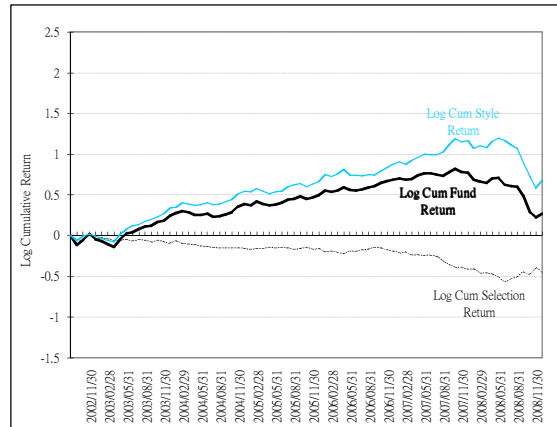


Table H.1.1 Annualised Geometric Return

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	11.62%	11.62%	9.70%	9.68%	10.25%	10.81%	9.07%	7.06%	8.14%	7.50%	11.62%
		45%	11.62%	11.62%	9.90%	9.70%	10.44%	11.01%	8.54%	7.11%	8.56%	6.68%	11.62%
		40%	11.62%	11.62%	9.94%	9.70%	10.49%	11.06%	8.58%	7.32%	9.04%	7.24%	11.62%
		35%	11.62%	11.62%	10.05%	9.90%	10.60%	11.16%	9.35%	8.48%	7.55%	6.61%	11.62%
		30%	11.62%	11.62%	10.26%	10.05%	10.81%	11.38%	9.72%	9.22%	8.41%	7.71%	11.62%
		25%	11.62%	11.62%	10.26%	10.24%	10.81%	11.38%	9.67%	9.52%	8.91%	8.22%	11.62%
		20%	11.62%	11.62%	10.69%	10.26%	11.24%	11.81%	10.27%	10.53%	10.33%	10.16%	11.62%
		15%	11.62%	11.62%	10.69%	10.26%	11.24%	11.81%	10.37%	10.88%	10.60%	10.94%	11.62%
		10%	11.62%	11.62%	10.69%	10.69%	11.24%	11.81%	10.93%	11.06%	10.29%	10.67%	11.62%
		5%	11.62%	11.62%	11.17%	10.58%	11.72%	12.29%	11.76%	12.52%	11.35%	12.78%	11.62%
	0%	11.62%	11.62%	11.17%	10.58%	11.72%	12.29%	11.87%	12.51%	10.99%	11.55%	11.62%	

Table H.1.2 Annualised Standard Deviation

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	15.08%	15.08%	14.21%	14.07%	14.04%	13.85%	12.61%	10.98%	9.60%	5.75%	15.08%
		45%	15.08%	15.08%	14.50%	14.21%	14.34%	14.15%	12.83%	11.21%	10.08%	7.70%	15.08%
		40%	15.08%	15.08%	14.50%	14.21%	14.34%	14.15%	12.83%	11.23%	10.16%	7.87%	15.08%
		35%	15.08%	15.08%	14.51%	14.51%	14.34%	14.15%	13.15%	11.90%	11.03%	8.76%	15.08%
		30%	15.08%	15.08%	14.53%	14.51%	14.36%	14.17%	13.20%	12.00%	11.23%	8.98%	15.08%
		25%	15.08%	15.08%	14.53%	14.53%	14.36%	14.17%	13.35%	12.19%	11.28%	9.20%	15.08%
		20%	15.08%	15.08%	14.63%	14.53%	14.46%	14.28%	13.63%	12.55%	11.80%	9.65%	15.08%
		15%	15.08%	15.08%	14.63%	14.53%	14.46%	14.28%	13.79%	12.76%	11.98%	10.24%	15.08%
		10%	15.08%	15.08%	14.63%	14.63%	14.46%	14.28%	13.91%	13.14%	12.46%	11.47%	15.08%
		5%	15.08%	15.08%	14.96%	14.64%	14.79%	14.61%	14.31%	13.63%	13.15%	12.60%	15.08%
	0%	15.08%	15.08%	14.96%	14.64%	14.79%	14.61%	14.31%	13.66%	13.69%	13.97%	15.08%	

Table H.1.3 5% Value at Risk (VaR)

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	-5.99%	-5.99%	-5.99%	-5.99%	-5.88%	-5.63%	-5.20%	-4.52%	-3.32%	-0.96%	-5.99%
		45%	-5.99%	-5.99%	-5.99%	-5.99%	-5.88%	-5.63%	-5.45%	-4.80%	-3.43%	-2.03%	-5.99%
		40%	-5.99%	-5.99%	-5.99%	-5.99%	-5.88%	-5.63%	-5.45%	-4.80%	-3.43%	-2.03%	-5.99%
		35%	-5.99%	-5.99%	-5.99%	-5.99%	-5.88%	-5.63%	-5.45%	-4.80%	-4.17%	-3.29%	-5.99%
		30%	-5.99%	-5.99%	-5.99%	-5.99%	-5.88%	-5.63%	-5.45%	-4.80%	-4.17%	-3.29%	-5.99%
		25%	-5.99%	-5.99%	-5.99%	-5.99%	-5.88%	-5.63%	-5.45%	-4.80%	-4.17%	-3.36%	-5.99%
		20%	-5.99%	-5.99%	-5.99%	-5.99%	-5.88%	-5.63%	-5.45%	-4.80%	-4.17%	-3.36%	-5.99%
		15%	-5.99%	-5.99%	-5.99%	-5.99%	-5.88%	-5.63%	-5.47%	-5.18%	-4.44%	-3.54%	-5.99%
		10%	-5.99%	-5.99%	-5.99%	-5.99%	-5.88%	-5.63%	-5.47%	-5.45%	-5.18%	-4.17%	-5.99%
		5%	-5.99%	-5.99%	-5.99%	-5.99%	-5.88%	-5.63%	-5.47%	-5.45%	-5.18%	-4.33%	-5.99%
	0%	-5.99%	-5.99%	-5.99%	-5.99%	-5.88%	-5.63%	-5.47%	-5.45%	-5.47%	-5.45%	-5.99%	

Table H.1.4 Annualised Sharpe Ratio

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	24.30%	24.30%	12.27%	12.23%	16.29%	20.59%	8.76%	-8.16%	1.90%	-8.04%	24.30%
		45%	24.30%	24.30%	13.37%	12.27%	17.32%	21.55%	4.48%	-7.61%	5.96%	-16.61%	24.30%
		40%	24.30%	24.30%	13.68%	12.27%	17.64%	21.88%	4.83%	-5.66%	10.58%	-9.13%	24.30%
		35%	24.30%	24.30%	14.41%	13.37%	18.38%	22.63%	10.60%	4.41%	-3.71%	-15.40%	24.30%
		30%	24.30%	24.30%	15.85%	14.41%	19.84%	24.11%	13.29%	10.53%	4.01%	-2.82%	24.30%
		25%	24.30%	24.30%	15.85%	15.73%	19.84%	24.11%	12.82%	12.76%	8.42%	2.85%	24.30%
		20%	24.30%	24.30%	18.67%	15.85%	22.68%	26.97%	16.93%	20.49%	20.08%	22.84%	24.30%
		15%	24.30%	24.30%	18.67%	15.85%	22.68%	26.97%	17.50%	22.88%	22.01%	29.07%	24.30%
		10%	24.30%	24.30%	18.67%	18.67%	22.68%	26.97%	21.32%	23.62%	18.68%	23.66%	24.30%
		5%	24.30%	24.30%	21.43%	17.93%	25.40%	29.64%	26.57%	33.41%	25.76%	38.26%	24.30%
	0%	24.30%	24.30%	21.43%	17.93%	25.40%	29.64%	27.29%	33.29%	22.13%	25.68%	24.30%	

Table H.1.5 Percentage of Months in Cash

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	0.00%	0.00%	7.41%	12.50%	7.87%	8.33%	24.07%	42.13%	48.61%	81.94%	0.00%
		45%	0.00%	0.00%	4.17%	7.41%	4.63%	5.09%	22.22%	39.81%	43.98%	76.85%	0.00%
		40%	0.00%	0.00%	3.70%	7.41%	4.17%	4.63%	21.76%	38.89%	42.59%	75.46%	0.00%
		35%	0.00%	0.00%	3.24%	4.17%	3.70%	4.17%	19.91%	32.87%	31.94%	62.50%	0.00%
		30%	0.00%	0.00%	2.31%	3.24%	2.78%	3.24%	18.52%	30.09%	28.70%	58.33%	0.00%
		25%	0.00%	0.00%	2.31%	2.78%	2.78%	3.24%	11.57%	21.76%	26.39%	53.24%	0.00%
		20%	0.00%	0.00%	1.85%	2.31%	2.31%	2.78%	6.02%	15.28%	23.15%	46.76%	0.00%
		15%	0.00%	0.00%	1.85%	2.31%	2.31%	2.78%	6.02%	14.81%	21.30%	42.59%	0.00%
		10%	0.00%	0.00%	1.85%	1.85%	2.31%	2.78%	5.09%	12.50%	15.74%	34.26%	0.00%
		5%	0.00%	0.00%	0.46%	1.39%	0.93%	1.39%	3.24%	8.80%	10.65%	24.07%	0.00%
	0%	0.00%	0.00%	0.46%	1.39%	0.93%	1.39%	3.24%	7.87%	13.43%	18.52%	0.00%	

Table H.1.6 Maximum Drawdown

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	-40.12%	-40.12%	-40.12%	-40.12%	-34.05%	-27.10%	-29.34%	-19.03%	-18.40%	-11.12%	-40.12%
		45%	-40.12%	-40.12%	-43.90%	-40.12%	-37.77%	-30.71%	-28.76%	-18.40%	-18.40%	-19.19%	-40.12%
		40%	-40.12%	-40.12%	-43.41%	-40.12%	-37.22%	-30.10%	-28.76%	-18.40%	-18.40%	-18.40%	-40.12%
		35%	-40.12%	-40.12%	-42.25%	-43.90%	-35.94%	-28.67%	-25.07%	-18.40%	-18.40%	-18.40%	-40.12%
		30%	-40.12%	-40.12%	-40.12%	-42.25%	-34.05%	-27.10%	-25.88%	-18.40%	-18.40%	-18.40%	-40.12%
		25%	-40.12%	-40.12%	-40.12%	-40.12%	-34.05%	-27.10%	-24.01%	-18.40%	-18.40%	-18.40%	-40.12%
		20%	-40.12%	-40.12%	-40.12%	-40.12%	-34.05%	-27.10%	-24.01%	-18.40%	-18.40%	-18.40%	-40.12%
		15%	-40.12%	-40.12%	-40.12%	-40.12%	-34.05%	-27.10%	-24.01%	-20.13%	-20.13%	-20.13%	-40.12%
		10%	-40.12%	-40.12%	-40.12%	-40.12%	-34.05%	-27.10%	-24.01%	-22.66%	-21.00%	-24.30%	-40.12%
		5%	-40.12%	-40.12%	-41.51%	-40.60%	-35.11%	-27.75%	-24.78%	-22.96%	-23.93%	-24.30%	-40.12%
	0%	-40.12%	-40.12%	-41.51%	-40.60%	-35.11%	-27.75%	-24.78%	-22.96%	-39.38%	-40.79%	-40.12%	

Table H.1.7 Number of Signals

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	0	0	1	1	1	1	3	5	5	5	0
		45%	0	0	1	1	1	1	4	6	5	6	0
		40%	0	0	1	1	1	1	4	6	5	6	0
		35%	0	0	1	1	1	1	4	6	7	9	0
		30%	0	0	1	1	1	1	4	6	7	9	0
		25%	0	0	1	1	1	1	4	6	7	10	0
		20%	0	0	1	1	1	1	4	6	7	10	0
		15%	0	0	1	1	1	1	4	6	8	11	0
		10%	0	0	1	1	1	1	4	7	10	13	0
		5%	0	0	1	2	1	1	4	7	10	13	0
	0%	0	0	1	2	1	1	4	8	9	15	0	

Table H.2.1 Annualised Geometric Return

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	11.62%	11.62%	10.69%	10.69%	10.97%	11.27%	10.43%	9.47%	10.06%	9.81%	11.62%
		45%	11.62%	11.62%	10.78%	10.69%	11.06%	11.35%	10.15%	9.48%	10.25%	9.36%	11.62%
		40%	11.62%	11.62%	10.80%	10.69%	11.08%	11.38%	10.18%	9.59%	10.49%	9.64%	11.62%
		35%	11.62%	11.62%	10.86%	10.78%	11.14%	11.43%	10.56%	10.16%	9.71%	9.30%	11.62%
		30%	11.62%	11.62%	10.96%	10.86%	11.24%	11.54%	10.74%	10.53%	10.14%	9.85%	11.62%
		25%	11.62%	11.62%	10.96%	10.95%	11.24%	11.54%	10.71%	10.67%	10.39%	10.11%	11.62%
		20%	11.62%	11.62%	11.17%	10.96%	11.46%	11.75%	11.00%	11.17%	11.10%	11.08%	11.62%
		15%	11.62%	11.62%	11.17%	10.96%	11.46%	11.75%	11.05%	11.34%	11.22%	11.45%	11.62%
		10%	11.62%	11.62%	11.17%	11.17%	11.46%	11.75%	11.32%	11.42%	11.05%	11.28%	11.62%
		5%	11.62%	11.62%	11.40%	11.12%	11.68%	11.98%	11.72%	12.13%	11.56%	12.30%	11.62%
	0%	11.62%	11.62%	11.40%	11.12%	11.68%	11.98%	11.78%	12.12%	11.36%	11.63%	11.62%	

Table H.2.2 Annualised Standard Deviation

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	15.08%	15.08%	14.42%	14.31%	14.29%	14.16%	13.25%	12.12%	11.18%	8.97%	15.08%
		45%	15.08%	15.08%	14.64%	14.42%	14.51%	14.38%	13.41%	12.28%	11.50%	10.02%	15.08%
		40%	15.08%	15.08%	14.64%	14.42%	14.51%	14.38%	13.41%	12.29%	11.55%	10.11%	15.08%
		35%	15.08%	15.08%	14.64%	14.64%	14.52%	14.38%	13.64%	12.75%	12.16%	10.66%	15.08%
		30%	15.08%	15.08%	14.66%	14.64%	14.53%	14.40%	13.68%	12.82%	12.29%	10.79%	15.08%
		25%	15.08%	15.08%	14.66%	14.66%	14.53%	14.40%	13.79%	12.95%	12.32%	10.92%	15.08%
		20%	15.08%	15.08%	14.74%	14.66%	14.61%	14.48%	13.99%	13.21%	12.68%	11.21%	15.08%
		15%	15.08%	15.08%	14.74%	14.66%	14.61%	14.48%	14.11%	13.37%	12.81%	11.60%	15.08%
		10%	15.08%	15.08%	14.74%	14.74%	14.61%	14.48%	14.20%	13.64%	13.16%	12.45%	15.08%
		5%	15.08%	15.08%	14.98%	14.74%	14.86%	14.73%	14.50%	14.01%	13.65%	13.26%	15.08%
	0%	15.08%	15.08%	14.98%	14.74%	14.86%	14.73%	14.51%	14.03%	14.04%	14.24%	15.08%	

Table H.2.3 5% Value at Risk (VaR)

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	-5.99%	-5.99%	-5.99%	-5.99%	-5.88%	-5.63%	-5.20%	-4.79%	-4.01%	-3.65%	-5.99%
		45%	-5.99%	-5.99%	-5.99%	-5.99%	-5.88%	-5.63%	-5.45%	-4.96%	-4.16%	-4.16%	-5.99%
		40%	-5.99%	-5.99%	-5.99%	-5.99%	-5.88%	-5.63%	-5.45%	-4.96%	-4.16%	-4.16%	-5.99%
		35%	-5.99%	-5.99%	-5.99%	-5.99%	-5.88%	-5.63%	-5.45%	-4.96%	-4.52%	-4.25%	-5.99%
		30%	-5.99%	-5.99%	-5.99%	-5.99%	-5.88%	-5.63%	-5.45%	-4.96%	-4.52%	-4.25%	-5.99%
		25%	-5.99%	-5.99%	-5.99%	-5.99%	-5.88%	-5.63%	-5.45%	-4.96%	-4.52%	-4.25%	-5.99%
		20%	-5.99%	-5.99%	-5.99%	-5.99%	-5.88%	-5.63%	-5.45%	-4.96%	-4.52%	-4.25%	-5.99%
		15%	-5.99%	-5.99%	-5.99%	-5.99%	-5.88%	-5.63%	-5.47%	-5.18%	-4.79%	-4.38%	-5.99%
		10%	-5.99%	-5.99%	-5.99%	-5.99%	-5.88%	-5.63%	-5.47%	-5.45%	-5.18%	-4.52%	-5.99%
		5%	-5.99%	-5.99%	-5.99%	-5.99%	-5.88%	-5.63%	-5.47%	-5.45%	-5.18%	-4.52%	-5.99%
	0%	-5.99%	-5.99%	-5.99%	-5.99%	-5.88%	-5.63%	-5.47%	-5.45%	-5.47%	-5.45%	-5.99%	

Table H.2.4 Annualised Sharpe Ratio

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	24.30%	24.30%	18.96%	19.05%	21.09%	23.36%	18.64%	12.42%	18.73%	20.68%	24.30%
		45%	24.30%	24.30%	19.26%	18.96%	21.37%	23.60%	16.36%	12.38%	19.96%	13.95%	24.30%
		40%	24.30%	24.30%	19.42%	18.96%	21.53%	23.76%	16.53%	13.26%	21.93%	16.63%	24.30%
		35%	24.30%	24.30%	19.78%	19.26%	21.89%	24.12%	19.05%	17.27%	14.41%	12.54%	24.30%
		30%	24.30%	24.30%	20.48%	19.78%	22.60%	24.84%	20.31%	20.07%	17.76%	17.54%	24.30%
		25%	24.30%	24.30%	20.48%	20.42%	22.60%	24.84%	19.95%	20.95%	19.76%	19.68%	24.30%
		20%	24.30%	24.30%	21.80%	20.48%	23.92%	26.17%	21.73%	24.32%	24.72%	27.83%	24.30%
		15%	24.30%	24.30%	21.80%	20.48%	23.92%	26.17%	21.89%	25.29%	25.48%	30.10%	24.30%
		10%	24.30%	24.30%	21.80%	21.80%	23.92%	26.17%	23.66%	25.36%	23.50%	26.68%	24.30%
		5%	24.30%	24.30%	22.95%	21.43%	25.04%	27.26%	25.96%	29.73%	26.36%	32.70%	24.30%
	0%	24.30%	24.30%	22.95%	21.43%	25.04%	27.26%	26.31%	29.66%	24.23%	25.78%	24.30%	

Table H.2.5 Percentage of Months in Partial Cash

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	0.00%	0.00%	7.41%	12.50%	7.87%	8.33%	24.07%	42.13%	48.61%	81.94%	0.00%
		45%	0.00%	0.00%	4.17%	7.41%	4.63%	5.09%	22.22%	39.81%	43.98%	76.85%	0.00%
		40%	0.00%	0.00%	3.70%	7.41%	4.17%	4.63%	21.76%	38.89%	42.59%	75.46%	0.00%
		35%	0.00%	0.00%	3.24%	4.17%	3.70%	4.17%	19.91%	32.87%	31.94%	62.50%	0.00%
		30%	0.00%	0.00%	2.31%	3.24%	2.78%	3.24%	18.52%	30.09%	28.70%	58.33%	0.00%
		25%	0.00%	0.00%	2.31%	2.78%	2.78%	3.24%	11.57%	21.76%	26.39%	53.24%	0.00%
		20%	0.00%	0.00%	1.85%	2.31%	2.31%	2.78%	6.02%	15.28%	23.15%	46.76%	0.00%
		15%	0.00%	0.00%	1.85%	2.31%	2.31%	2.78%	6.02%	14.81%	21.30%	42.59%	0.00%
		10%	0.00%	0.00%	1.85%	1.85%	2.31%	2.78%	5.09%	12.50%	15.74%	34.26%	0.00%
		5%	0.00%	0.00%	0.46%	1.39%	0.93%	1.39%	3.24%	8.80%	10.65%	24.07%	0.00%
	0%	0.00%	0.00%	0.46%	1.39%	0.93%	1.39%	3.24%	7.87%	13.43%	18.52%	0.00%	

Table H.2.6 Maximum Drawdown

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	-40.12%	-40.12%	-40.12%	-40.12%	-36.85%	-33.26%	-29.64%	-26.42%	-25.90%	-18.22%	-40.12%
		45%	-40.12%	-40.12%	-40.12%	-40.12%	-36.85%	-33.26%	-29.64%	-26.42%	-25.90%	-19.17%	-40.12%
		40%	-40.12%	-40.12%	-40.12%	-40.12%	-36.85%	-33.26%	-29.64%	-26.42%	-25.90%	-19.17%	-40.12%
		35%	-40.12%	-40.12%	-40.12%	-40.12%	-36.85%	-33.26%	-29.64%	-26.42%	-25.90%	-19.95%	-40.12%
		30%	-40.12%	-40.12%	-40.12%	-40.12%	-36.85%	-33.26%	-29.64%	-26.42%	-25.90%	-19.95%	-40.12%
		25%	-40.12%	-40.12%	-40.12%	-40.12%	-36.85%	-33.26%	-29.64%	-26.42%	-25.90%	-19.95%	-40.12%
		20%	-40.12%	-40.12%	-40.12%	-40.12%	-36.85%	-33.26%	-29.64%	-26.42%	-25.90%	-19.95%	-40.12%
		15%	-40.12%	-40.12%	-40.12%	-40.12%	-36.85%	-33.26%	-29.64%	-26.42%	-25.90%	-19.95%	-40.12%
		10%	-40.12%	-40.12%	-40.12%	-40.12%	-36.85%	-33.26%	-29.64%	-26.42%	-25.90%	-24.02%	-40.12%
		5%	-40.12%	-40.12%	-40.12%	-40.12%	-36.85%	-33.26%	-29.64%	-26.42%	-25.90%	-24.02%	-40.12%
	0%	-40.12%	-40.12%	-40.12%	-40.12%	-36.85%	-33.26%	-29.64%	-27.19%	-39.75%	-40.45%	-40.12%	

Table H.2.7 Number of Signals

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	0	0	1	1	1	1	3	5	5	5	0
		45%	0	0	1	1	1	1	4	6	5	6	0
		40%	0	0	1	1	1	1	4	6	5	6	0
		35%	0	0	1	1	1	1	4	6	7	9	0
		30%	0	0	1	1	1	1	4	6	7	9	0
		25%	0	0	1	1	1	1	4	6	7	10	0
		20%	0	0	1	1	1	1	4	6	7	10	0
		15%	0	0	1	1	1	1	4	6	8	11	0
		10%	0	0	1	1	1	1	4	7	10	13	0
		5%	0	0	1	2	1	1	4	7	10	13	0
	0%	0	0	1	2	1	1	4	8	9	15	0	

Table H.3.1 Annualised Geometric Return

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	100%	100%	11.62%										
	90%	100%	12.41%										
	80%	100%	12.57%	11.08%									
	70%	100%	11.00%	10.33%	10.01%								
	SLOW MOVING AVERAGE	60%	100%	10.44%	10.24%	10.29%	10.52%						
		50%	100%	10.01%	10.68%	10.65%	10.72%	10.25%					
		40%	100%	10.89%	11.05%	11.08%	10.47%	10.54%	10.35%				
		30%	100%	10.91%	10.69%	10.83%	10.14%	10.88%	11.02%	11.16%			
		20%	100%	11.69%	11.66%	11.66%	11.19%	11.52%	11.73%	11.13%	12.00%		
	10%	100%	11.46%	12.13%	11.81%	11.81%	11.67%	12.12%	11.63%	11.75%	11.48%		
	0%	100%	11.57%	11.57%	11.57%	11.02%	11.02%	11.02%	11.02%	11.37%	11.96%	11.96%	11.62%

Table H.3.2 Annualised Standard Deviation

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	100%	100%	15.08%										
	90%	100%	10.81%										
	80%	100%	10.77%	11.36%									
	70%	100%	11.36%	11.31%	11.37%								
	SLOW MOVING AVERAGE	60%	100%	11.30%	11.36%	11.39%	11.37%						
		50%	100%	11.40%	11.38%	11.39%	11.48%	11.76%					
		40%	100%	11.41%	11.41%	11.61%	11.78%	11.80%	11.87%				
		30%	100%	11.65%	11.70%	11.71%	11.86%	12.08%	12.10%	11.92%			
		20%	100%	12.12%	12.16%	12.16%	12.04%	12.06%	12.27%	12.45%	12.70%		
	10%	100%	12.84%	13.02%	12.95%	12.95%	12.96%	13.04%	13.34%	13.53%	13.54%		
	0%	100%	14.39%	14.39%	14.39%	14.56%	14.56%	14.56%	14.56%	14.70%	15.01%	15.01%	15.08%

Table H.3.3 5% Value at Risk (VaR)

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	100%	100%	-5.99%										
	90%	100%	-3.42%										
	80%	100%	-3.36%	-3.65%									
	70%	100%	-3.65%	-3.65%	-3.81%								
	SLOW MOVING AVERAGE	60%	100%	-3.65%	-3.81%	-3.81%	-3.81%						
		50%	100%	-3.81%	-3.81%	-3.81%	-4.01%	-4.44%					
		40%	100%	-3.81%	-3.81%	-4.01%	-4.44%	-4.44%	-4.44%				
		30%	100%	-4.01%	-4.17%	-4.17%	-4.44%	-4.44%	-4.44%	-4.17%			
		20%	100%	-4.17%	-4.17%	-4.17%	-4.17%	-4.44%	-4.44%	-4.80%	-4.80%		
	10%	100%	-5.18%	-5.18%	-5.18%	-5.18%	-5.18%	-5.18%	-5.45%	-5.45%	-5.45%		
	0%	100%	-5.88%	-5.88%	-5.88%	-5.99%	-5.99%	-5.99%	-5.99%	-5.99%	-5.99%	-5.99%	-5.99%

Table H.3.4 Annualised Sharpe Ratio

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	100%	100%	24.30%										
	90%	100%	41.12%										
	80%	100%	42.84%	27.47%									
	70%	100%	26.78%	20.91%	18.00%								
	SLOW MOVING AVERAGE	60%	100%	21.96%	20.07%	20.45%	22.53%						
		50%	100%	18.00%	23.90%	23.61%	24.02%	19.48%					
		40%	100%	25.63%	27.07%	26.90%	21.26%	21.86%	20.11%				
		30%	100%	25.35%	23.37%	24.50%	18.40%	24.16%	25.26%	26.84%			
		20%	100%	30.77%	30.45%	30.40%	26.82%	29.53%	30.74%	25.44%	31.83%		
	10%	100%	27.28%	32.03%	29.69%	29.69%	28.65%	31.88%	27.51%	27.99%	26.01%		
	0%	100%	25.09%	25.09%	25.09%	21.02%	21.02%	21.02%	21.02%	23.21%	26.62%	26.62%	24.30%

Table H.3.5 Percentage of Months in Cash

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	100%	100%	0.00%										
	90%	100%	34.72%										
	80%	100%	35.19%	34.26%									
	70%	100%	34.26%	32.87%	29.63%								
	SLOW MOVING AVERAGE	60%	100%	33.33%	30.56%	29.63%	29.63%						
		50%	100%	29.63%	29.17%	29.63%	27.78%	23.61%					
		40%	100%	28.70%	27.78%	25.00%	22.69%	21.76%	20.37%				
		30%	100%	23.15%	22.69%	22.22%	20.83%	20.83%	19.91%	18.52%			
		20%	100%	20.37%	18.98%	18.52%	18.52%	16.20%	15.74%	14.35%	14.35%		
	10%	100%	12.96%	12.04%	12.50%	12.50%	12.96%	12.04%	12.04%	11.57%	11.11%		
	0%	100%	2.78%	2.78%	2.78%	2.31%	2.31%	2.31%	2.31%	1.39%	0.46%	0.46%	0.00%

Table H.3.6 Maximum Drawdown

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	100%	100%	-40.12%										
	90%	100%	-16.27%										
	80%	100%	-16.27%	-18.40%									
	70%	100%	-18.40%	-18.40%	-18.40%								
	SLOW MOVING AVERAGE	60%	100%	-18.40%	-18.40%	-18.40%	-18.40%						
		50%	100%	-18.40%	-18.40%	-18.40%	-18.40%	-18.40%					
		40%	100%	-18.40%	-18.40%	-18.40%	-18.40%	-18.40%	-18.40%				
		30%	100%	-18.40%	-18.40%	-18.40%	-18.40%	-18.40%	-18.68%	-20.13%			
		20%	100%	-18.40%	-18.40%	-18.40%	-18.40%	-18.40%	-20.49%	-20.36%			
	10%	100%	-21.00%	-21.00%	-21.00%	-21.00%	-22.66%	-22.66%	-30.80%	-24.01%	-24.01%		
	0%	100%	-34.05%	-34.05%	-34.05%	-40.12%	-40.12%	-40.12%	-40.12%	-40.12%	-40.12%	-40.12%	-40.12%

Table H.3.7 Number of Signals

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	100%	100%	0										
	90%	100%	49										
	80%	100%	47	44									
	70%	100%	45	43	39								
	SLOW MOVING AVERAGE	60%	100%	43	38	34	32						
		50%	100%	37	31	30	25	22					
		40%	100%	30	26	23	21	20	18				
		30%	100%	22	21	20	20	17	16	14			
		20%	100%	18	16	15	15	13	10	9	7		
	10%	100%	9	7	7	7	7	6	5	4	4		
	0%	100%	2	2	2	2	2	2	2	2	1	1	0

Table H.4.1 Annualised Geometric Return

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	50%	100%	11.62%										
		90%	12.17%										
		80%	12.26%	11.49%									
		70%	11.45%	11.11%	10.95%								
	SLOW MOVING AVERAGE	60%	11.17%	11.06%	11.09%	11.21%							
		50%	10.95%	11.29%	11.27%	11.30%	11.06%						
		40%	11.39%	11.47%	11.48%	11.16%	11.20%	11.10%					
		30%	11.39%	11.28%	11.35%	11.00%	11.36%	11.43%	11.51%				
		20%	11.77%	11.75%	11.75%	11.52%	11.69%	11.78%	11.47%	11.90%			
	10%	11.63%	11.96%	11.80%	11.80%	11.73%	11.95%	11.69%	11.75%	11.61%			
0%	11.62%	11.62%	11.62%	11.34%	11.34%	11.34%	11.34%	11.51%	11.79%	11.79%	11.62%		

Table H.4.2 Annualised Standard Deviation

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	50%	100%	15.08%										
		90%	12.01%										
		80%	11.98%	12.37%									
		70%	12.37%	12.34%	12.37%								
	SLOW MOVING AVERAGE	60%	12.33%	12.37%	12.39%	12.38%							
		50%	12.40%	12.38%	12.39%	12.45%	12.65%						
		40%	12.41%	12.40%	12.54%	12.66%	12.68%	12.72%					
		30%	12.57%	12.61%	12.61%	12.72%	12.88%	12.89%	12.76%				
		20%	12.90%	12.93%	12.93%	12.84%	12.86%	13.01%	13.15%	13.32%			
	10%	13.43%	13.56%	13.51%	13.51%	13.52%	13.57%	13.78%	13.92%	13.93%			
0%	14.56%	14.56%	14.56%	14.69%	14.69%	14.69%	14.69%	14.79%	15.03%	15.03%	15.08%		

Table H.4.3 5% Value at Risk (VaR)

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	50%	100%	-5.99%										
		90%	-4.31%										
		80%	-4.31%	-4.31%									
		70%	-4.31%	-4.31%	-4.31%								
	SLOW MOVING AVERAGE	60%	-4.31%	-4.31%	-4.31%	-4.31%							
		50%	-4.31%	-4.31%	-4.31%	-4.52%	-4.79%						
		40%	-4.31%	-4.31%	-4.52%	-4.79%	-4.79%	-4.79%	-4.52%				
		30%	-4.52%	-4.52%	-4.52%	-4.79%	-4.79%	-4.79%	-4.96%	-4.96%			
		20%	-4.52%	-4.52%	-4.52%	-4.52%	-4.79%	-4.79%	-4.96%	-4.96%	-4.96%		
	10%	-5.18%	-5.18%	-5.18%	-5.18%	-5.18%	-5.18%	-5.45%	-5.45%	-5.45%			
0%	-5.88%	-5.88%	-5.88%	-5.99%	-5.99%	-5.99%	-5.99%	-5.99%	-5.99%	-5.99%	-5.99%		

Table H.4.4 Annualised Sharpe Ratio

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	50%	100%	24.30%										
		90%	35.07%										
		80%	35.86%	28.52%									
		70%	28.20%	25.53%	24.14%								
	SLOW MOVING AVERAGE	60%	26.02%	25.10%	25.25%	26.22%							
		50%	24.11%	26.85%	26.71%	26.83%	24.48%						
		40%	27.63%	28.29%	28.07%	25.30%	25.57%	24.69%					
		30%	27.32%	26.36%	26.87%	23.89%	26.43%	26.93%	27.81%				
		20%	29.51%	29.32%	29.30%	27.71%	28.96%	29.37%	26.73%	29.59%			
	10%	27.31%	29.47%	28.40%	28.40%	27.89%	29.39%	27.09%	27.19%	26.22%			
0%	25.16%	25.16%	25.16%	23.02%	23.02%	23.02%	23.02%	24.01%	25.50%	25.50%	24.30%		

Table H.4.5 Percentage of Months in Partial Cash

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	50%	100%	0.00%										
		90%	34.72%										
		80%	35.19%	34.26%									
		70%	34.26%	32.87%	29.63%								
	SLOW MOVING AVERAGE	60%	33.33%	30.56%	29.63%	29.63%							
		50%	29.63%	29.17%	29.63%	27.78%	23.61%						
		40%	28.70%	27.78%	25.00%	22.69%	21.76%	20.37%					
		30%	23.15%	22.69%	22.22%	20.83%	20.83%	19.91%	18.52%				
		20%	20.37%	18.98%	18.52%	18.52%	16.20%	15.74%	14.35%	14.35%			
	10%	12.96%	12.04%	12.50%	12.50%	12.96%	12.04%	12.04%	11.57%	11.11%			
0%	2.78%	2.78%	2.78%	2.31%	2.31%	2.31%	2.31%	1.39%	0.46%	0.46%	0.00%		

Table H.4.6 Maximum Drawdown

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	50%	100%	-40.12%										
		90%	-27.24%										
		80%	-27.24%	-27.63%									
		70%	-27.63%	-28.24%	-28.24%								
	SLOW MOVING AVERAGE	60%	-28.24%	-28.24%	-28.24%	-27.09%							
		50%	-28.24%	-27.09%	-27.09%	-27.09%	-27.09%						
		40%	-27.09%	-27.09%	-27.09%	-27.09%	-27.09%	-27.25%	-27.54%				
		30%	-27.09%	-27.09%	-27.09%	-27.09%	-27.09%	-26.70%	-25.90%	-25.90%			
		20%	-26.47%	-27.09%	-27.37%	-27.37%	-26.70%	-26.70%	-25.90%	-25.90%	-26.35%		
	10%	-25.90%	-25.90%	-25.90%	-25.90%	-25.90%	-25.90%	-27.40%	-26.42%	-26.35%			
0%	-36.85%	-36.85%	-36.85%	-40.12%	-40.12%	-40.12%	-40.12%	-40.12%	-40.12%	-40.12%	-40.12%		

Table H.4.7 Number of Signals

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	50%	100%	0										
		90%	49										
		80%	47	44									
		70%	45	43	39								
	SLOW MOVING AVERAGE	60%	43	38	34	32							
		50%	37	31	30	25	22						
		40%	30	26	23	21	20	18					
		30%	22	21	20	20	17	16	14				
		20%	18	16	15	15	13	10	9	7			
	10%	9	7	7	7	7	6	5	4	4			
0%	2	2	2	2	2	2	2	2	1	1	0		

Table L1.1 Annualised Geometric Return

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	6.10%	2.98%	4.15%	4.77%	4.93%	6.76%	5.71%	8.66%	5.01%	4.34%	6.10%
		45%	6.10%	3.32%	4.49%	5.12%	5.28%	7.12%	5.71%	9.02%	5.55%	4.68%	6.10%
		40%	6.10%	3.57%	4.75%	5.37%	5.53%	7.37%	6.13%	9.28%	6.46%	4.77%	6.10%
		35%	6.10%	3.57%	4.75%	5.37%	5.53%	7.37%	6.08%	9.28%	6.68%	5.39%	6.10%
	DRAWUP LEVEL (into Equities)	30%	6.10%	4.00%	5.18%	5.81%	5.97%	7.82%	6.75%	9.74%	7.48%	6.35%	6.10%
		25%	6.10%	4.22%	5.40%	6.03%	6.19%	8.04%	7.22%	9.96%	8.15%	6.67%	6.10%
		20%	6.10%	4.33%	5.51%	6.14%	6.31%	8.16%	7.54%	10.09%	8.47%	6.66%	6.10%
		15%	6.10%	4.70%	5.76%	6.52%	6.68%	8.54%	8.05%	10.47%	9.19%	7.63%	6.10%
		10%	6.10%	4.90%	5.59%	6.73%	6.89%	8.76%	8.46%	10.69%	10.12%	8.21%	6.10%
		5%	6.10%	5.16%	6.15%	6.98%	6.96%	7.68%	7.57%	8.67%	7.71%	3.65%	6.10%
		0%	6.10%	5.16%	6.04%	6.75%	6.89%	7.92%	8.01%	8.21%	8.29%	4.80%	6.10%

Table L1.2 Annualised Standard Deviation

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	14.69%	13.90%	13.34%	13.11%	12.86%	11.77%	11.14%	10.74%	9.28%	4.54%	14.69%
		45%	14.69%	14.03%	13.47%	13.24%	12.99%	11.92%	11.19%	10.90%	9.50%	5.02%	14.69%
		40%	14.69%	14.04%	13.49%	13.26%	13.01%	11.93%	11.23%	10.91%	9.73%	5.86%	14.69%
		35%	14.69%	14.04%	13.49%	13.26%	13.01%	11.93%	11.28%	10.91%	9.78%	6.19%	14.69%
	DRAWUP LEVEL (into Equities)	30%	14.69%	14.09%	13.54%	13.31%	13.06%	11.98%	11.36%	10.96%	10.03%	6.69%	14.69%
		25%	14.69%	14.12%	13.56%	13.33%	13.08%	12.00%	11.42%	10.98%	10.17%	7.09%	14.69%
		20%	14.69%	14.12%	13.57%	13.34%	13.09%	12.01%	11.49%	10.98%	10.26%	8.02%	14.69%
		15%	14.69%	14.15%	13.59%	13.36%	13.11%	12.03%	11.58%	11.00%	10.33%	8.27%	14.69%
		10%	14.69%	14.39%	13.65%	13.62%	13.37%	12.31%	11.91%	11.31%	10.82%	9.16%	14.69%
		5%	14.69%	14.43%	13.73%	13.65%	13.44%	13.08%	12.79%	12.57%	12.32%	13.45%	14.69%
		0%	14.69%	14.43%	14.02%	13.89%	13.74%	13.10%	12.85%	12.78%	12.98%	14.38%	14.69%

Table L1.3 5% Value at Risk (VaR)

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	-6.54%	-6.54%	-6.19%	-6.08%	-5.80%	-5.40%	-5.39%	-4.43%	-4.32%	0.07%	-6.54%
		45%	-6.54%	-6.54%	-6.19%	-6.08%	-5.80%	-5.40%	-5.39%	-4.43%	-4.32%	-1.63%	-6.54%
		40%	-6.54%	-6.54%	-6.19%	-6.08%	-5.80%	-5.40%	-5.39%	-4.43%	-4.32%	-2.05%	-6.54%
		35%	-6.54%	-6.54%	-6.19%	-6.08%	-5.80%	-5.40%	-5.39%	-4.43%	-4.32%	-2.34%	-6.54%
	DRAWUP LEVEL (into Equities)	30%	-6.54%	-6.54%	-6.19%	-6.08%	-5.80%	-5.40%	-5.39%	-4.43%	-4.32%	-2.38%	-6.54%
		25%	-6.54%	-6.54%	-6.19%	-6.08%	-5.80%	-5.40%	-5.39%	-4.43%	-4.32%	-2.66%	-6.54%
		20%	-6.54%	-6.54%	-6.19%	-6.08%	-5.80%	-5.40%	-5.39%	-4.43%	-4.32%	-2.71%	-6.54%
		15%	-6.54%	-6.54%	-6.19%	-6.08%	-5.80%	-5.40%	-5.39%	-4.43%	-4.32%	-2.71%	-6.54%
		10%	-6.54%	-6.54%	-6.19%	-6.08%	-5.80%	-5.40%	-5.39%	-4.43%	-4.32%	-3.15%	-6.54%
		5%	-6.54%	-6.54%	-6.19%	-6.08%	-5.80%	-6.08%	-6.08%	-5.66%	-5.66%	-6.19%	-6.54%
		0%	-6.54%	-6.54%	-6.33%	-6.19%	-6.08%	-6.08%	-6.08%	-5.80%	-6.08%	-6.54%	-6.54%

Table L1.4 Annualised Sharpe Ratio

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	14.99%	-6.56%	1.91%	6.68%	8.08%	24.36%	16.30%	44.36%	12.08%	9.88%	14.99%
		45%	14.99%	-4.06%	4.47%	9.25%	10.69%	27.05%	16.20%	47.07%	17.40%	15.71%	14.99%
		40%	14.99%	-2.29%	6.32%	11.14%	12.62%	29.18%	19.96%	49.42%	26.37%	14.87%	14.99%
		35%	14.99%	-2.29%	6.32%	11.14%	12.62%	29.18%	19.35%	49.42%	28.49%	24.20%	14.99%
	DRAWUP LEVEL (into Equities)	30%	14.99%	0.79%	9.52%	14.40%	15.94%	32.79%	25.18%	53.34%	35.81%	36.70%	14.99%
		25%	14.99%	2.28%	11.08%	15.99%	17.56%	34.55%	29.08%	55.27%	41.91%	39.24%	14.99%
		20%	14.99%	3.11%	11.95%	16.88%	18.46%	35.55%	31.79%	56.38%	44.58%	34.55%	14.99%
		15%	14.99%	5.68%	13.75%	19.63%	21.27%	38.64%	35.86%	59.79%	51.28%	45.21%	14.99%
		10%	14.99%	7.03%	12.41%	20.80%	22.43%	39.49%	38.32%	60.10%	57.52%	47.19%	14.99%
		5%	14.99%	8.75%	16.45%	22.63%	22.79%	28.98%	28.78%	38.03%	31.01%	-1.80%	14.99%
		0%	14.99%	8.75%	15.34%	20.58%	21.81%	30.71%	32.03%	33.75%	33.84%	6.30%	14.99%

Table L1.5 Percentage of Months in Cash

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	0.00%	12.50%	13.89%	14.35%	18.52%	19.44%	33.33%	24.54%	46.30%	89.81%	0.00%
		45%	0.00%	8.33%	9.72%	10.19%	14.35%	15.28%	31.48%	20.37%	41.67%	83.33%	0.00%
		40%	0.00%	7.41%	8.80%	9.26%	13.43%	14.35%	30.09%	19.44%	39.81%	78.24%	0.00%
		35%	0.00%	7.41%	8.80%	9.26%	13.43%	14.35%	27.78%	19.44%	37.96%	74.07%	0.00%
	DRAWUP LEVEL (into Equities)	30%	0.00%	6.48%	7.87%	8.33%	12.50%	13.43%	25.46%	18.52%	33.33%	68.06%	0.00%
		25%	0.00%	6.02%	7.41%	7.87%	12.04%	12.96%	24.54%	18.06%	30.56%	63.43%	0.00%
		20%	0.00%	5.56%	6.94%	7.41%	11.57%	12.50%	22.22%	17.59%	27.31%	57.87%	0.00%
		15%	0.00%	4.17%	6.02%	6.02%	10.19%	11.11%	18.06%	16.20%	24.54%	50.46%	0.00%
		10%	0.00%	1.39%	5.09%	3.24%	7.41%	8.33%	13.89%	13.43%	19.44%	41.20%	0.00%
		5%	0.00%	0.93%	4.17%	2.78%	6.02%	2.78%	7.41%	4.63%	9.26%	20.37%	0.00%
		0%	0.00%	0.93%	3.24%	1.85%	3.24%	2.31%	4.63%	3.70%	5.09%	8.33%	0.00%

Table L1.6 Maximum Drawdown

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	-48.20%	-54.73%	-44.56%	-40.49%	-40.49%	-27.44%	-27.57%	-16.47%	-21.13%	-6.67%	-48.20%
		45%	-48.20%	-51.94%	-42.87%	-40.49%	-40.49%	-27.82%	-27.60%	-16.47%	-21.13%	-6.67%	-48.20%
		40%	-48.20%	-49.82%	-41.57%	-40.49%	-40.49%	-27.44%	-26.46%	-16.47%	-15.25%	-9.65%	-48.20%
		35%	-48.20%	-49.82%	-41.57%	-40.49%	-40.49%	-27.44%	-26.46%	-16.47%	-15.25%	-9.65%	-48.20%
	DRAWUP LEVEL (into Equities)	30%	-48.20%	-48.20%	-41.57%	-40.49%	-40.49%	-27.44%	-26.46%	-16.47%	-15.25%	-9.65%	-48.20%
		25%	-48.20%	-48.20%	-41.57%	-40.49%	-40.49%	-27.44%	-26.46%	-16.47%	-15.25%	-9.65%	-48.20%
		20%	-48.20%	-48.20%	-41.57%	-40.49%	-40.49%	-27.44%	-26.46%	-16.47%	-15.25%	-15.73%	-48.20%
		15%	-48.20%	-48.20%	-41.57%	-40.49%	-40.49%	-27.44%	-26.46%	-16.47%	-15.25%	-15.02%	-48.20%
		10%	-48.20%	-50.02%	-44.11%	-40.71%	-40.49%	-32.69%	-29.22%	-18.81%	-18.81%	-13.45%	-48.20%
		5%	-48.20%	-48.20%	-41.66%	-40.49%	-40.49%	-43.86%	-42.56%	-41.87%	-41.87%	-49.94%	-48.20%
		0%	-48.20%	-48.20%	-46.91%	-40.66%	-40.49%	-41.63%	-40.27%	-46.22%	-45.65%	-47.65%	-48.20%

Table L1.7 Number of Signals

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	0	2	2	2	2	2	2	2	4	4	0
		45%	0	2	2	2	2	2	3	2	4	4	0
		40%	0	2	2	2	2	2	3	2	4	5	0
		35%	0	2	2	2	2	2	3	2	4	5	0
	DRAWUP LEVEL (into Equities)	30%	0	2	2	2	2	2	3	2	4	5	0
		25%	0	2	2	2	2	2	3	2	4	6	0
		20%	0	2	2	2	2	2	3	2	4	7	0
		15%	0	2	2	2	2	2	3	2	4	7	0
		10%	0	2	3	2	2	2	3	2	4	9	0
		5%	0	2	3	2	3	2	4	2	5	12	0
		0%	0	2	4	2	4	2	4	3	5	15	0

Table I.2.1 Annualised Geometric Return

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	6.10%	4.56%	5.17%	5.49%	5.58%	6.54%	6.03%	7.51%	5.73%	5.48%	6.10%
		45%	6.10%	4.73%	5.34%	5.66%	5.75%	6.71%	6.03%	7.69%	5.99%	5.65%	6.10%
		40%	6.10%	4.85%	5.47%	5.79%	5.88%	6.84%	6.24%	7.81%	6.45%	5.68%	6.10%
		35%	6.10%	4.85%	5.47%	5.79%	5.88%	6.84%	6.21%	7.81%	6.55%	5.99%	6.10%
		30%	6.10%	5.07%	5.68%	6.01%	6.10%	7.06%	6.55%	8.04%	6.95%	6.46%	6.10%
		25%	6.10%	5.17%	5.79%	6.11%	6.20%	7.17%	6.77%	8.15%	7.28%	6.61%	6.10%
		20%	6.10%	5.23%	5.85%	6.17%	6.26%	7.23%	6.94%	8.21%	7.43%	6.59%	6.10%
		15%	6.10%	5.41%	5.97%	6.36%	6.45%	7.41%	7.18%	8.39%	7.78%	7.06%	6.10%
		10%	6.10%	5.51%	5.88%	6.45%	6.54%	7.51%	7.37%	8.49%	8.23%	7.33%	6.10%
		5%	6.10%	5.63%	6.16%	6.58%	6.57%	7.54%	7.41%	8.46%	7.99%	7.46%	6.10%
	0%	6.10%	5.63%	6.10%	6.45%	6.53%	7.07%	7.12%	7.22%	7.25%	5.46%	6.10%	

Table I.2.2 Annualised Standard Deviation

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	14.69%	14.09%	13.68%	13.51%	13.33%	12.57%	12.12%	11.87%	10.90%	8.34%	14.69%
		45%	14.69%	14.18%	13.78%	13.61%	13.43%	12.67%	12.16%	11.98%	11.03%	8.55%	14.69%
		40%	14.69%	14.19%	13.79%	13.62%	13.44%	12.68%	12.18%	11.99%	11.18%	8.94%	14.69%
		35%	14.69%	14.19%	13.79%	13.62%	13.44%	12.68%	12.22%	11.99%	11.22%	9.10%	14.69%
		30%	14.69%	14.23%	13.83%	13.66%	13.48%	12.73%	12.28%	12.04%	11.39%	9.36%	14.69%
		25%	14.69%	14.25%	13.85%	13.68%	13.50%	12.74%	12.33%	12.06%	11.49%	9.58%	14.69%
		20%	14.69%	14.25%	13.85%	13.68%	13.50%	12.75%	12.38%	12.06%	11.55%	10.12%	14.69%
		15%	14.69%	14.27%	13.87%	13.70%	13.52%	12.77%	12.45%	12.08%	11.61%	10.28%	14.69%
		10%	14.69%	14.46%	13.91%	13.90%	13.72%	12.97%	12.69%	12.30%	11.96%	10.83%	14.69%
		5%	14.69%	14.48%	13.98%	13.92%	13.77%	13.51%	13.30%	13.16%	12.97%	13.77%	14.69%
	0%	14.69%	14.48%	14.19%	14.10%	13.99%	13.53%	13.35%	13.30%	13.45%	14.46%	14.69%	

Table I.2.3 5% Value at Risk (VaR)

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	-6.54%	-6.54%	-6.33%	-6.19%	-6.08%	-5.80%	-5.80%	-5.35%	-5.26%	-4.21%	-6.54%
		45%	-6.54%	-6.54%	-6.33%	-6.19%	-6.08%	-5.80%	-5.80%	-5.35%	-5.26%	-4.21%	-6.54%
		40%	-6.54%	-6.54%	-6.33%	-6.19%	-6.08%	-5.80%	-5.80%	-5.35%	-5.26%	-4.27%	-6.54%
		35%	-6.54%	-6.54%	-6.33%	-6.19%	-6.08%	-5.80%	-5.80%	-5.35%	-5.26%	-4.27%	-6.54%
		30%	-6.54%	-6.54%	-6.33%	-6.19%	-6.08%	-5.80%	-5.80%	-5.35%	-5.26%	-4.27%	-6.54%
		25%	-6.54%	-6.54%	-6.33%	-6.19%	-6.08%	-5.80%	-5.80%	-5.35%	-5.26%	-4.39%	-6.54%
		20%	-6.54%	-6.54%	-6.33%	-6.19%	-6.08%	-5.80%	-5.80%	-5.35%	-5.26%	-4.39%	-6.54%
		15%	-6.54%	-6.54%	-6.33%	-6.19%	-6.08%	-5.80%	-5.80%	-5.35%	-5.26%	-4.39%	-6.54%
		10%	-6.54%	-6.54%	-6.33%	-6.19%	-6.08%	-5.80%	-5.80%	-5.35%	-5.26%	-4.73%	-6.54%
		5%	-6.54%	-6.54%	-6.33%	-6.19%	-6.08%	-6.33%	-6.33%	-6.08%	-6.08%	-6.19%	-6.54%
	0%	-6.54%	-6.54%	-6.48%	-6.33%	-6.19%	-6.33%	-6.33%	-6.19%	-6.33%	-6.54%	-6.54%	

Table I.2.4 Annualised Sharpe Ratio

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	14.99%	4.71%	9.33%	11.82%	12.67%	21.05%	17.63%	30.47%	16.88%	19.03%	14.99%
		45%	14.99%	5.88%	10.50%	12.99%	13.85%	22.23%	17.56%	31.65%	19.04%	20.52%	14.99%
		40%	14.99%	6.75%	11.40%	13.91%	14.77%	23.22%	19.27%	32.69%	22.82%	19.95%	14.99%
		35%	14.99%	6.75%	11.40%	13.91%	14.77%	23.22%	18.96%	32.69%	23.72%	23.01%	14.99%
		30%	14.99%	8.25%	12.94%	15.46%	16.35%	24.87%	21.60%	34.42%	26.82%	27.39%	14.99%
		25%	14.99%	9.88%	13.69%	16.22%	17.12%	25.68%	23.37%	35.27%	29.45%	28.39%	14.99%
		20%	14.99%	9.39%	14.11%	16.65%	17.55%	26.14%	24.59%	35.75%	30.61%	26.62%	14.99%
		15%	14.99%	10.66%	14.99%	17.97%	18.89%	27.56%	26.42%	37.25%	33.51%	30.85%	14.99%
		10%	14.99%	11.18%	14.29%	18.41%	19.32%	27.87%	27.44%	37.39%	36.24%	31.75%	14.99%
		5%	14.99%	12.02%	16.22%	19.28%	19.46%	22.63%	22.66%	27.10%	23.90%	7.40%	14.99%
	0%	14.99%	12.02%	15.52%	18.17%	18.84%	23.45%	24.17%	25.01%	24.98%	10.82%	14.99%	

Table I.2.5 Percentage of Months in Partial Cash

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	0.00%	12.50%	13.89%	14.35%	18.52%	19.44%	33.33%	24.54%	46.30%	89.81%	0.00%
		45%	0.00%	8.33%	9.72%	10.19%	14.35%	15.28%	31.48%	20.37%	41.67%	83.33%	0.00%
		40%	0.00%	7.41%	8.80%	9.26%	13.43%	14.35%	30.09%	19.44%	39.81%	78.24%	0.00%
		35%	0.00%	7.41%	8.80%	9.26%	13.43%	14.35%	27.78%	19.44%	37.96%	74.07%	0.00%
		30%	0.00%	6.48%	7.87%	8.33%	12.50%	13.43%	25.46%	18.52%	33.33%	68.06%	0.00%
		25%	0.00%	6.02%	7.41%	7.87%	12.04%	12.96%	24.54%	18.06%	30.56%	63.43%	0.00%
		20%	0.00%	5.56%	6.94%	7.41%	11.57%	12.50%	22.22%	17.59%	27.31%	57.87%	0.00%
		15%	0.00%	4.17%	6.02%	6.02%	10.19%	11.11%	18.06%	16.20%	24.54%	50.46%	0.00%
		10%	0.00%	1.39%	5.09%	3.24%	7.41%	8.33%	13.89%	13.43%	19.44%	41.20%	0.00%
		5%	0.00%	0.93%	4.17%	2.78%	6.02%	2.78%	7.41%	4.63%	9.26%	20.37%	0.00%
	0%	0.00%	0.93%	3.24%	1.85%	3.24%	2.31%	4.63%	3.70%	5.09%	8.33%	0.00%	

Table I.2.6 Maximum Drawdown

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	-48.20%	-48.20%	-44.34%	-44.34%	-44.34%	-37.76%	-37.76%	-33.47%	-31.17%	-26.47%	-48.20%
		45%	-48.20%	-48.20%	-44.34%	-44.34%	-44.34%	-37.76%	-37.76%	-33.47%	-31.17%	-26.47%	-48.20%
		40%	-48.20%	-48.20%	-44.34%	-44.34%	-44.34%	-37.76%	-37.76%	-33.47%	-31.17%	-30.42%	-48.20%
		35%	-48.20%	-48.20%	-44.34%	-44.34%	-44.34%	-37.76%	-37.76%	-33.47%	-31.17%	-30.42%	-48.20%
		30%	-48.20%	-48.20%	-44.34%	-44.34%	-44.34%	-37.76%	-37.76%	-33.47%	-31.17%	-30.42%	-48.20%
		25%	-48.20%	-48.20%	-44.34%	-44.34%	-44.34%	-37.76%	-37.76%	-33.47%	-31.17%	-30.42%	-48.20%
		20%	-48.20%	-48.20%	-44.34%	-44.34%	-44.34%	-37.76%	-37.76%	-33.47%	-31.17%	-30.42%	-48.20%
		15%	-48.20%	-48.20%	-44.34%	-44.34%	-44.34%	-37.76%	-37.76%	-33.47%	-31.17%	-30.42%	-48.20%
		10%	-48.20%	-48.20%	-44.34%	-44.34%	-44.34%	-38.71%	-37.76%	-33.47%	-31.17%	-30.42%	-48.20%
		5%	-48.20%	-48.20%	-44.34%	-44.34%	-44.34%	-44.36%	-43.64%	-43.32%	-43.32%	-49.07%	-48.20%
	0%	-48.20%	-48.20%	-45.86%	-44.34%	-44.34%	-43.28%	-42.54%	-45.55%	-45.34%	-47.92%	-48.20%	

Table I.2.7 Number of Signals

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	0	2	2	2	2	2	2	4	4	0	
		45%	0	2	2	2	2	2	3	2	4	0	
		40%	0	2	2	2	2	2	3	2	4	0	
		35%	0	2	2	2	2	2	3	2	4	0	
		30%	0	2	2	2	2	2	3	2	4	0	
		25%	0	2	2	2	2	2	3	2	4	0	
		20%	0	2	2	2	2	2	3	2	4	0	
		15%	0	2	2	2	2	2	3	2	4	0	
		10%	0	2	3	2	2	2	3	2	4	9	
		5%	0	2	3	2	3	2	4	2	5	12	
	0%	0	2	4	2	4	2	4	3	5	15		

Table J.1.1 Annualised Geometric Return

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	14.90%	7.55%	7.10%	7.39%	7.76%	8.92%	6.88%	7.17%	5.90%	5.94%	9.04%
		45%	9.04%	7.71%	7.37%	7.56%	8.03%	9.20%	6.74%	7.50%	6.45%	5.66%	9.04%
		40%	9.04%	7.83%	7.51%	7.68%	8.17%	9.34%	7.02%	7.79%	7.08%	6.00%	9.04%
		35%	9.04%	7.83%	7.57%	7.79%	8.23%	9.40%	7.52%	8.54%	6.39%	5.96%	9.04%
	DRAWUP LEVEL (into Equities)	30%	9.04%	8.04%	7.89%	8.07%	8.55%	9.72%	8.01%	9.13%	7.36%	6.99%	9.04%
		25%	9.04%	8.14%	7.99%	8.28%	8.65%	9.82%	8.28%	9.47%	8.05%	7.32%	9.04%
		20%	9.04%	8.20%	8.27%	8.34%	8.94%	10.11%	8.68%	10.00%	8.80%	8.27%	9.04%
		15%	9.04%	8.37%	8.39%	8.52%	9.11%	10.29%	8.97%	10.37%	9.40%	9.13%	9.04%
		10%	9.04%	8.47%	8.31%	8.84%	9.21%	10.39%	9.69%	10.80%	9.88%	9.85%	9.04%
		5%	9.04%	8.59%	8.82%	8.91%	9.49%	10.14%	9.81%	10.73%	9.50%	8.44%	9.04%
	0%	9.04%	8.59%	8.77%	8.80%	9.46%	10.25%	10.07%	10.50%	9.62%	8.39%	9.04%	

Table J.1.2 Annualised Standard Deviation

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	14.58%	13.82%	13.64%	13.51%	12.93%	11.53%	10.39%	8.59%	4.87%	14.90%	
		45%	14.90%	14.63%	14.04%	13.77%	13.74%	13.17%	11.70%	10.62%	9.00%	6.31%	14.90%
		40%	14.90%	14.63%	14.05%	13.78%	13.74%	13.17%	11.71%	10.64%	9.24%	6.74%	14.90%
		35%	14.90%	14.63%	14.05%	13.94%	13.74%	13.17%	11.95%	11.04%	9.83%	7.43%	14.90%
	DRAWUP LEVEL (into Equities)	30%	14.90%	14.65%	14.08%	13.97%	13.78%	13.20%	12.14%	11.26%	10.21%	7.76%	14.90%
		25%	14.90%	14.66%	14.09%	13.99%	13.78%	13.21%	12.32%	11.45%	10.32%	8.10%	14.90%
		20%	14.90%	14.66%	14.15%	13.99%	13.85%	13.27%	12.59%	11.75%	10.76%	8.89%	14.90%
		15%	14.90%	14.67%	14.16%	13.99%	13.85%	13.28%	12.73%	11.89%	10.91%	9.34%	14.90%
		10%	14.90%	14.78%	14.19%	14.17%	13.97%	13.40%	13.01%	12.31%	11.62%	10.46%	14.90%
		5%	14.90%	14.79%	14.41%	14.19%	14.18%	13.92%	13.63%	13.15%	12.75%	13.02%	14.90%
	0%	14.90%	14.79%	14.53%	14.29%	14.31%	13.93%	13.65%	13.26%	13.35%	14.14%	14.90%	

Table J.1.3 5% Value at Risk (VaR)

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	-6.26%	-6.26%	-6.12%	-6.05%	-5.91%	-5.58%	-5.29%	-4.31%	-2.82%	-0.30%	-6.26%
		45%	-6.26%	-6.26%	-6.12%	-6.05%	-5.91%	-5.58%	-5.39%	-4.38%	-3.35%	-1.71%	-6.26%
		40%	-6.26%	-6.26%	-6.12%	-6.05%	-5.91%	-5.58%	-5.39%	-4.38%	-3.41%	-1.82%	-6.26%
		35%	-6.26%	-6.26%	-6.12%	-6.05%	-5.91%	-5.58%	-5.39%	-4.38%	-4.09%	-2.42%	-6.26%
	DRAWUP LEVEL (into Equities)	30%	-6.26%	-6.26%	-6.12%	-6.05%	-5.91%	-5.58%	-5.39%	-4.57%	-4.17%	-2.43%	-6.26%
		25%	-6.26%	-6.26%	-6.12%	-6.05%	-5.91%	-5.58%	-5.39%	-4.57%	-4.17%	-2.78%	-6.26%
		20%	-6.26%	-6.26%	-6.12%	-6.05%	-5.91%	-5.58%	-5.46%	-4.68%	-4.25%	-3.14%	-6.26%
		15%	-6.26%	-6.26%	-6.12%	-6.05%	-5.91%	-5.58%	-5.47%	-4.87%	-4.29%	-3.37%	-6.26%
		10%	-6.26%	-6.26%	-6.12%	-6.05%	-5.91%	-5.58%	-5.47%	-5.15%	-4.78%	-3.86%	-6.26%
		5%	-6.26%	-6.26%	-6.12%	-6.05%	-5.91%	-5.91%	-5.87%	-5.47%	-5.46%	-5.39%	-6.26%
	0%	-6.26%	-6.26%	-6.19%	-6.12%	-6.00%	-5.91%	-5.87%	-5.58%	-5.78%	-6.04%	-6.26%	

Table J.1.4 Annualised Sharpe Ratio

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	19.95%	10.18%	7.52%	9.70%	12.56%	22.11%	7.10%	10.69%	-1.88%	-2.54%	19.95%
		45%	19.95%	11.27%	9.31%	10.88%	14.32%	23.79%	5.75%	13.52%	4.30%	-6.32%	19.95%
		40%	19.95%	12.09%	10.32%	11.75%	15.36%	24.89%	8.12%	16.24%	10.99%	-0.91%	19.95%
		35%	19.95%	12.09%	10.72%	12.35%	15.77%	25.31%	12.17%	22.40%	3.34%	-1.44%	19.95%
	DRAWUP LEVEL (into Equities)	30%	19.95%	13.48%	12.96%	14.38%	18.06%	27.71%	16.02%	27.21%	12.69%	11.90%	19.95%
		25%	19.95%	14.17%	13.67%	15.82%	18.79%	28.47%	18.03%	29.76%	19.26%	15.46%	19.95%
		20%	19.95%	14.55%	15.60%	16.29%	20.75%	30.49%	20.79%	33.50%	25.43%	24.82%	19.95%
		15%	19.95%	15.73%	16.42%	17.53%	22.01%	31.82%	22.85%	36.19%	30.55%	32.87%	19.95%
		10%	19.95%	16.29%	15.80%	19.62%	22.54%	32.29%	27.90%	38.51%	32.84%	36.19%	19.95%
		5%	19.95%	17.08%	19.15%	20.04%	24.18%	29.28%	27.49%	35.45%	26.95%	18.26%	19.95%
	0%	19.95%	17.08%	18.63%	19.13%	23.74%	30.05%	29.33%	33.47%	26.63%	16.47%	19.95%	

Table J.1.5 Percentage of Months in Cash

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	0.00%	0.00%	7.41%	12.50%	7.87%	8.33%	24.07%	42.13%	48.61%	81.94%	0.00%
		45%	0.00%	0.00%	4.17%	7.41%	4.63%	5.09%	22.22%	39.81%	43.98%	76.85%	0.00%
		40%	0.00%	0.00%	3.70%	7.41%	4.17%	4.63%	21.76%	38.89%	42.59%	75.46%	0.00%
		35%	0.00%	0.00%	3.24%	4.17%	3.70%	4.17%	19.91%	32.87%	31.94%	62.50%	0.00%
	DRAWUP LEVEL (into Equities)	30%	0.00%	0.00%	2.31%	3.24%	2.78%	3.24%	18.52%	30.09%	28.70%	58.33%	0.00%
		25%	0.00%	0.00%	2.31%	2.78%	2.78%	3.24%	11.57%	21.76%	26.39%	53.24%	0.00%
		20%	0.00%	0.00%	1.85%	2.31%	2.31%	2.78%	6.02%	15.28%	23.15%	46.76%	0.00%
		15%	0.00%	0.00%	1.85%	2.31%	2.31%	2.78%	6.02%	14.81%	21.30%	42.59%	0.00%
		10%	0.00%	0.00%	1.85%	1.85%	2.31%	2.78%	5.09%	12.50%	15.74%	34.26%	0.00%
		5%	0.00%	0.00%	0.46%	1.39%	0.93%	1.39%	3.24%	8.80%	10.65%	24.07%	0.00%
	0%	0.00%	0.00%	0.46%	1.39%	0.93%	1.39%	3.24%	7.87%	13.43%	18.52%	0.00%	

Table J.1.6 Maximum Drawdown

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	-48.20%	-54.73%	-44.56%	-40.49%	-40.49%	-27.44%	-29.34%	-19.03%	-21.13%	-11.12%	-48.20%
		45%	-48.20%	-51.94%	-43.90%	-40.49%	-40.49%	-30.71%	-28.76%	-18.40%	-21.13%	-19.19%	-48.20%
		40%	-48.20%	-49.82%	-43.41%	-40.49%	-40.49%	-30.10%	-28.76%	-18.40%	-18.40%	-18.40%	-48.20%
		35%	-48.20%	-49.82%	-42.25%	-43.90%	-40.49%	-28.67%	-26.46%	-18.40%	-18.40%	-18.40%	-48.20%
	DRAWUP LEVEL (into Equities)	30%	-48.20%	-48.20%	-41.57%	-42.25%	-40.49%	-27.44%	-26.73%	-18.40%	-18.40%	-18.40%	-48.20%
		25%	-48.20%	-48.20%	-41.57%	-40.49%	-40.49%	-27.44%	-26.46%	-18.40%	-18.40%	-18.40%	-48.20%
		20%	-48.20%	-48.20%	-41.57%	-40.49%	-40.49%	-27.44%	-26.62%	-18.40%	-18.40%	-18.40%	-48.20%
		15%	-48.20%	-48.20%	-41.57%	-40.49%	-40.49%	-27.44%	-26.62%	-20.13%	-20.13%	-20.13%	-48.20%
		10%	-48.20%	-50.02%	-44.11%	-40.71%	-40.49%	-32.69%	-29.22%	-22.66%	-21.24%	-24.30%	-48.20%
		5%	-48.20%	-48.20%	-41.66%	-40.60%	-40.49%	-43.86%	-42.56%	-41.87%	-41.87%	-49.94%	-48.20%
	0%	-48.20%	-48.20%	-46.91%	-40.66%	-40.49%	-41.63%	-40.27%	-46.22%	-45.65%	-47.65%	-48.20%	

Table J.1.7 Number of Signals

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	0	2	3	3	3	3	5	7	9	8	0
		45%	0	2	3	3	3	3	7	8	9	9	0
		40%	0	2	3	3	3	3	7	8	9	10	0
		35%	0	2	3	3	3	3	7	8	11	13	0
	DRAWUP LEVEL (into Equities)	30%	0	2	3	3	3	3	7	8	11	13	0
		25%	0	2	3	3	3	3	7	8	11	16	0
		20%	0	2	3	3	3	3	7	8	12	17	0
		15%	0	2	3	3	3	3	7	8	13	18	0
		10%	0	2	4	3	3	3	7	9	15	21	0
		5%	0	2	4	4	4	3	8	9	16	25	0
	0%	0	2	5	4	5	3	8	11	15	30	0	

Table J.2.1 Annualised Geometric Return

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	14.90%	8.30%	8.11%	8.26%	8.45%	9.06%	8.08%	8.26%	7.66%	7.75%	9.04%
		45%	9.04%	8.39%	8.24%	8.34%	8.58%	9.19%	8.00%	8.42%	7.93%	7.59%	9.04%
		40%	9.04%	8.45%	8.31%	8.40%	8.65%	9.26%	8.14%	8.56%	8.24%	7.75%	9.04%
		35%	9.04%	8.45%	8.33%	8.45%	8.68%	9.29%	8.38%	8.93%	7.88%	7.72%	9.04%
	DRAWUP LEVEL (into Equities)	30%	9.04%	8.55%	8.49%	8.59%	8.84%	9.45%	8.63%	9.21%	8.36%	8.23%	9.04%
		25%	9.04%	8.60%	8.54%	8.69%	8.89%	9.50%	8.76%	9.38%	8.70%	8.39%	9.04%
		20%	9.04%	8.63%	8.68%	8.72%	9.03%	9.64%	8.95%	9.63%	9.07%	8.85%	9.04%
		15%	9.04%	8.71%	8.74%	8.81%	9.12%	9.73%	9.09%	9.81%	9.36%	9.27%	9.04%
		10%	9.04%	8.76%	8.70%	8.97%	9.16%	9.77%	9.44%	10.01%	9.58%	9.60%	9.04%
		5%	9.04%	8.82%	8.95%	9.00%	9.29%	9.63%	9.47%	9.95%	9.35%	8.81%	9.04%
	0%	9.04%	8.82%	8.92%	8.94%	9.27%	9.68%	9.60%	9.83%	9.39%	8.75%	9.04%	

Table J.2.2 Annualised Standard Deviation

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	14.90%	14.64%	14.09%	13.95%	13.86%	13.45%	12.45%	11.68%	10.51%	8.53%	14.90%
		45%	14.90%	14.68%	14.25%	14.05%	14.03%	13.62%	12.56%	11.83%	10.76%	9.22%	14.90%
		40%	14.90%	14.69%	14.26%	14.06%	14.03%	13.62%	12.58%	11.85%	10.92%	9.44%	14.90%
		35%	14.90%	14.69%	14.26%	14.18%	14.03%	13.63%	12.74%	12.12%	11.31%	9.83%	14.90%
	DRAWUP LEVEL (into Equities)	30%	14.90%	14.70%	14.28%	14.20%	14.06%	13.65%	12.88%	12.27%	11.56%	10.02%	14.90%
		25%	14.90%	14.71%	14.29%	14.22%	14.07%	13.66%	13.01%	12.41%	11.63%	10.21%	14.90%
		20%	14.90%	14.71%	14.34%	14.22%	14.12%	13.71%	13.21%	12.62%	11.93%	10.70%	14.90%
		15%	14.90%	14.72%	14.34%	14.22%	14.12%	13.72%	13.31%	12.72%	12.04%	10.99%	14.90%
		10%	14.90%	14.80%	14.37%	14.36%	14.21%	13.80%	13.52%	13.02%	12.53%	11.74%	14.90%
		5%	14.90%	14.81%	14.53%	14.37%	14.37%	14.18%	13.96%	13.62%	13.33%	13.50%	14.90%
	0%	14.90%	14.81%	14.63%	14.45%	14.47%	14.19%	13.98%	13.70%	13.76%	14.32%	14.90%	

Table J.2.3 5% Value at Risk (VaR)

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	-6.26%	-6.26%	-6.19%	-6.12%	-6.00%	-5.78%	-5.58%	-4.96%	-4.32%	-3.79%	-6.26%
		45%	-6.26%	-6.26%	-6.19%	-6.12%	-6.00%	-5.78%	-5.58%	-5.15%	-4.36%	-4.16%	-6.26%
		40%	-6.26%	-6.26%	-6.19%	-6.12%	-6.00%	-5.78%	-5.58%	-5.15%	-4.36%	-4.22%	-6.26%
		35%	-6.26%	-6.26%	-6.19%	-6.12%	-6.00%	-5.78%	-5.58%	-5.15%	-4.59%	-4.24%	-6.26%
	DRAWUP LEVEL (into Equities)	30%	-6.26%	-6.26%	-6.19%	-6.12%	-6.00%	-5.78%	-5.58%	-5.15%	-4.84%	-4.24%	-6.26%
		25%	-6.26%	-6.26%	-6.19%	-6.12%	-6.00%	-5.78%	-5.58%	-5.15%	-4.84%	-4.32%	-6.26%
		20%	-6.26%	-6.26%	-6.19%	-6.12%	-6.00%	-5.78%	-5.69%	-5.29%	-4.94%	-4.35%	-6.26%
		15%	-6.26%	-6.26%	-6.19%	-6.12%	-6.00%	-5.78%	-5.69%	-5.39%	-4.96%	-4.39%	-6.26%
		10%	-6.26%	-6.26%	-6.19%	-6.12%	-6.00%	-5.78%	-5.69%	-5.46%	-5.29%	-4.59%	-6.26%
		5%	-6.26%	-6.26%	-6.19%	-6.12%	-6.00%	-6.05%	-6.05%	-5.69%	-5.59%	-5.46%	-6.26%
	0%	-6.26%	-6.26%	-6.26%	-6.19%	-6.05%	-6.05%	-6.05%	-5.87%	-6.00%	-6.04%	-6.26%	

Table J.2.4 Annualised Sharpe Ratio

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	19.95%	15.30%	14.52%	15.73%	17.23%	22.27%	16.18%	18.80%	15.20%	19.79%	19.95%
		45%	19.95%	15.81%	15.24%	16.21%	17.93%	22.93%	15.40%	19.88%	17.34%	16.53%	19.95%
		40%	19.95%	16.21%	15.73%	16.63%	18.44%	23.45%	16.50%	21.09%	19.95%	17.88%	19.95%
		35%	19.95%	16.21%	15.93%	16.81%	18.63%	23.65%	18.22%	23.61%	16.03%	16.81%	19.95%
	DRAWUP LEVEL (into Equities)	30%	19.95%	16.90%	17.01%	17.80%	19.73%	24.78%	19.89%	25.67%	19.84%	21.65%	19.95%
		25%	19.95%	17.23%	17.36%	18.49%	20.08%	25.14%	20.72%	26.73%	22.67%	22.78%	19.95%
		20%	19.95%	17.42%	18.27%	18.72%	21.00%	26.07%	21.84%	28.29%	25.16%	26.07%	19.95%
		15%	19.95%	18.00%	18.67%	19.32%	21.61%	26.70%	22.73%	29.46%	27.37%	29.22%	19.95%
		10%	19.95%	18.21%	18.34%	20.24%	21.80%	26.86%	24.98%	30.34%	28.03%	30.13%	19.95%
		5%	19.95%	18.60%	19.86%	20.43%	22.48%	25.13%	24.43%	28.51%	24.66%	20.35%	19.95%
	0%	19.95%	18.60%	19.53%	19.92%	22.19%	25.50%	25.31%	27.50%	24.17%	18.72%	19.95%	

Table J.2.5 Percentage of Months in Partial Cash

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	0.00%	0.00%	7.41%	12.50%	7.87%	8.33%	24.07%	42.13%	48.61%	81.94%	0.00%
		45%	0.00%	0.00%	4.17%	7.41%	4.63%	5.09%	22.22%	39.81%	43.98%	76.85%	0.00%
		40%	0.00%	0.00%	3.70%	7.41%	4.17%	4.63%	21.76%	38.89%	42.59%	75.46%	0.00%
		35%	0.00%	0.00%	3.24%	4.17%	3.70%	4.17%	19.91%	32.87%	31.94%	62.50%	0.00%
	DRAWUP LEVEL (into Equities)	30%	0.00%	0.00%	2.31%	3.24%	2.78%	3.24%	18.52%	30.09%	28.70%	58.33%	0.00%
		25%	0.00%	0.00%	2.31%	2.78%	2.78%	3.24%	11.57%	21.76%	26.39%	53.24%	0.00%
		20%	0.00%	0.00%	1.85%	2.31%	2.31%	2.78%	6.02%	15.28%	23.15%	46.76%	0.00%
		15%	0.00%	0.00%	1.85%	2.31%	2.31%	2.78%	6.02%	14.81%	21.30%	42.59%	0.00%
		10%	0.00%	0.00%	1.85%	1.85%	2.31%	2.78%	5.09%	12.50%	15.74%	34.26%	0.00%
		5%	0.00%	0.00%	0.46%	1.39%	0.93%	1.39%	3.24%	8.80%	10.65%	24.07%	0.00%
	0%	0.00%	0.00%	0.46%	1.39%	0.93%	1.39%	3.24%	7.87%	13.43%	18.52%	0.00%	

Table J.2.6 Maximum Drawdown

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	-48.20%	-48.20%	-44.34%	-44.34%	-44.34%	-37.76%	-37.76%	-33.47%	-31.17%	-26.47%	-48.20%
		45%	-48.20%	-48.20%	-44.34%	-44.34%	-44.34%	-37.76%	-37.76%	-33.47%	-31.17%	-26.47%	-48.20%
		40%	-48.20%	-48.20%	-44.34%	-44.34%	-44.34%	-37.76%	-37.76%	-33.47%	-31.17%	-30.42%	-48.20%
		35%	-48.20%	-48.20%	-44.34%	-44.34%	-44.34%	-37.76%	-37.76%	-33.47%	-31.17%	-30.42%	-48.20%
	DRAWUP LEVEL (into Equities)	30%	-48.20%	-48.20%	-44.34%	-44.34%	-44.34%	-37.76%	-37.76%	-33.47%	-31.17%	-30.42%	-48.20%
		25%	-48.20%	-48.20%	-44.34%	-44.34%	-44.34%	-37.76%	-37.76%	-33.47%	-31.17%	-30.42%	-48.20%
		20%	-48.20%	-48.20%	-44.34%	-44.34%	-44.34%	-37.76%	-37.76%	-33.47%	-31.17%	-30.42%	-48.20%
		15%	-48.20%	-48.20%	-44.34%	-44.34%	-44.34%	-37.76%	-37.76%	-33.47%	-31.17%	-30.42%	-48.20%
		10%	-48.20%	-48.20%	-44.34%	-44.34%	-44.34%	-38.71%	-37.76%	-33.47%	-32.46%	-30.42%	-48.20%
		5%	-48.20%	-48.20%	-44.34%	-44.34%	-44.34%	-44.36%	-43.64%	-43.32%	-43.32%	-49.07%	-48.20%
	0%	-48.20%	-48.20%	-45.86%	-44.34%	-44.34%	-43.28%	-42.54%	-45.55%	-45.34%	-47.92%	-48.20%	

Table J.2.7 Number of Signals

		DRAWDOWN LEVEL (into Cash)												
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%		
CASH:	50%	50%	0	2	3	3	3	3	5	7	9	8	0	
		45%	0	2	3	3	3	3	7	8	9	9	0	
		40%	0	2	3	3	3	3	7	8	9	10	0	
		35%	0	2	3	3	3	3	7	8	11	13	0	
	DRAWUP LEVEL (into Equities)	30%	0	2	3	3	3	3	3	7	8	11	13	0
		25%	0	2	3	3	3	3	3	7	8	11	16	0
		20%	0	2	3	3	3	3	3	7	8	12	17	0
		15%	0	2	3	3	3	3	3	7	8	13	18	0
		10%	0	2	4	3	3	3	3	7	9	15	21	0
		5%	0	2	4	4	4	4	3	8	9	16	25	0
	0%	0	2	5	4	5	3	8	11	15	30	0		

Table J.3.1 Annualised Geometric Return

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	SLOW MOVING AVERAGE	100%	9.04%										
		90%	10.09%										
		80%	9.66%	8.65%									
		70%	8.55%	8.01%	7.87%								
		60%	8.21%	8.10%	8.07%	8.35%							
		50%	8.02%	8.24%	8.54%	8.97%	8.77%						
		40%	8.76%	9.46%	9.33%	8.93%	9.41%	9.58%					
		30%	9.84%	9.58%	9.74%	9.61%	10.20%	10.30%	10.19%				
		20%	10.58%	10.73%	10.74%	10.22%	10.39%	10.76%	10.48%	11.17%			
		10%	10.54%	10.72%	10.58%	10.72%	10.65%	11.03%	10.71%	10.68%	10.23%		
		0%	9.01%	9.01%	9.01%	8.72%	8.72%	8.72%	8.72%	8.90%	9.21%	9.21%	9.04%

Table J.3.2 Annualised Standard Deviation

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	SLOW MOVING AVERAGE	100%	14.90%										
		90%	10.73%										
		80%	10.63%	10.78%									
		70%	10.77%	10.74%	10.78%								
		60%	10.73%	10.79%	10.80%	10.84%							
		50%	10.80%	10.80%	10.91%	10.86%	11.03%						
		40%	10.91%	10.86%	10.95%	11.11%	11.08%	11.24%					
		30%	11.02%	11.03%	11.04%	11.25%	11.41%	11.38%	11.08%				
		20%	11.38%	11.45%	11.45%	11.29%	11.31%	11.33%	11.44%	11.68%			
		10%	11.95%	12.01%	11.97%	11.98%	11.98%	12.03%	12.20%	12.33%	12.42%		
		0%	14.53%	14.53%	14.53%	14.62%	14.62%	14.62%	14.62%	14.70%	14.87%	14.87%	14.90%

Table J.3.3 5% Value at Risk (VaR)

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	SLOW MOVING AVERAGE	100%	-6.26%										
		90%	-4.17%										
		80%	-4.27%	-4.27%									
		70%	-4.27%	-4.27%	-4.27%								
		60%	-4.27%	-4.27%	-4.27%	-4.27%							
		50%	-4.27%	-4.27%	-4.27%	-4.27%	-4.31%						
		40%	-4.27%	-4.17%	-4.27%	-4.33%	-4.33%	-4.33%	-4.29%				
		30%	-4.27%	-4.29%	-4.29%	-4.33%	-4.33%	-4.33%	-4.29%	-4.33%			
		20%	-4.31%	-4.31%	-4.31%	-4.31%	-4.31%	-4.31%	-4.33%	-4.33%	-4.33%		
		10%	-4.87%	-4.87%	-4.87%	-4.87%	-4.87%	-4.87%	-5.15%	-5.15%	-5.29%		
		0%	-6.19%	-6.19%	-6.19%	-6.26%	-6.26%	-6.26%	-6.26%	-6.26%	-6.26%	-6.26%	-6.26%

Table J.3.4 Annualised Sharpe Ratio

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	SLOW MOVING AVERAGE	100%	19.95%										
		90%	37.55%										
		80%	33.87%	23.99%									
		70%	23.13%	18.13%	16.76%								
		60%	19.99%	18.83%	18.61%	21.12%							
		50%	18.08%	20.18%	22.66%	26.77%	24.53%						
		40%	24.70%	31.26%	29.83%	25.79%	30.23%	31.31%					
		30%	34.23%	31.89%	33.28%	31.50%	36.27%	37.20%	37.22%				
		20%	39.69%	40.72%	40.82%	36.78%	38.30%	41.50%	38.59%	43.69%			
		10%	37.46%	38.75%	37.76%	38.84%	38.31%	41.28%	38.04%	37.43%	33.54%		
		0%	20.27%	20.27%	20.27%	18.17%	18.17%	18.17%	18.17%	19.33%	21.18%	21.18%	19.95%

Table J.3.5 Percentage of Months in Cash

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	SLOW MOVING AVERAGE	100%	0.00%										
		90%	34.72%										
		80%	35.19%	34.26%									
		70%	34.26%	32.87%	29.63%								
		60%	33.33%	30.56%	29.63%	29.63%							
		50%	29.63%	29.17%	29.63%	27.78%	23.61%						
		40%	28.70%	27.78%	25.00%	22.69%	21.76%	20.37%					
		30%	23.15%	22.69%	22.22%	20.83%	20.83%	19.91%	18.52%				
		20%	20.37%	18.98%	18.52%	18.52%	16.20%	15.74%	14.35%	14.35%			
		10%	12.96%	12.04%	12.50%	12.50%	12.96%	12.04%	12.04%	11.57%	11.11%		
		0%	2.78%	2.78%	2.78%	2.31%	2.31%	2.31%	2.31%	1.39%	0.46%	0.46%	0.00%

Table J.3.6 Maximum Drawdown

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	SLOW MOVING AVERAGE	100%	-48.20%										
		90%	-25.90%										
		80%	-25.90%	-22.17%									
		70%	-22.17%	-23.38%	-23.38%								
		60%	-23.38%	-23.38%	-28.19%	-30.46%							
		50%	-26.38%	-28.31%	-26.80%	-18.40%	-20.25%						
		40%	-24.54%	-18.40%	-18.40%	-24.27%	-24.27%	-18.40%					
		30%	-18.40%	-24.27%	-24.27%	-19.05%	-18.40%	-18.68%	-20.13%				
		20%	-22.17%	-18.40%	-18.40%	-20.27%	-19.23%	-24.57%	-23.92%	-22.40%			
		10%	-21.00%	-23.93%	-23.93%	-23.23%	-24.84%	-24.84%	-33.18%	-26.62%	-24.02%		
		0%	-48.20%	-48.20%	-48.20%	-48.20%	-48.20%	-48.20%	-48.20%	-48.20%	-48.20%	-48.20%	-48.20%

Table J.3.7 Number of Signals

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	SLOW MOVING AVERAGE	100%	0										
		90%	95										
		80%	93	86									
		70%	87	81	75								
		60%	80	73	67	62							
		50%	70	64	59	50	46						
		40%	60	50	46	43	37	30					
		30%	42	40	37	32	27	24	21				
		20%	29	26	24	23	21	17	15	11			
		10%	16	13	12	11	11	8	7	6	6		
		0%	2	2	2	2	2	2	2	2	1	1	0

Table J.4.1 Annualised Geometric Return

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	50%	100%	9.04%										
		90%	9.71%										
		80%	9.50%	8.99%									
	SLOW MOVING AVERAGE	70%	8.94%	8.67%	8.60%								
		60%	8.77%	8.71%	8.70%	8.84%							
		50%	8.67%	8.79%	8.93%	9.15%	9.04%						
	AVERAGE	40%	9.04%	9.39%	9.33%	9.12%	9.36%	9.44%					
		30%	9.58%	9.45%	9.53%	9.45%	9.75%	9.79%	9.75%				
		20%	9.93%	10.00%	10.01%	9.76%	9.84%	10.03%	9.88%	10.22%			
	10%	9.90%	9.98%	9.92%	9.98%	9.95%	10.14%	9.97%	9.95%	9.73%			
	0%	9.04%	9.04%	9.04%	8.89%	8.89%	8.89%	8.89%	8.89%	8.98%	9.13%	9.13%	9.04%

Table J.4.2 Annualised Standard Deviation

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	50%	100%	14.90%										
		90%	11.91%										
		80%	11.84%	11.94%									
	SLOW MOVING AVERAGE	70%	11.93%	11.91%	11.93%								
		60%	11.90%	11.94%	11.95%	11.98%							
		50%	11.95%	11.95%	12.02%	11.99%	12.11%						
	AVERAGE	40%	12.02%	12.00%	12.06%	12.16%	12.15%	12.26%					
		30%	12.11%	12.12%	12.13%	12.27%	12.38%	12.36%	12.15%				
		20%	12.36%	12.41%	12.41%	12.30%	12.31%	12.33%	12.41%	12.58%			
	10%	12.77%	12.81%	12.78%	12.79%	12.79%	12.83%	12.94%	13.03%	13.09%			
	0%	14.62%	14.62%	14.62%	14.69%	14.69%	14.69%	14.69%	14.75%	14.88%	14.88%	14.88%	14.90%

Table J.4.3 5% Value at Risk (VaR)

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	50%	100%	-6.26%										
		90%	-4.94%										
		80%	-4.94%	-4.90%									
	SLOW MOVING AVERAGE	70%	-4.90%	-4.90%	-4.90%								
		60%	-4.90%	-4.90%	-4.90%	-4.90%							
		50%	-4.90%	-4.90%	-4.90%	-4.90%	-4.94%						
	AVERAGE	40%	-4.90%	-4.77%	-4.90%	-4.90%	-4.94%	-4.96%	-4.85%				
		30%	-4.90%	-4.85%	-4.85%	-4.96%	-4.96%	-4.96%	-4.85%	-4.96%			
		20%	-4.94%	-4.94%	-4.94%	-4.94%	-4.94%	-4.94%	-4.96%	-4.96%	-5.49%		
	10%	-5.39%	-5.39%	-5.39%	-5.39%	-5.39%	-5.39%	-5.46%	-5.46%	-5.49%			
	0%	-6.19%	-6.19%	-6.19%	-6.26%	-6.26%	-6.26%	-6.26%	-6.26%	-6.26%	-6.26%	-6.26%	-6.26%

Table J.4.4 Annualised Sharpe Ratio

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	50%	100%	19.95%										
		90%	30.64%										
		80%	29.05%	24.52%									
	SLOW MOVING AVERAGE	70%	24.13%	21.88%	21.23%								
		60%	22.74%	22.17%	22.06%	23.17%							
		50%	21.82%	22.78%	23.83%	25.72%	24.59%						
	AVERAGE	40%	24.76%	27.75%	27.05%	25.12%	27.16%	27.55%					
		30%	29.00%	27.93%	28.56%	27.63%	29.74%	30.17%	30.32%				
		20%	31.31%	31.74%	31.79%	30.03%	30.71%	32.14%	30.76%	33.00%			
	10%	30.02%	30.59%	30.15%	30.65%	30.40%	31.75%	30.17%	29.84%	27.98%			
	0%	20.33%	20.33%	20.33%	19.23%	19.23%	19.23%	19.23%	19.76%	20.58%	20.58%	20.58%	19.95%

Table J.4.5 Percentage of Months in Partial Cash

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	50%	100%	0.00%										
		90%	34.72%										
		80%	35.19%	34.26%									
	SLOW MOVING AVERAGE	70%	34.26%	32.87%	29.63%								
		60%	33.33%	30.56%	29.63%	29.63%							
		50%	29.63%	29.17%	29.63%	27.78%	23.61%						
	AVERAGE	40%	28.70%	27.78%	25.00%	22.69%	21.76%	20.37%					
		30%	23.15%	22.69%	22.22%	20.83%	20.83%	19.91%	18.52%				
		20%	20.37%	18.98%	18.52%	18.52%	16.20%	15.74%	14.35%	14.35%			
	10%	12.96%	12.04%	12.50%	12.50%	12.96%	12.04%	12.04%	11.57%	11.11%			
	0%	2.78%	2.78%	2.78%	2.31%	2.31%	2.31%	2.31%	1.39%	0.46%	0.46%	0.46%	0.00%

Table J.4.6 Maximum Drawdown

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	50%	100%	-48.20%										
		90%	-35.24%										
		80%	-35.24%	-32.67%									
	SLOW MOVING AVERAGE	70%	-32.67%	-33.96%	-33.96%								
		60%	-33.96%	-33.96%	-36.07%	-37.10%							
		50%	-35.28%	-36.12%	-35.84%	-31.66%	-31.83%						
	AVERAGE	40%	-34.85%	-31.66%	-31.83%	-31.83%	-31.28%	-33.59%					
		30%	-30.92%	-30.92%	-31.28%	-33.59%	-33.59%	-33.59%	-30.42%				
		20%	-33.25%	-33.59%	-33.59%	-33.59%	-33.59%	-33.59%	-30.42%	-31.17%			
	10%	-33.25%	-33.96%	-33.96%	-33.96%	-33.61%	-32.46%	-32.46%	-33.47%	-33.84%			
	0%	-48.20%	-48.20%	-48.20%	-48.20%	-48.20%	-48.20%	-48.20%	-48.20%	-48.20%	-48.20%	-48.20%	-48.20%

Table J.4.7 Number of Signals

		FAST MOVING AVERAGE											
		100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	
CASH:	50%	100%	0										
		90%	95										
		80%	93	86									
	SLOW MOVING AVERAGE	70%	87	81	75								
		60%	80	73	67	62							
		50%	70	64	59	50	46						
	AVERAGE	40%	60	50	46	43	37	30					
		30%	42	40	37	32	27	24	21				
		20%	29	26	24	23	21	17	15	11			
	10%	16	13	12	11	11	8	7	6	6			
	0%	2	2	2	2	2	2	2	2	2	1	1	0

Table K.1.1 Annualised Geometric Return

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	14.77%	14.27%	12.98%	13.84%	15.17%	15.74%	13.82%	15.19%	12.05%	6.60%	14.77%
		45%	14.77%	14.27%	13.16%	14.02%	15.36%	15.93%	14.57%	15.37%	12.40%	7.37%	14.77%
		40%	14.77%	14.27%	13.16%	14.02%	15.36%	15.93%	14.64%	15.94%	13.36%	8.20%	14.77%
		35%	14.77%	14.27%	13.56%	14.42%	15.76%	16.34%	15.31%	16.35%	13.95%	9.09%	14.77%
	DRAWUP LEVEL (into Equities)	30%	14.77%	14.27%	13.86%	14.72%	16.06%	16.63%	15.60%	16.65%	14.50%	11.83%	14.77%
		25%	14.77%	14.27%	13.86%	14.72%	16.06%	16.63%	15.89%	16.65%	15.24%	11.73%	14.77%
		20%	14.77%	14.27%	13.86%	14.72%	16.06%	16.63%	16.17%	17.64%	16.31%	12.92%	14.77%
		15%	14.77%	14.27%	14.62%	15.48%	16.84%	17.42%	17.29%	18.43%	17.64%	15.38%	14.77%
		10%	14.77%	14.27%	13.91%	15.67%	16.66%	17.24%	17.18%	18.61%	16.70%	15.56%	14.77%
		5%	14.77%	14.27%	14.57%	15.90%	16.60%	17.17%	16.97%	16.57%	15.63%	15.15%	14.77%
	0%	14.77%	14.27%	14.81%	15.76%	16.05%	16.62%	16.18%	16.51%	15.56%	15.92%	14.77%	

Table K.1.2 Annualised Standard Deviation

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	18.96%	18.90%	18.02%	17.83%	17.27%	17.13%	16.24%	15.29%	13.62%	9.55%	18.96%
		45%	18.96%	18.90%	18.03%	17.83%	17.28%	17.13%	16.36%	15.30%	13.90%	9.84%	18.96%
		40%	18.96%	18.90%	18.03%	17.83%	17.28%	17.13%	16.46%	15.42%	14.09%	10.10%	18.96%
		35%	18.96%	18.90%	18.07%	17.87%	17.32%	17.18%	16.52%	15.47%	14.17%	10.29%	18.96%
	DRAWUP LEVEL (into Equities)	30%	18.96%	18.90%	18.07%	17.87%	17.32%	17.18%	16.52%	15.47%	14.18%	11.97%	18.96%
		25%	18.96%	18.90%	18.07%	17.87%	17.32%	17.18%	16.54%	15.47%	14.32%	12.15%	18.96%
		20%	18.96%	18.90%	18.07%	17.87%	17.32%	17.18%	16.68%	15.89%	14.89%	12.73%	18.96%
		15%	18.96%	18.90%	18.19%	17.99%	17.43%	17.29%	16.83%	16.01%	15.06%	13.62%	18.96%
		10%	18.96%	18.90%	18.40%	17.99%	17.83%	17.69%	17.24%	16.48%	16.03%	14.72%	18.96%
		5%	18.96%	18.90%	18.49%	18.22%	17.99%	17.85%	17.61%	17.24%	16.86%	16.01%	18.96%
	0%	18.96%	18.90%	18.57%	18.35%	18.15%	18.01%	17.85%	17.43%	17.11%	16.56%	18.96%	

Table K.1.3 5% Value at Risk (VaR)

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	-8.10%	-8.10%	-7.37%	-7.28%	-7.01%	-6.92%	-6.90%	-6.24%	-5.49%	-4.25%	-8.10%
		45%	-8.10%	-8.10%	-7.37%	-7.28%	-7.01%	-6.92%	-6.90%	-6.24%	-5.59%	-4.25%	-8.10%
		40%	-8.10%	-8.10%	-7.37%	-7.28%	-7.01%	-6.92%	-6.90%	-6.24%	-5.59%	-4.25%	-8.10%
		35%	-8.10%	-8.10%	-7.37%	-7.28%	-7.01%	-6.92%	-6.90%	-6.24%	-5.59%	-4.25%	-8.10%
	DRAWUP LEVEL (into Equities)	30%	-8.10%	-8.10%	-7.37%	-7.28%	-7.01%	-6.92%	-6.90%	-6.24%	-5.59%	-4.25%	-8.10%
		25%	-8.10%	-8.10%	-7.37%	-7.28%	-7.01%	-6.92%	-6.90%	-6.24%	-5.59%	-4.73%	-8.10%
		20%	-8.10%	-8.10%	-7.37%	-7.28%	-7.01%	-6.92%	-6.90%	-6.24%	-5.59%	-4.73%	-8.10%
		15%	-8.10%	-8.10%	-7.37%	-7.28%	-7.01%	-6.92%	-6.90%	-6.24%	-5.59%	-5.22%	-8.10%
		10%	-8.10%	-8.10%	-7.59%	-7.28%	-7.28%	-7.01%	-6.92%	-6.66%	-6.24%	-5.56%	-8.10%
		5%	-8.10%	-8.10%	-7.59%	-7.37%	-7.37%	-7.26%	-7.26%	-7.01%	-7.01%	-6.85%	-8.10%
	0%	-8.10%	-8.10%	-7.59%	-7.37%	-7.37%	-7.26%	-7.26%	-7.26%	-7.26%	-6.99%	-8.10%	

Table K.1.4 Annualised Sharpe Ratio

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	57.35%	54.91%	50.42%	55.78%	65.28%	69.14%	61.16%	73.83%	59.92%	28.33%	57.35%
		45%	57.35%	54.91%	51.43%	56.80%	66.35%	70.23%	65.24%	75.04%	61.21%	35.38%	57.35%
		40%	57.35%	54.91%	51.43%	56.80%	66.35%	70.23%	65.28%	78.12%	67.22%	42.69%	57.35%
		35%	57.35%	54.91%	53.52%	58.92%	68.55%	72.44%	69.08%	80.53%	70.97%	50.52%	57.35%
	DRAWUP LEVEL (into Equities)	30%	57.35%	54.91%	55.12%	60.56%	70.26%	74.18%	70.87%	82.46%	74.82%	66.27%	57.35%
		25%	57.35%	54.91%	55.12%	60.56%	70.26%	74.18%	72.54%	82.46%	79.22%	64.52%	57.35%
		20%	57.35%	54.91%	55.12%	60.56%	70.26%	74.18%	73.58%	86.50%	83.38%	70.90%	57.35%
		15%	57.35%	54.91%	58.96%	64.44%	74.25%	78.21%	79.58%	90.76%	91.28%	84.30%	57.35%
		10%	57.35%	54.91%	54.40%	65.45%	71.60%	75.43%	77.08%	89.32%	79.91%	79.24%	57.35%
		5%	57.35%	54.91%	57.73%	65.91%	70.62%	74.40%	74.26%	73.55%	69.65%	70.29%	57.35%
	0%	57.35%	54.91%	58.78%	64.69%	66.97%	70.66%	68.84%	72.37%	68.18%	72.66%	57.35%	

Table K.1.5 Percentage of Months in Cash

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	0.00%	0.46%	14.35%	18.06%	19.44%	19.91%	31.02%	24.54%	50.93%	63.89%	0.00%
		45%	0.00%	0.46%	13.89%	17.59%	18.98%	19.44%	30.09%	24.07%	45.83%	61.57%	0.00%
		40%	0.00%	0.46%	13.89%	17.59%	18.98%	19.44%	28.70%	23.61%	44.44%	60.19%	0.00%
		35%	0.00%	0.46%	13.43%	17.13%	18.52%	18.98%	27.78%	23.15%	41.67%	57.41%	0.00%
	DRAWUP LEVEL (into Equities)	30%	0.00%	0.46%	12.50%	16.20%	17.59%	18.06%	26.85%	22.22%	39.81%	52.78%	0.00%
		25%	0.00%	0.46%	12.50%	16.20%	17.59%	18.06%	26.39%	22.22%	38.89%	51.39%	0.00%
		20%	0.00%	0.46%	12.50%	16.20%	17.59%	18.06%	24.07%	21.76%	36.11%	49.54%	0.00%
		15%	0.00%	0.46%	11.57%	15.28%	16.67%	17.13%	22.22%	20.83%	33.80%	43.52%	0.00%
		10%	0.00%	0.46%	8.33%	13.43%	8.80%	9.26%	13.89%	12.50%	20.83%	29.17%	0.00%
		5%	0.00%	0.46%	3.70%	5.56%	4.17%	4.63%	7.87%	3.70%	10.19%	16.67%	0.00%
	0%	0.00%	0.46%	1.85%	3.70%	1.85%	2.31%	4.63%	2.78%	6.94%	8.80%	0.00%	

Table K.1.6 Maximum Drawdown

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	-48.76%	-48.76%	-46.31%	-40.87%	-35.87%	-30.12%	-30.12%	-22.15%	-18.73%	-16.88%	-48.76%
		45%	-48.76%	-48.76%	-44.72%	-40.87%	-33.97%	-30.12%	-30.12%	-22.15%	-18.37%	-16.88%	-48.76%
		40%	-48.76%	-48.76%	-44.72%	-40.87%	-33.97%	-30.12%	-30.12%	-19.59%	-18.37%	-13.63%	-48.76%
		35%	-48.76%	-48.76%	-42.46%	-40.87%	-33.60%	-30.12%	-30.12%	-19.59%	-18.37%	-13.63%	-48.76%
	DRAWUP LEVEL (into Equities)	30%	-48.76%	-48.76%	-42.46%	-40.87%	-33.60%	-30.12%	-30.12%	-19.59%	-18.37%	-13.63%	-48.76%
		25%	-48.76%	-48.76%	-42.46%	-40.87%	-33.60%	-30.12%	-30.12%	-19.59%	-18.37%	-13.63%	-48.76%
		20%	-48.76%	-48.76%	-42.46%	-40.87%	-33.60%	-30.12%	-30.12%	-19.59%	-18.37%	-13.63%	-48.76%
		15%	-48.76%	-48.76%	-42.46%	-40.87%	-33.60%	-30.12%	-30.12%	-19.59%	-18.37%	-13.63%	-48.76%
		10%	-48.76%	-48.76%	-49.53%	-40.87%	-40.82%	-35.33%	-30.12%	-25.01%	-25.01%	-21.75%	-48.76%
		5%	-48.76%	-48.76%	-48.35%	-41.88%	-41.41%	-35.96%	-36.71%	-45.13%	-45.13%	-38.26%	-48.76%
	0%	-48.76%	-48.76%	-47.53%	-41.31%	-46.19%	-41.19%	-41.88%	-45.65%	-45.65%	-38.84%	-48.76%	

Table K.1.7 Number of Signals

		DRAWDOWN LEVEL (into Cash)												
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%		
CASH:	100%	50%	0	1	2	2	2	2	3	3	5	7	0	
		45%	0	1	2	2	2	2	3	3	5	7	0	
		40%	0	1	2	2	2	2	3	3	5	7	0	
		35%	0	1	2	2	2	2	3	3	5	7	0	
	DRAWUP LEVEL (into Equities)	30%	0	1	2	2	2	2	2	3	3	5	7	0
		25%	0	1	2	2	2	2	2	3	3	5	8	0
		20%	0	1	2	2	2	2	2	3	3	5	8	0
		15%	0	1	2	2	2	2	2	3	3	5	9	0
		10%	0	1	3	3	2	2	2	3	3	7	11	0
		5%	0	1	3	3	2	2	2	4	3	7	12	0
	0%	0	1	3	4	2	2	5	3	9	12	0		

Table K.2.1 Annualised Geometric Return

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	18.96%	14.52%	13.93%	14.37%	15.06%	15.35%	14.44%	15.16%	13.66%	10.98%	14.77%
		45%	14.77%	14.52%	14.02%	14.46%	15.15%	15.44%	14.81%	15.26%	13.83%	11.38%	14.77%
		40%	14.77%	14.52%	14.02%	14.46%	15.15%	15.44%	14.84%	15.53%	14.30%	11.80%	14.77%
		35%	14.77%	14.52%	14.22%	14.66%	15.35%	15.65%	15.17%	15.73%	14.59%	12.25%	14.77%
		30%	14.77%	14.52%	14.36%	14.80%	15.50%	15.79%	15.31%	15.88%	14.87%	13.60%	14.77%
DRAWUP LEVEL (into Equities)	25%	14.77%	14.52%	14.36%	14.80%	15.50%	15.79%	15.46%	15.88%	15.23%	13.55%	14.77%	
	20%	14.77%	14.52%	14.36%	14.80%	15.50%	15.79%	15.59%	16.35%	15.74%	14.13%	14.77%	
	15%	14.77%	14.52%	14.74%	15.18%	15.88%	16.17%	16.13%	16.73%	16.39%	15.33%	14.77%	
	10%	14.77%	14.52%	14.37%	15.27%	15.77%	16.06%	16.06%	16.80%	15.88%	15.38%	14.77%	
	5%	14.77%	14.52%	14.69%	15.37%	15.73%	16.02%	15.94%	15.76%	15.31%	15.11%	14.77%	
	0%	14.77%	14.52%	14.81%	15.30%	15.45%	15.74%	15.53%	15.72%	15.26%	15.47%	14.77%	

Table K.2.2 Annualised Standard Deviation

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	18.96%	18.90%	18.24%	18.10%	17.71%	17.61%	16.94%	16.28%	15.09%	12.55%	18.96%
		45%	18.96%	18.90%	18.24%	18.10%	17.71%	17.62%	17.03%	16.29%	15.29%	12.71%	18.96%
		40%	18.96%	18.90%	18.24%	18.10%	17.71%	17.62%	17.10%	16.38%	15.42%	12.86%	18.96%
		35%	18.96%	18.90%	18.28%	18.14%	17.75%	17.65%	17.16%	16.43%	15.49%	12.97%	18.96%
		30%	18.96%	18.90%	18.28%	18.14%	17.76%	17.66%	17.16%	16.43%	15.50%	14.01%	18.96%
DRAWUP LEVEL (into Equities)	25%	18.96%	18.90%	18.28%	18.14%	17.76%	17.66%	17.18%	16.43%	15.61%	14.12%	18.96%	
	20%	18.96%	18.90%	18.28%	18.14%	17.76%	17.66%	17.29%	16.75%	16.02%	14.51%	18.96%	
	15%	18.96%	18.90%	18.38%	18.24%	17.85%	17.76%	17.42%	16.85%	16.16%	15.13%	18.96%	
	10%	18.96%	18.90%	18.53%	18.25%	18.14%	18.05%	17.72%	17.19%	16.83%	15.89%	18.96%	
	5%	18.96%	18.90%	18.61%	18.43%	18.26%	18.17%	17.99%	17.71%	17.42%	16.80%	18.96%	
	0%	18.96%	18.90%	18.67%	18.52%	18.37%	18.28%	18.15%	17.85%	17.60%	17.21%	18.96%	

Table K.2.3 5% Value at Risk (VaR)

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	-8.10%	-8.10%	-7.37%	-7.28%	-7.28%	-7.01%	-6.92%	-6.90%	-6.24%	-5.46%	-8.10%
		45%	-8.10%	-8.10%	-7.37%	-7.28%	-7.28%	-7.01%	-6.92%	-6.90%	-6.61%	-5.46%	-8.10%
		40%	-8.10%	-8.10%	-7.37%	-7.28%	-7.28%	-7.01%	-6.92%	-6.90%	-6.61%	-5.46%	-8.10%
		35%	-8.10%	-8.10%	-7.37%	-7.28%	-7.28%	-7.01%	-6.92%	-6.90%	-6.61%	-5.46%	-8.10%
		30%	-8.10%	-8.10%	-7.37%	-7.28%	-7.28%	-7.01%	-6.92%	-6.90%	-6.61%	-5.46%	-8.10%
DRAWUP LEVEL (into Equities)	25%	-8.10%	-8.10%	-7.37%	-7.28%	-7.28%	-7.01%	-6.92%	-6.90%	-6.61%	-5.49%	-8.10%	
	20%	-8.10%	-8.10%	-7.37%	-7.28%	-7.28%	-7.01%	-6.92%	-6.90%	-6.61%	-5.49%	-8.10%	
	15%	-8.10%	-8.10%	-7.37%	-7.28%	-7.28%	-7.01%	-6.92%	-6.90%	-6.61%	-5.59%	-8.10%	
	10%	-8.10%	-8.10%	-7.59%	-7.28%	-7.50%	-7.28%	-7.01%	-6.92%	-6.92%	-6.24%	-8.10%	
	5%	-8.10%	-8.10%	-7.59%	-7.37%	-7.50%	-7.37%	-7.37%	-7.42%	-7.42%	-7.26%	-8.10%	
	0%	-8.10%	-8.10%	-7.59%	-7.37%	-7.50%	-7.37%	-7.37%	-7.50%	-7.50%	-7.37%	-8.10%	

Table K.2.4 Annualised Sharpe Ratio

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	57.35%	56.23%	55.02%	57.86%	63.06%	65.06%	62.28%	69.21%	64.71%	56.50%	57.35%
		45%	57.35%	56.23%	55.51%	58.36%	63.57%	65.57%	64.08%	69.75%	64.96%	58.89%	57.35%
		40%	57.35%	56.23%	55.51%	58.36%	63.57%	65.57%	63.98%	71.04%	67.49%	61.51%	57.35%
		35%	57.35%	56.23%	56.48%	59.34%	64.56%	66.57%	65.71%	72.09%	69.09%	64.46%	57.35%
		30%	57.35%	56.23%	57.26%	60.12%	65.37%	67.39%	66.54%	72.96%	70.81%	69.29%	57.35%
DRAWUP LEVEL (into Equities)	25%	57.35%	56.23%	57.26%	60.12%	65.37%	67.39%	67.30%	72.96%	72.65%	68.36%	57.35%	
	20%	57.35%	56.23%	57.26%	60.12%	65.37%	67.39%	67.64%	74.40%	73.98%	70.55%	57.35%	
	15%	57.35%	56.23%	59.00%	61.87%	67.13%	69.15%	70.27%	76.21%	77.35%	75.57%	57.35%	
	10%	57.35%	56.23%	56.53%	62.34%	65.46%	67.43%	68.68%	75.11%	71.24%	72.26%	57.35%	
	5%	57.35%	56.23%	58.06%	62.31%	64.82%	66.77%	66.95%	66.99%	65.56%	66.77%	57.35%	
	0%	57.35%	56.23%	58.48%	61.59%	62.90%	64.82%	64.13%	66.23%	64.59%	67.29%	57.35%	

Table K.2.5 Percentage of Months in Partial Cash

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	0.00%	0.46%	14.35%	18.06%	19.44%	19.91%	31.02%	24.54%	50.93%	63.89%	0.00%
		45%	0.00%	0.46%	13.89%	17.59%	18.98%	19.44%	30.09%	24.07%	45.83%	61.57%	0.00%
		40%	0.00%	0.46%	13.89%	17.59%	18.98%	19.44%	28.70%	23.61%	44.44%	60.19%	0.00%
		35%	0.00%	0.46%	13.43%	17.13%	18.52%	18.98%	27.78%	23.15%	41.67%	57.41%	0.00%
		30%	0.00%	0.46%	12.50%	16.20%	17.59%	18.06%	26.85%	22.22%	39.81%	52.78%	0.00%
DRAWUP LEVEL (into Equities)	25%	0.00%	0.46%	12.50%	16.20%	17.59%	18.06%	26.39%	22.22%	38.89%	51.39%	0.00%	
	20%	0.00%	0.46%	12.50%	16.20%	17.59%	18.06%	24.07%	21.76%	36.11%	49.54%	0.00%	
	15%	0.00%	0.46%	11.57%	15.28%	16.67%	17.13%	22.22%	20.83%	33.80%	43.52%	0.00%	
	10%	0.00%	0.46%	8.33%	13.43%	8.80%	9.26%	13.89%	12.50%	20.83%	29.17%	0.00%	
	5%	0.00%	0.46%	3.70%	5.56%	4.17%	4.63%	7.87%	3.70%	10.19%	16.67%	0.00%	
	0%	0.00%	0.46%	1.85%	3.70%	1.85%	2.31%	4.63%	2.78%	6.94%	8.80%	0.00%	

Table K.2.6 Maximum Drawdown

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	-48.76%	-48.76%	-44.81%	-44.81%	-39.77%	-39.77%	-39.77%	-33.75%	-30.84%	-30.84%	-48.76%
		45%	-48.76%	-48.76%	-44.81%	-44.81%	-39.77%	-39.77%	-39.77%	-33.75%	-30.84%	-30.84%	-48.76%
		40%	-48.76%	-48.76%	-44.81%	-44.81%	-39.77%	-39.77%	-39.77%	-33.75%	-30.84%	-30.84%	-48.76%
		35%	-48.76%	-48.76%	-44.81%	-44.81%	-39.77%	-39.77%	-39.77%	-33.75%	-30.84%	-30.84%	-48.76%
		30%	-48.76%	-48.76%	-44.81%	-44.81%	-39.77%	-39.77%	-39.77%	-33.75%	-30.84%	-30.84%	-48.76%
DRAWUP LEVEL (into Equities)	25%	-48.76%	-48.76%	-44.81%	-44.81%	-39.77%	-39.77%	-39.77%	-33.75%	-30.84%	-30.84%	-48.76%	
	20%	-48.76%	-48.76%	-44.81%	-44.81%	-39.77%	-39.77%	-39.77%	-33.75%	-30.84%	-30.84%	-48.76%	
	15%	-48.76%	-48.76%	-44.81%	-44.81%	-39.77%	-39.77%	-39.77%	-33.75%	-30.84%	-30.84%	-48.76%	
	10%	-48.76%	-48.76%	-46.90%	-44.81%	-42.48%	-39.81%	-39.77%	-34.96%	-35.52%	-35.52%	-48.76%	
	5%	-48.76%	-48.76%	-45.74%	-44.81%	-42.84%	-40.18%	-40.47%	-44.67%	-44.67%	-41.20%	-48.76%	
	0%	-48.76%	-48.76%	-45.96%	-44.81%	-45.28%	-42.74%	-43.01%	-45.01%	-45.01%	-41.57%	-48.76%	

Table K.2.7 Number of Signals

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	0	1	2	2	2	2	3	3	5	7	0
		45%	0	1	2	2	2	2	3	3	5	7	0
		40%	0	1	2	2	2	2	3	3	5	7	0
		35%	0	1	2	2	2	2	3	3	5	7	0
		30%	0	1	2	2	2	2	3	3	5	7	0
DRAWUP LEVEL (into Equities)	25%	0	1	2	2	2	2	2	3	3	5	8	0
	20%	0	1	2	2	2	2	2	3	3	5	8	0
	15%	0	1	2	2	2	2	2	3	3	5	9	0
	10%	0	1	3	3	2	2	2	3	3	7	11	0
	5%	0	1	3	3	2	2	2	4	3	7	12	0
	0%	0	1	3	4	2	2	5	3	9	12	0	

Appendix L: Cash Protection on the Global Value Proxy

L: 1

Table L.1.1 Annualised Geometric Return

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	12.58%	13.47%	13.47%	13.47%	15.18%	15.18%	13.20%	11.11%	12.24%	6.66%	13.27%
		45%	12.58%	13.47%	13.47%	13.47%	15.18%	15.18%	13.68%	11.73%	12.86%	7.07%	13.27%
		40%	12.58%	13.47%	13.47%	13.47%	15.18%	15.18%	13.93%	11.97%	13.10%	7.56%	13.27%
		35%	12.58%	13.47%	13.47%	13.47%	15.18%	15.18%	14.11%	12.61%	13.74%	9.01%	13.27%
	DRAWUP LEVEL (into Equities)	30%	12.58%	13.47%	13.47%	13.47%	15.18%	15.18%	14.28%	12.96%	14.10%	9.65%	13.27%
		25%	12.58%	13.47%	13.47%	13.47%	15.18%	15.18%	14.66%	13.59%	13.48%	10.41%	13.27%
		20%	12.58%	13.47%	13.47%	13.47%	15.18%	15.18%	14.90%	12.65%	13.13%	10.77%	13.27%
		15%	12.58%	13.47%	13.47%	13.47%	15.18%	15.18%	14.90%	12.98%	13.64%	11.82%	13.27%
		10%	12.58%	13.47%	13.47%	13.47%	15.18%	15.18%	15.36%	13.54%	14.65%	13.29%	13.27%
		5%	12.58%	13.47%	13.47%	13.47%	15.18%	15.18%	15.36%	14.01%	13.50%	9.76%	13.27%
		0%	12.58%	13.47%	13.47%	13.47%	15.18%	15.18%	15.36%	14.01%	13.69%	10.35%	13.27%

Table L.1.2 Annualised Standard Deviation

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	16.34%	15.99%	15.99%	15.99%	14.89%	14.89%	14.07%	11.91%	10.26%	7.91%	16.52%
		45%	16.34%	15.99%	15.99%	15.99%	14.89%	14.89%	14.16%	12.09%	10.46%	8.43%	16.52%
		40%	16.34%	15.99%	15.99%	15.99%	14.89%	14.89%	14.17%	12.11%	10.48%	8.50%	16.52%
		35%	16.34%	15.99%	15.99%	15.99%	14.89%	14.89%	14.17%	12.22%	10.61%	8.86%	16.52%
	DRAWUP LEVEL (into Equities)	30%	16.34%	15.99%	15.99%	15.99%	14.89%	14.89%	14.18%	12.33%	10.73%	9.18%	16.52%
		25%	16.34%	15.99%	15.99%	15.99%	14.89%	14.89%	14.19%	12.36%	11.48%	9.48%	16.52%
		20%	16.34%	15.99%	15.99%	15.99%	14.89%	14.89%	14.20%	13.14%	11.95%	10.19%	16.52%
		15%	16.34%	15.99%	15.99%	15.99%	14.89%	14.89%	14.20%	13.19%	12.02%	10.39%	16.52%
		10%	16.34%	15.99%	15.99%	15.99%	14.89%	14.89%	14.28%	13.38%	12.63%	11.48%	16.52%
		5%	16.34%	15.99%	15.99%	15.99%	14.89%	14.89%	14.28%	13.41%	13.42%	14.86%	16.52%
		0%	16.34%	15.99%	15.99%	15.99%	14.89%	14.89%	14.28%	13.41%	13.43%	14.91%	16.52%

Table L.1.3 5% Value at Risk (VaR)

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	-5.58%	-5.12%	-5.12%	-5.12%	-4.80%	-4.80%	-4.68%	-4.27%	-3.59%	-2.76%	-5.58%
		45%	-5.58%	-5.12%	-5.12%	-5.12%	-4.80%	-4.80%	-4.68%	-4.27%	-3.59%	-3.26%	-5.58%
		40%	-5.58%	-5.12%	-5.12%	-5.12%	-4.80%	-4.80%	-4.68%	-4.27%	-3.59%	-3.26%	-5.58%
		35%	-5.58%	-5.12%	-5.12%	-5.12%	-4.80%	-4.80%	-4.68%	-4.27%	-3.59%	-3.26%	-5.58%
	DRAWUP LEVEL (into Equities)	30%	-5.58%	-5.12%	-5.12%	-5.12%	-4.80%	-4.80%	-4.68%	-4.27%	-3.59%	-3.26%	-5.58%
		25%	-5.58%	-5.12%	-5.12%	-5.12%	-4.80%	-4.80%	-4.68%	-4.27%	-3.80%	-3.46%	-5.58%
		20%	-5.58%	-5.12%	-5.12%	-5.12%	-4.80%	-4.80%	-4.68%	-4.68%	-4.06%	-3.59%	-5.58%
		15%	-5.58%	-5.12%	-5.12%	-5.12%	-4.80%	-4.80%	-4.68%	-4.68%	-4.06%	-3.59%	-5.58%
		10%	-5.58%	-5.12%	-5.12%	-5.12%	-4.80%	-4.80%	-4.68%	-4.68%	-4.27%	-3.80%	-5.58%
		5%	-5.58%	-5.12%	-5.12%	-5.12%	-4.80%	-4.80%	-4.68%	-4.68%	-4.64%	-4.80%	-5.58%
		0%	-5.58%	-5.12%	-5.12%	-5.12%	-4.80%	-4.80%	-4.68%	-4.68%	-4.64%	-4.80%	-5.58%

Table L.1.4 Annualised Sharpe Ratio

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	53.18%	59.87%	59.87%	59.87%	75.79%	75.79%	66.19%	60.62%	81.33%	34.92%	56.73%
		45%	53.18%	59.87%	59.87%	59.87%	75.79%	75.79%	69.15%	64.83%	85.73%	37.71%	56.73%
		40%	53.18%	59.87%	59.87%	59.87%	75.79%	75.79%	70.82%	66.73%	87.89%	43.09%	56.73%
		35%	53.18%	59.87%	59.87%	59.87%	75.79%	75.79%	72.09%	71.30%	92.87%	57.72%	56.73%
	DRAWUP LEVEL (into Equities)	30%	53.18%	59.87%	59.87%	59.87%	75.79%	75.79%	73.25%	73.54%	95.13%	62.72%	56.73%
		25%	53.18%	59.87%	59.87%	59.87%	75.79%	75.79%	75.87%	78.47%	83.54%	68.76%	56.73%
		20%	53.18%	59.87%	59.87%	59.87%	75.79%	75.79%	77.49%	66.65%	77.30%	67.43%	56.73%
		15%	53.18%	59.87%	59.87%	59.87%	75.79%	75.79%	77.49%	68.89%	81.12%	76.32%	56.73%
		10%	53.18%	59.87%	59.87%	59.87%	75.79%	75.79%	80.31%	72.06%	85.19%	81.86%	56.73%
		5%	53.18%	59.87%	59.87%	59.87%	75.79%	75.79%	80.31%	75.45%	71.59%	39.49%	56.73%
		0%	53.18%	59.87%	59.87%	59.87%	75.79%	75.79%	80.31%	75.45%	72.99%	43.31%	56.73%

Table L.1.5 Percentage of Months in Cash

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	0.46%	0.93%	0.93%	0.93%	1.39%	1.39%	6.48%	20.37%	31.94%	68.52%	0.00%
		45%	0.46%	0.93%	0.93%	0.93%	1.39%	1.39%	6.02%	18.06%	29.63%	62.96%	0.00%
		40%	0.46%	0.93%	0.93%	0.93%	1.39%	1.39%	5.56%	17.59%	29.17%	61.57%	0.00%
		35%	0.46%	0.93%	0.93%	0.93%	1.39%	1.39%	5.09%	16.67%	28.24%	57.87%	0.00%
	DRAWUP LEVEL (into Equities)	30%	0.46%	0.93%	0.93%	0.93%	1.39%	1.39%	4.63%	15.28%	26.85%	52.78%	0.00%
		25%	0.46%	0.93%	0.93%	0.93%	1.39%	1.39%	3.70%	13.43%	20.83%	46.30%	0.00%
		20%	0.46%	0.93%	0.93%	0.93%	1.39%	1.39%	3.24%	10.19%	17.59%	39.35%	0.00%
		15%	0.46%	0.93%	0.93%	0.93%	1.39%	1.39%	3.24%	9.72%	15.74%	36.11%	0.00%
		10%	0.46%	0.93%	0.93%	0.93%	1.39%	1.39%	2.78%	6.48%	9.26%	23.61%	0.00%
		5%	0.46%	0.93%	0.93%	0.93%	1.39%	1.39%	2.78%	5.56%	6.94%	11.57%	0.00%
		0%	0.46%	0.93%	0.93%	0.93%	1.39%	1.39%	2.78%	5.56%	6.48%	9.26%	0.00%

Table L.1.6 Maximum Drawdown

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	-54.58%	-47.72%	-47.72%	-47.72%	-31.63%	-31.63%	-20.94%	-23.89%	-19.13%	-16.36%	-54.58%
		45%	-54.58%	-47.72%	-47.72%	-47.72%	-31.63%	-31.63%	-20.94%	-22.07%	-17.20%	-14.36%	-54.58%
		40%	-54.58%	-47.72%	-47.72%	-47.72%	-31.63%	-31.63%	-20.94%	-22.07%	-17.20%	-14.36%	-54.58%
		35%	-54.58%	-47.72%	-47.72%	-47.72%	-31.63%	-31.63%	-20.94%	-19.73%	-14.01%	-14.01%	-54.58%
	DRAWUP LEVEL (into Equities)	30%	-54.58%	-47.72%	-47.72%	-47.72%	-31.63%	-31.63%	-20.94%	-19.85%	-14.85%	-14.85%	-54.58%
		25%	-54.58%	-47.72%	-47.72%	-47.72%	-31.63%	-31.63%	-20.94%	-19.73%	-20.18%	-14.01%	-54.58%
		20%	-54.58%	-47.72%	-47.72%	-47.72%	-31.63%	-31.63%	-20.94%	-29.90%	-26.14%	-16.00%	-54.58%
		15%	-54.58%	-47.72%	-47.72%	-47.72%	-31.63%	-31.63%	-20.94%	-29.90%	-25.97%	-16.00%	-54.58%
		10%	-54.58%	-47.72%	-47.72%	-47.72%	-31.63%	-31.63%	-20.94%	-28.42%	-29.31%	-24.35%	-54.58%
		5%	-54.58%	-47.72%	-47.72%	-47.72%	-31.63%	-31.63%	-20.94%	-22.83%	-32.14%	-55.97%	-54.58%
		0%	-54.58%	-47.72%	-47.72%	-47.72%	-31.63%	-31.63%	-20.94%	-22.83%	-32.14%	-54.61%	-54.58%

Table L.1.7 Number of Signals

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	100%	50%	1	1	1	1	1	1	2	3	3	5	0
		45%	1	1	1	1	1	1	2	3	3	6	0
		40%	1	1	1	1	1	1	2	3	3	6	0
		35%	1	1	1	1	1	1	2	3	3	6	0
	DRAWUP LEVEL (into Equities)	30%	1	1	1	1	1	1	2	3	3	6	0
		25%	1	1	1	1	1	1	2	3	4	7	0
		20%	1	1	1	1	1	1	2	4	5	8	0
		15%	1	1	1	1	1	1	2	4	5	8	0
		10%	1	1	1	1	1	1	2	5	5	9	0
		5%	1	1	1	1	1	1	2	5	7	11	0
		0%	1	1	1	1	1	1	2	5	7	12	0

Table L.2.1 Annualised Geometric Return

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	12.93%	13.39%	13.39%	13.39%	14.30%	14.30%	13.36%	12.38%	13.00%	10.22%	13.27%
		45%	12.93%	13.39%	13.39%	13.39%	14.30%	14.30%	13.59%	12.69%	13.31%	10.42%	13.27%
		40%	12.93%	13.39%	13.39%	13.39%	14.30%	14.30%	13.71%	12.81%	13.43%	10.67%	13.27%
		35%	12.93%	13.39%	13.39%	13.39%	14.30%	14.30%	13.80%	13.12%	13.74%	11.40%	13.27%
		30%	12.93%	13.39%	13.39%	13.39%	14.30%	14.30%	13.88%	13.30%	13.92%	11.72%	13.27%
DRAWUP LEVEL (into Equities)	25%	25%	12.93%	13.39%	13.39%	13.39%	14.30%	14.30%	14.07%	13.61%	13.58%	12.10%	13.27%
		20%	12.93%	13.39%	13.39%	13.39%	14.30%	14.30%	14.19%	13.11%	13.39%	12.26%	13.27%
		15%	12.93%	13.39%	13.39%	13.39%	14.30%	14.30%	14.19%	13.27%	13.65%	12.79%	13.27%
		10%	12.93%	13.39%	13.39%	13.39%	14.30%	14.30%	14.42%	13.54%	14.13%	13.49%	13.27%
		5%	12.93%	13.39%	13.39%	13.39%	14.30%	14.30%	14.42%	13.78%	13.52%	11.57%	13.27%
	0%	12.93%	13.39%	13.39%	13.39%	14.30%	14.30%	14.42%	13.78%	13.62%	11.87%	13.27%	

Table L.2.2 Annualised Standard Deviation

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	16.37%	16.13%	16.13%	16.13%	15.34%	15.34%	14.71%	13.19%	12.11%	10.70%	16.52%
		45%	16.37%	16.13%	16.13%	16.13%	15.34%	15.34%	14.78%	13.31%	12.25%	10.99%	16.52%
		40%	16.37%	16.13%	16.13%	16.13%	15.34%	15.34%	14.80%	13.33%	12.27%	11.03%	16.52%
		35%	16.37%	16.13%	16.13%	16.13%	15.34%	15.34%	14.80%	13.41%	12.36%	11.24%	16.52%
		30%	16.37%	16.13%	16.13%	16.13%	15.34%	15.34%	14.81%	13.49%	12.45%	11.43%	16.52%
DRAWUP LEVEL (into Equities)	25%	25%	16.37%	16.13%	16.13%	16.13%	15.34%	15.34%	14.83%	13.52%	12.93%	11.62%	16.52%
		20%	16.37%	16.13%	16.13%	16.13%	15.34%	15.34%	14.84%	14.05%	13.24%	12.06%	16.52%
		15%	16.37%	16.13%	16.13%	16.13%	15.34%	15.34%	14.84%	14.09%	13.29%	12.19%	16.52%
		10%	16.37%	16.13%	16.13%	16.13%	15.34%	15.34%	14.90%	14.23%	13.73%	12.92%	16.52%
		5%	16.37%	16.13%	16.13%	16.13%	15.34%	15.34%	14.90%	14.26%	14.26%	15.26%	16.52%
	0%	16.37%	16.13%	16.13%	16.13%	15.34%	15.34%	14.90%	14.26%	14.27%	15.30%	16.52%	

Table L.2.3 5% Value at Risk (VaR)

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.38%	-5.08%	-4.47%	-5.58%
		45%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.38%	-5.08%	-4.75%	-5.58%
		40%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.38%	-5.08%	-4.75%	-5.58%
		35%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.38%	-5.08%	-4.75%	-5.58%
		30%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.38%	-5.08%	-4.75%	-5.58%
DRAWUP LEVEL (into Equities)	25%	25%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.38%	-5.08%	-4.80%	-5.58%
		20%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.38%	-5.08%	-4.80%	-5.58%
		15%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.08%	-4.80%	-5.58%
		10%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.08%	-4.80%	-5.58%
		5%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.19%	-5.19%	-5.58%
	0%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.58%	-5.19%	-5.19%	-5.58%	

Table L.2.4 Annualised Sharpe Ratio

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	55.21%	58.90%	58.90%	58.90%	67.84%	67.84%	64.32%	64.38%	75.19%	59.10%	56.73%
		45%	55.21%	58.90%	58.90%	58.90%	67.84%	67.84%	65.60%	66.06%	76.85%	59.38%	56.73%
		40%	55.21%	58.90%	58.90%	58.90%	67.84%	67.84%	66.36%	66.89%	77.73%	61.42%	56.73%
		35%	55.21%	58.90%	58.90%	58.90%	67.84%	67.84%	66.94%	68.81%	79.71%	66.82%	56.73%
		30%	55.21%	58.90%	58.90%	58.90%	67.84%	67.84%	67.48%	69.69%	80.57%	68.50%	56.73%
DRAWUP LEVEL (into Equities)	25%	25%	55.21%	58.90%	58.90%	58.90%	67.84%	67.84%	68.67%	71.86%	74.98%	70.64%	56.73%
		20%	55.21%	58.90%	58.90%	58.90%	67.84%	67.84%	69.40%	65.59%	71.76%	69.36%	56.73%
		15%	55.21%	58.90%	58.90%	58.90%	67.84%	67.84%	69.40%	66.57%	73.39%	72.94%	56.73%
		10%	55.21%	58.90%	58.90%	58.90%	67.84%	67.84%	70.62%	67.79%	74.56%	74.25%	56.73%
		5%	55.21%	58.90%	58.90%	58.90%	67.84%	67.84%	70.62%	69.31%	67.52%	50.33%	56.73%
	0%	55.21%	58.90%	58.90%	58.90%	67.84%	67.84%	70.62%	69.31%	68.16%	52.13%	56.73%	

Table L.2.5 Percentage of Months in Partial Cash

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	0.46%	0.93%	0.93%	0.93%	1.39%	1.39%	6.48%	20.37%	31.94%	68.52%	0.00%
		45%	0.46%	0.93%	0.93%	0.93%	1.39%	1.39%	6.02%	18.06%	29.63%	62.96%	0.00%
		40%	0.46%	0.93%	0.93%	0.93%	1.39%	1.39%	5.56%	17.59%	29.17%	61.57%	0.00%
		35%	0.46%	0.93%	0.93%	0.93%	1.39%	1.39%	5.09%	16.67%	28.24%	57.87%	0.00%
		30%	0.46%	0.93%	0.93%	0.93%	1.39%	1.39%	4.63%	15.28%	26.85%	52.78%	0.00%
DRAWUP LEVEL (into Equities)	25%	25%	0.46%	0.93%	0.93%	0.93%	1.39%	1.39%	3.70%	13.43%	20.83%	46.30%	0.00%
		20%	0.46%	0.93%	0.93%	0.93%	1.39%	1.39%	3.24%	10.19%	17.59%	39.35%	0.00%
		15%	0.46%	0.93%	0.93%	0.93%	1.39%	1.39%	3.24%	9.72%	15.74%	36.11%	0.00%
		10%	0.46%	0.93%	0.93%	0.93%	1.39%	1.39%	2.78%	6.48%	9.26%	23.61%	0.00%
		5%	0.46%	0.93%	0.93%	0.93%	1.39%	1.39%	2.78%	5.56%	6.94%	11.57%	0.00%
	0%	0.46%	0.93%	0.93%	0.93%	1.39%	1.39%	2.78%	5.56%	6.48%	9.26%	0.00%	

Table L.2.6 Maximum Drawdown

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	-54.58%	-51.15%	-51.15%	-51.15%	-43.61%	-43.61%	-39.16%	-38.65%	-35.01%	-35.01%	-54.58%
		45%	-54.58%	-51.15%	-51.15%	-51.15%	-43.61%	-43.61%	-39.16%	-38.65%	-35.01%	-35.01%	-54.58%
		40%	-54.58%	-51.15%	-51.15%	-51.15%	-43.61%	-43.61%	-39.16%	-38.65%	-35.01%	-35.01%	-54.58%
		35%	-54.58%	-51.15%	-51.15%	-51.15%	-43.61%	-43.61%	-39.16%	-38.65%	-35.01%	-35.01%	-54.58%
		30%	-54.58%	-51.15%	-51.15%	-51.15%	-43.61%	-43.61%	-39.16%	-38.65%	-35.01%	-35.01%	-54.58%
DRAWUP LEVEL (into Equities)	25%	25%	-54.58%	-51.15%	-51.15%	-51.15%	-43.61%	-43.61%	-39.16%	-38.65%	-35.01%	-35.01%	-54.58%
		20%	-54.58%	-51.15%	-51.15%	-51.15%	-43.61%	-43.61%	-39.16%	-38.65%	-35.01%	-35.01%	-54.58%
		15%	-54.58%	-51.15%	-51.15%	-51.15%	-43.61%	-43.61%	-39.16%	-38.65%	-35.01%	-35.01%	-54.58%
		10%	-54.58%	-51.15%	-51.15%	-51.15%	-43.61%	-43.61%	-39.16%	-38.65%	-35.01%	-35.01%	-54.58%
		5%	-54.58%	-51.15%	-51.15%	-51.15%	-43.61%	-43.61%	-39.16%	-38.65%	-39.58%	-55.27%	-54.58%
	0%	-54.58%	-51.15%	-51.15%	-51.15%	-43.61%	-43.61%	-39.16%	-38.65%	-38.66%	-54.59%	-54.58%	

Table L.2.7 Number of Signals

		DRAWDOWN LEVEL (into Cash)											
		-50%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	
CASH:	50%	50%	1	1	1	1	1	1	2	3	3	5	0
		45%	1	1	1	1	1	1	2	3	3	6	0
		40%	1	1	1	1	1	1	2	3	3	6	0
		35%	1	1	1	1	1	1	2	3	3	6	0
		30%	1	1	1	1	1	1	2	3	3	6	0
DRAWUP LEVEL (into Equities)	25%	25%	1	1	1	1	1	1	2	3	4	7	0
		20%	1	1	1	1	1	1	2	4	5	8	0
		15%	1	1	1	1	1	1	2	4	5	8	0
		10%	1	1	1	1	1	1	2	5	5	9	0
		5%	1	1	1	1	1	1	2	5	7	11	0
	0%	1	1	1	1	1	1	2	5	7	12	0	

